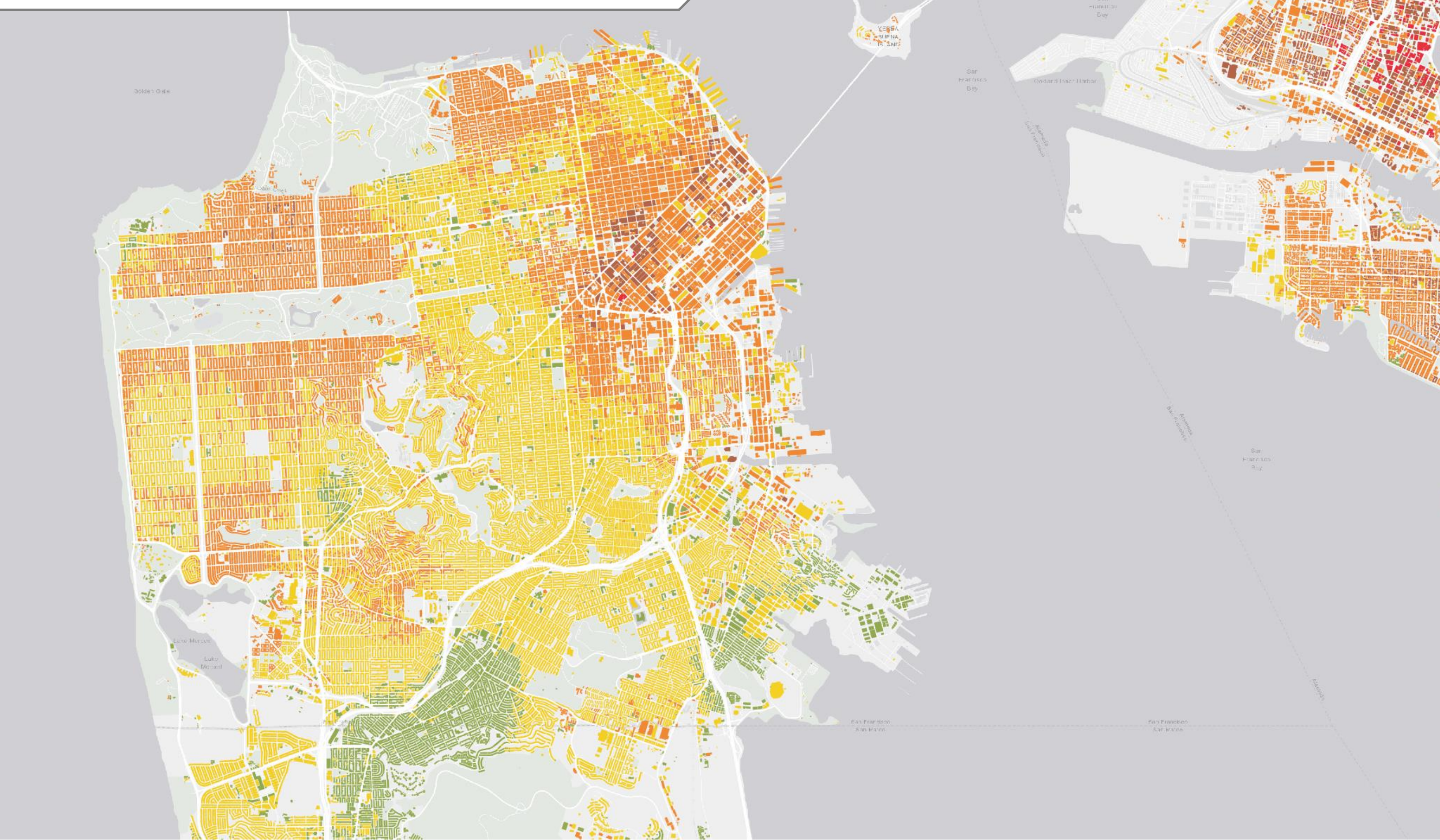
SimCenter NHERI
Center for Computational Modeling and Simulation

Report No. 2021-01
DOI: 10.5281/zenodo.2579581

State of the Art in Computational Simulation for Natural Hazards Engineering

Second Edition
February 2021

Edited by:
Gregory G. Deierlein
Adam Zsarnóczay



Preface

This report is a product of the NHERI SimCenter under the auspices of the U.S. National Science Foundation (NSF). It provides an overview and review of simulation requirements and software tools for natural hazards engineering (NHE) of the built environment. The simulations discussed in this report are an essential component of research to address the three grand challenge areas and associated research questions outlined in the NHERI Science Plan (Edge et al., 2020). These grand challenges entail: (1) identifying and quantifying the characteristics of natural hazards that are damaging to civil infrastructure and disruptive to communities; (2) evaluating the physical vulnerability of civil infrastructure and the social vulnerability of populations in at-risk communities; and (3) creation of technologies and tools to design, retrofit, and operate a resilient and sustainable infrastructure for the Nation. Accordingly, required simulation technologies encompass a broad range of phenomena and considerations, from characterization and simulation of natural hazards and their damaging effects on buildings and civil infrastructure, to quantifying the resulting economic losses, disruption, and other consequences on society. Ultimately, the goal is to enable high-fidelity and high-resolution models in regional simulations that can support technological, economic, and policy solutions to mitigate the threat of natural hazards.

The natural hazards addressed in this report include earthquakes, tsunami, storm and tornado winds, and storm surge. While not an exhaustive list of all possible natural hazards, these are the hazards addressed under NSF's NHERI research program. The first chapter of the report provides an introduction to the SimCenter and its goals, including an overview of the plans and status for software tool development. The subsequent chapters of the report are organized into five parts in a sequential fashion, including: (1) simulation methods to characterize the natural hazards; (2) response simulation of structural and geotechnical systems and localized wind and water flows; (3) quantifying the resulting damage and its effects on the performance of buildings, transportation systems, and utility infrastructure systems; (4) strategies and emerging tools to model recovery from natural disasters; and (5) the cross-cutting applications of uncertainty quantification methods and artificial intelligence to NHE.

Owing to the broad scope of the simulation topics, this review of the state of the art is presented with the goal of educating and informing researchers—including both simulation tool developers and users—on key requirements and capabilities within each simulation topic. The report is also a guide to the on-going development of simulation capabilities by the NSF NHERI SimCenter. Each chapter of the report begins with a brief overview of the purpose of the simulation component, including a discussion of the goals of the analysis (what is being calculated), the underlying physics or principles involved in the simulation, common modeling assumptions and simplifications, and typical input and output of the simulations.

With the aim of taking stock of computational simulation capabilities, informing the NHERI community of research advances to date, and positioning the work of the NHERI SimCenter as it relates to computational simulation, the summaries identify and review commonly used simulation software that is widely known and used for research in academia and industry. Particular emphasis is placed on open-source or other software that is hosted on DesignSafe or is otherwise easily accessible to researchers. Summary tables of the simulation software tools is provided as an appendix to the report. In addition to summarizing the state of the art in the various topic areas, each chapter of the report identifies major research gaps and needs, with the intent that these could motivate research proposals to NSF or other agencies that will lead to future advancements.

This report is an update to a State of Art Report that the SimCenter first published in February 2019. This update reflects comments and suggestions that were solicited from leading researchers in NHE. It includes new chapters on disaster recovery modeling and applications of artificial intelligence technologies to NHE. Readers are encouraged to contribute feedback regarding this report and the SimCenter simulation tool development through the online SimCenter Forum at http://simcenter-messageboard.designsafe-ci.org/smf/.

Stanford University, *Gregory G. Deierlein*
February, 2021 *Adam Zsarnóczay*

Acknowledgments

This report is the result of concerted effort by more than 50 experts in the field of Natural Hazards Engineering. The editors are grateful for every contribution, feedback, and suggestion received since the first edition of the report was published in 2019. Special thanks are due to the twelve corresponding authors who organized and distilled content from various sources into 22 chapters. Finally, we would like to express our gratitude to Claire M. Johnson for editing and Claudio Perez for his invaluable help with formatting the document.

The identification of certain commercial systems and research tools in this report does not imply recommendation or endorsement by the National Science Foundation, the Computational Modeling and Simulation Center (SimCenter), or the academic institutions of contributing authors. Nor does such identification imply that those products are necessarily the best available for the task.

This material is based upon work supported by the National Science Foundation under Grant No. 1612843. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation or the Regents of the University of California.

Contents

List of Contributors

Pedro Arduino
Professor, University of Washington

Jack W. Baker
Professor, Stanford University

Jonathan D. Bray
Professor, University of California, Berkeley

Henry Burton
Associate Professor, University of California, Los Angeles

Luis Ceferino
Assistant Professor, New York University

Barbaros Cetiner
Postdoctoral Researcher, University of California, Los Angeles

Arindam G. Chowdhury
Professor, Florida International University

Joel P. Conte
Professor, University of California, San Diego

Rodrigo Costa
Postdoctoral Researcher, Stanford University

Brady Cox
Professor, Utah State University, Logan

Craig A. Davis
Independent Consultant, CA Davis Engineering

Gregory G. Deierlein
Professor, Stanford University

George Deodatis
Professor, Columbia University

Wael Elhaddad
Postdoctoral Researcher, University of California, Berkeley

Ann-Margaret Esnard
Professor, Georgia State University

Michael Gardner
Assistant Professor, University of Nevada, Reno

Paolo Gardoni
Professor, University of Illinois, Urbana-Champaign

Catherine Gorlé
Assistant Professor, Stanford University

Sanjay Govindjee
Professor, University of California, Berkeley

Ajay B. Harish
Postdoctoral Researcher, University of California, Berkeley

Sascha Hornauer
Postdoctoral Researcher, University of California, Berkeley

Liang Hu
Graduate Research Assistant, University of Notre Dame

Peter A. Irwin
Professor, Florida International University

Boris Jeremic
Professor, University of California, Davis

Ahsan Kareem
Professor, University of Notre Dame

Tracy Kijewski-Correa
Associate Professor, University of Notre Dame

Seung Jae Lee
Associate Professor, Florida International University

Kincho H. Law
Professor, Stanford University

Rick Luettich
Professor, University of North Carolina, Chapel Hill

Lance Manuel
Professor, University of Texas, Austin

Forrest Masters
Professor, University of Florida

David McCallen
Professor, University of Nevada, Reno

Frank McKenna
Project Scientist, University of California, Berkeley

Michael Motley
Associate Professor, University of Washington

Thomas O'Rourke
Professor, Cornell University

Satish Rao
Professor, University of California, Berkeley

Aakash B. Satish
Postdoctoral Researcher, University of California, Berkeley

Paneer Selvam
Professor, University of Arkansas

Michael D. Shields
Associate Professor, Johns Hopkins University

Rodrigo Silva-Lopez
Graduate Student, Stanford University

Vesna Terzic
Associate Professor, California State University, Long Beach

Ertugrul Taciroglu
Professor, University of California, Los Angeles

Alexandros Taflanidis
Associate Professor, University of Notre Dame

Iris Tien
Associate Professor, Georgia Institute of Technology

Chaofeng Wang
Postdoctoral Researcher, University of California, Berkeley

Andrew Winter
Postdoctoral Scholar, University of Washington

Chen Xinzhong
Professor, Texas Tech University

Sang-ri Yi
Postdoctoral Researcher, University of California, Berkeley

Qian Yu
Postdoctoral Researcher, University of California, Berkeley

Stella Yu
Director, Vision Group, ICSI, University of California, Berkeley

Adam Zsarnóczay
Postdoctoral Researcher, Stanford University

Acronyms

ABL	Atmospheric Boundary Layer
AI	Artificial Intelligence
AIJ	Architectural Institute of Japan
ANN	Artificial Neural Network
ATC	Applied Technology Council
BIM	Building Information Model
CEUS	Central and Eastern United States
CDF	Cumulative Distribution Function
CFD	Computational Fluid Dynamics
CGS	California Geological Survey
CNN	Convolutional Neural Network
CPT	Cone Penetration Test
CRR	Cyclic Resistance Ratio
CS	Conditional Spectrum
CSR	Cyclic Stress Ratio
CWE	Computational Wind Engineering
DEM	Discrete Element Method
DES	Detached Eddy Simulation
DFIRM	Digital Flood Insurance Rate Map
DL	Deep Learning
DM	Damage Measure
DNN	Deep Neural Network
DNS	Direct Numerical Simulation
DOE	Design of Experiments
DRM	Dimension Reduction Methods
DS	Damage State
DV	Decision Variable
EDP	Engineering Demand Parameter
FEMA	Federal Emergency Management Agency
FORM	First-Order Reliability Method
FSI	Fluid-Structure Interaction
FS	Factor of Safety
GEM	Global Earthquake Model
GMM	Ground Motion Model

GMPE	Ground Motion Prediction Equation
GMR	Ground Motion Record
GPR	Gaussian Process Regression
HPC	High-Performance Computing
IBM	Immersed Boundary Method
IM	Intensity Measure
IT	Information Technology
KBES	Knowledge-Based Expert System
KF	Kalman Filter
LBM	Lattice Boltzmann Method
LES	Large Eddy Simulation
LOD	Level of Detail
MCS	Monte Carlo Simulation
ML	Machine Learning
NACCS	North Atlantic Coastal Comprehensive Study
NIST	National Institute of Standards and Technology
NSF	National Science Foundation
NHE	Natural Hazards Engineering
NHERI	Natural Hazards Engineering Research Infrastructure
NOAA	National Oceanic & Atmospheric Administration
NS	Navier-Stokes equations
NWS	National Weather Service
PCA	Principal Component Analysis
PDF	Probability Density Function
PGA	Peak Ground Acceleration
PGV	Peak Ground Velocity
PBE	Performance-Based Engineering
PEER	Pacific Earthquake Engineering Research Center
PINN	Physics-informed Neural Network
PF	Particle Filter
PSHA	Probabilistic Seismic Hazard Assessment
QoI	Quantity of Interest
RANS	Reynolds-Averaged Navier-Stokes equations
RBDO	Reliability-Based Design Optimization
RC	Reinforced Concrete
RDO	Robust Design Optimization
RMW	Radius to Maximum Winds
Sa(T)	Spectral Acceleration at a given T vibration period
SAM	Structural Analysis Model
SCEC	Southern California Earthquake Center
SORM	Second-Order Reliability Method
SPH	Smooth Particle Hydrodynamics
SPT	Standard Penetration Test
SVM	Support Vector Machine
SVR	Support Vector Regression
TC	Tropical Cyclone
UHS	Uniform Hazard Spectrum

USGS	United States Geological Survey
UQ	Uncertainty Quantification
WRF	Weather Research and Forecasting models

Chapter 1
Overview of SimCenter Goals and Computational Tools

Gregory G. Deierlein, **Sanjay Govindjee**, and **Frank McKenna**, with contributions by Adam Zsarnóczay

Computational simulation is an essential component of natural hazards engineering (NHE) research and practice to assess and mitigate the damaging effects of earthquakes, wind storms and associated tsunami, and storm surge effects on communities. The recently published National Hazards Engineering Research Infrastructure Science Plan (Edge et al., 2020) outlines three grand challenges and five research questions, all of which depend on integration of data and models through computational simulations. Specifically, simulations are critical to (1) characterize natural hazard phenomena, (2) evaluate their damaging effects on buildings, civil infrastructure, and other physical assets, (3) quantify the socio-economic consequences of this damage, and (4) evaluate the effectiveness of alternative strategies to mitigate and recover from the damage. Each of these components entails simulations at varying scales, from detailed analyses of localized response of individual buildings or infrastructure components to multi-scale analyses of regionally distributed communities and infrastructure systems. The challenges are multi-disciplinary and require development and management of large datasets to translate data and analysis results between the simulation components. Recognizing the challenge as broad and multi-disciplinary, and encompassing natural hazards across a wide range of scales, the SimCenter's approach is to leverage existing software platforms by creating computational workflow technologies that can seamlessly integrate a broad array of simulation software with high-performance computing (HPC) platforms and data repositories. When necessary, the SimCenter also creates new software to implement established theories to achieve its end goals.

1.1 SimCenter Application Framework

The SimCenter's application framework leverages foundational advancements in performance-based engineering (PBE) to integrate models and data from the physical sciences, engineering, and social sciences to evaluate and design strategies to create resilient communities (Deierlein et al., 2020). The basic framework of PBE, illustrated in Figure 1.1, was originally developed for earthquake engineering design, but the concept is generally applicable to other natural hazards. Moving from left to right, the process begins with the definition of a constructed facility, based on its design features and location. The next steps are to perform (1) a hazard analysis to characterize the hazard effects (e.g., earthquake ground shaking) that the facility is subjected to; (2) structural analyses to assess the response of the facility to the hazard;

(3) damage analyses to quantify damage to facility components associated with the imposed calculated deformations and forces; and (4) consequence analyses to evaluate the resulting risks to life safety, economic losses, and downtime. Input and output variables from each stage of the assessment are clearly defined as part of an underlying probabilistic formulation to characterize and propagate statistical data through the analyses.

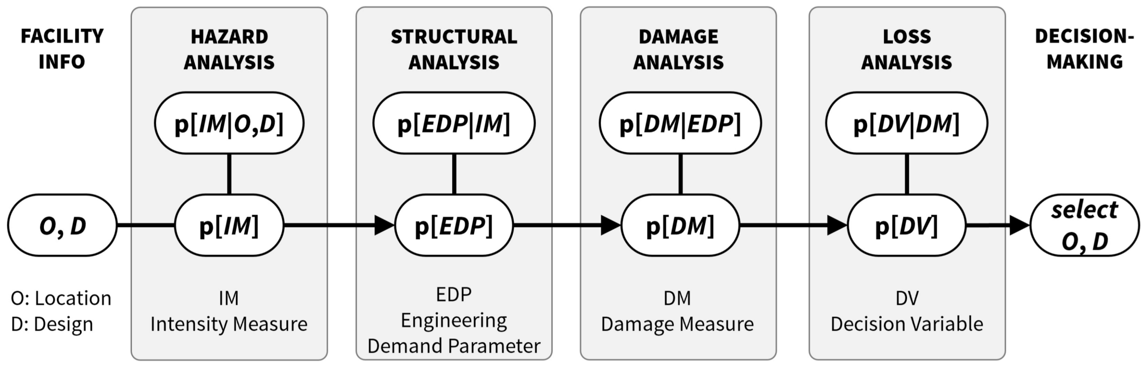


Fig. 1.1 Performance-based engineering framework for organizing data transfer between modeling components (after Porter, 2003).

As shown in Figure 1.2, computational workflows to implement the performance-based framework can be envisioned as a set of puzzle pieces, each of which encapsulates one or more software components with pre- and post-processing operations to facilitate transfer of data between the components. The framework allows users to (1) select from different applications for each jigsaw piece; (2) build a computational workflow with the selected components; and (3) then launch and monitor the running workflow. Workflow systems are configured to launch the individual applications and pass the needed input and output data between the applications. The application framework is designed to be modular and extensible, such that researchers can introduce their preferred application for any step in the process. Workflows can be configured for end-to-end simulations, from characterization of the natural hazard effects through to damage and impacts on individual facilities or large inventories of facilities, or alternatively for sub-portions of the system. As illustrated by the top grey bar in Figure 1.2, an important emphasis of the workflows is the ability to incorporate and propagate inherent variabilities and modeling uncertainties through the computational simulations. Another integrating aspect, illustrated by the lower grey bar in Figure 1.2, is to integrate the computational tools with supporting datasets that support various components of the workflow.

Figure 1.3 illustrates how the conceptual workflow puzzle is abstracted into software components, along with supporting datasets. The items listed across the bottom of the figure represent key components to the PBE workflow, and the bins up the right side refer to supporting databases. The boxes shown higher in the figure are workflow applications that integrate various components of the framework (McKenna, 2020). Details of these components, databases, and applications are described later. Figure 1.4 illustrates how the SimCenter's workflow components and applications are integrated into the NHERI cyber-infrastructure system, DesignSafe (Rathje et al., 2017), and other supporting online resources. As shown in Figure 1.4 and described by Rathje et al. (2017), DesignSafe provides computing hardware and software infrastructure for online databases and HPC.

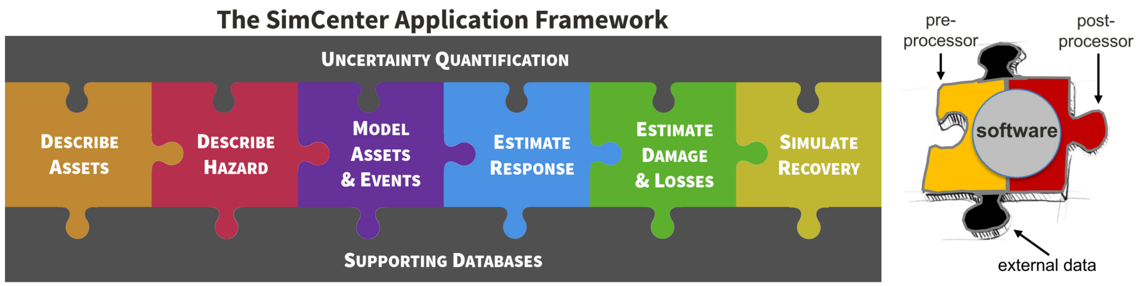


Fig. 1.2 Modular framework of the SimCenter computational workflow for end-to-end simulations of natural hazard effects on damage and recovery of the built environment and communities.

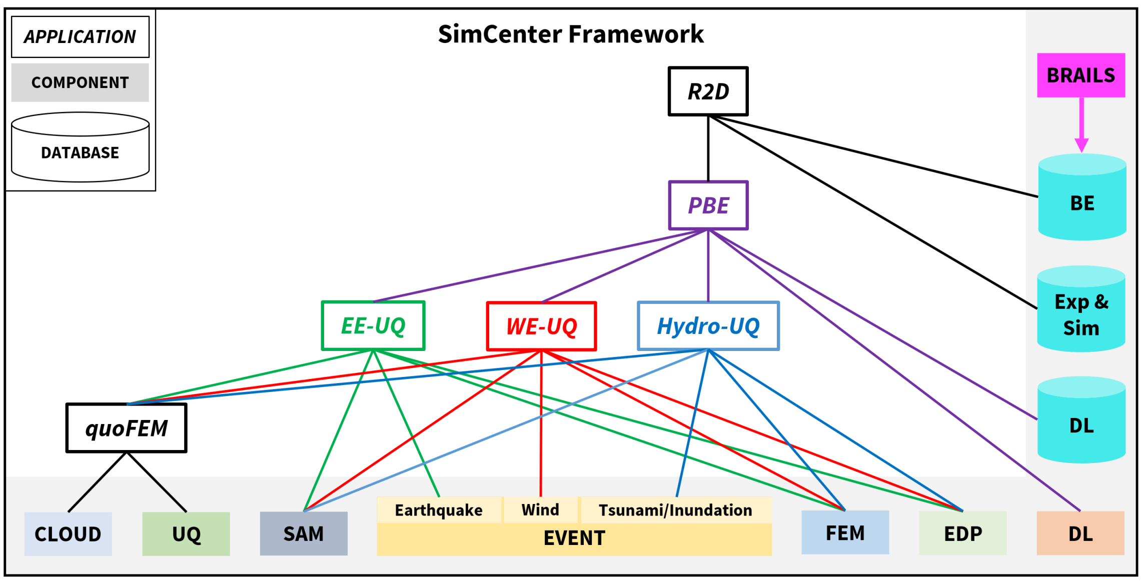


Fig. 1.3 Schematic diagram of simulation framework components, databases, and application tools.

1.2 SimCenter Framework Components

The following is a description of the modeling components and databases of the SimCenter framework shown in Figure 1.3:

BE—Built Environment Inventory

The BE consists of meta-data and data files that define the inventory of physical assets for a regional simulation. This includes buildings, transportation components and systems, utility infrastructure components and systems, etc. By providing a framework to organize and store databases on Design Safe, the SimCenter aims to promote best practices for the collection and sharing of inventory data. To help facilitate development of inventories, the SimCenter has developed artificial intelligence (AI) tools for building inventory data collection (*BRAILS* [10] – Building Recognition using AI at Large Scale) and for data enhancement (*SURF* [9] – Spatial Uncertainty Research Framework), along with web data query/collection techniques.

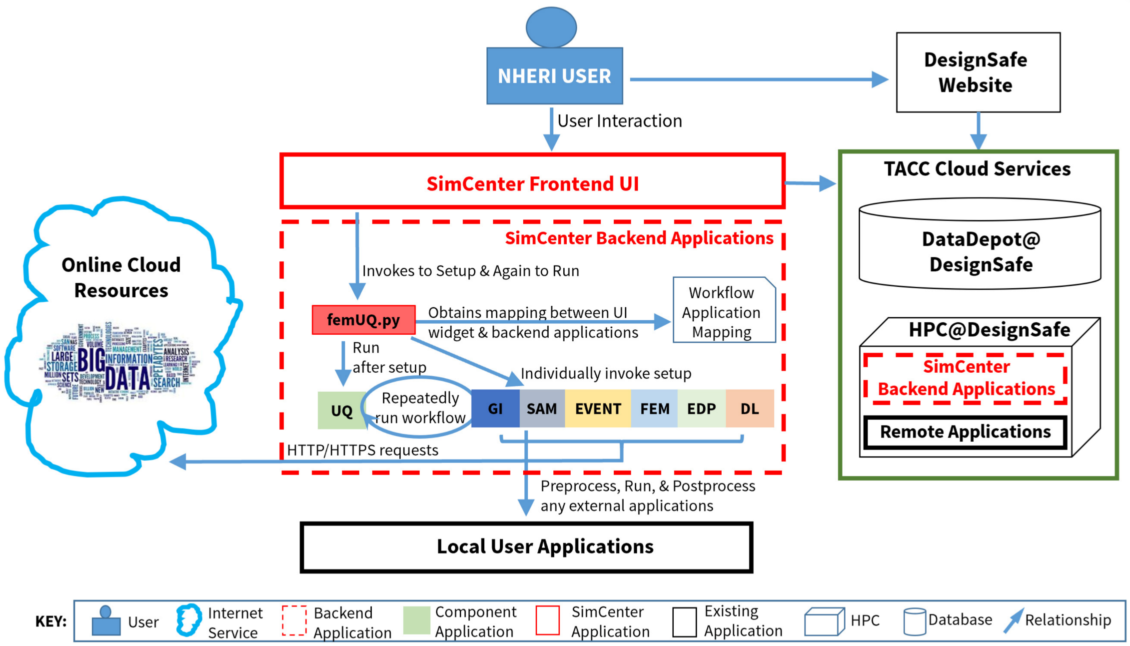


Fig. 1.4 Integration of the SimCenter workflow tools into the NHERI Computational Environment.

EVENT—Hazard Event

The EVENT consists of meta-data and data files that define the hazard data (e.g., earthquake ground motions, wind fields, storm surge inundation, and tsunami inundation). For earthquake hazard studies, the SimCenter workflow tools include software applications for (1) generating earthquake target spectra from the USGS OpenSHA web service; (2) selecting and scaling recorded ground motions from the PEER NGA database; (3) generating simulated stochastic ground motions; and (4) ingesting simulated ground motions from databases of simulated and recorded ground motions. For wind and storm surge studies, the workflow can support (1) generating wind field time histories stochastically or using *OpenFOAM* [5]; (2) incorporating experimental wind tunnel datasets utilizing online resources such as Vortex Winds (Kareem and Kwon, 2017) and the TPU Aerodynamic Database (TPU, 2020), or a user's own local dataset; and (3) interfaces for querying and ingesting wind speeds and storm surge inundation heights from external applications.

SAM-—Structural Analysis Model

The SAM is the workflow component that includes rule-based, AI and other types of applications to translate descriptive information from the BE into information to create finite-element or other types of models to simulate the structural response to the hazard effects.

FEM—Finite-Element Modeling

The FEM module consists primarily of wrappers for input/output to existing finite-element software to simulate the response of structures and geotechnical materials to earthquake ground shaking, wind, storm surge wave loading, and tsunami wave loading. Such analyses could also encompass computational fluid dynamics and structure-fluid interaction. OpenSees *OpenSees*

[6] and OpenFOAM *OpenFOAM* [5] are the main open-source applications that are called by the current FEM wrappers.

EDP—Engineering Demand Parameters

The EDP represents the workflow component that defines and manages the output of hazard-induced deformation or other demands from a finite-element or other type of analysis model for input into the damage and loss assessment.

DL—Damage and Losses

DL is the workflow component where damage and losses are calculated for the assets in the BE. Since these calculations are essential to all performance assessments and not readily available in existing software, the SimCenter developed an application framework called PELICUN, Probabilistic Estimation of Losses, Injuries, and Community Resilience Under Natural Disasters, (Zsarnóczay and Deierlein, 2020, *PELICUN* [12]) to generalize the FEMA P-58 methodology to evaluate damage and losses in buildings and other facilities under earthquakes, hurricanes, and other hazards.

UQ—Uncertainty Quantification

The UQ component provides an interface to software and routines for methods of uncertainty quantification, which can be interfaced with other components. One of the registered applications supported by UQ is DAKOTA (Adams et al., 2009), which offers a range of methods for uncertainty quantification. Additional UQ algorithms are provided by custom SimCenter software.

Cloud

Cloud is the workflow component that manages communication with remote computing and data service providers and sending/receiving data over the web.

DL Data

DL Data is the component consisting of databases of fragility curves for damage and loss calculations for various types of facilities (e.g., buildings, bridges, and infrastructure) subjected to demands from various hazards (e.g., earthquake, wind, and storm surge).

Exp/Sim Data

Exp/Sim Data is the component consisting of databases of experimental and/or computational research data that is utilized for machine-learning SAM applications and validation of FEM simulation tools.

1.3 SimCenter Desktop Applications and Backend Tools

Figure 1.3 shows the key desktop applications (*quoFEM*, *EE-UQ*, *WE-UQ*, *HydroUQ*, *PBE*, and *R2D*) with linkages to the underlying components used by each application. The workflow components are implemented into backend software modules and can be combined in multiple ways. The table in Figure 1.5 lists the SimCenter's current desktop applications and backend software modules, along with a set of educational applications. The columns of the table indicate how the various applications and software modules are related to the various hazards and stages of the PBE framework. Included below are brief descriptions of the desktop applications. For further detail on these applications, backend modules, and educational applications, the reader is referred to the SimCenter website: `https://simcenter.designsafe-ci.org/`.

quoFEM

The Quantified Uncertainty with Optimization for the Finite-Element Method (*quoFEM* [7]) tool connects state-of-the-art UQ engines (e.g., Dakota) with simulation tools to supports model calibration, optimization, uncertainty propagation, reliability analysis, surrogate modeling, and sensitivity analyses of numerical materials, components, and systems. The graphical user interface currently supports finite-element software (OpenSees and FEAP) and can also interface with custom analysis packages, including, but not limited to those based on the discrete element and finite difference method and other commercial software that cannot be bundled with the open-source SimCenter applications (e.g., LS-DYNA, ABAQUS). The GUI can also be configured by users to employ custom UQ engines that are not currently provided with the tool. Therefore, quoFEM provides users instant uncertainty analysis and optimization capabilities for numerical models. Furthermore, quoFEM provides an opportunity for researchers working with experimental facilities to use advanced UQ methods and tools to design experiments and calibrate numerical models. Some of the planned future capabilities of quoFEM include support for multi-fidelity models, sequential Bayesian updating, surrogate enhanced optimization and calibration, and optimization under uncertainty.

EE-UQ

The Earthquake Engineering with Uncertainty Quantification (*EE-UQ* [2]) application has features to determine the response of a structural and soil–structure systems to earthquake excitations. The current (V2.2.0) release focuses on quantifying the uncertainties in structural response, given that the properties of buildings (or other structures) and the earthquake events are not known precisely, and that many simplifying assumptions are present in the numerical models (epistemic uncertainties). By embedding features of the *quoFEM* tool, *EE-UQ* enables the user to specify statistical distributions of the model input parameters, then Monte Carlo and other sampling methods are used to characterize the output. The tool has features to select and input ground motions to match specified earthquake hazard targets. Work is underway to extend *EE-UQ* to include soil–structure interaction models where bedrock ground motions are propagated through nonlinear soil models into the structural system.

WE-UQ

This is a Wind Engineering with Uncertainty Quantification (*WE-UQ* [11]) application to assess the response of buildings to wind loading, taking into account that the properties of the building and the wind loads are not known exactly, and given that the simulation software and the user make simplifying assumptions in the numerical modeling of the structure. It is similar in composition to *EE-UQ* but with a wind *EVENT* component. The current (V2.0.0) version allows users to select from a variety of options for specifying wind forces on structures

Fig. 1.5 Overview of the current scope of SimCenter computational simulation tools.

from stochastic loading models and online wind engineering databases through to performing Computational Fluid Dynamics (CFD) analyses utilizing *OpenFOAM* [5]. The tool is intended to make detailed CFD modeling more accessible to NEHRI researchers in conjunction with wind tunnel testing (e.g., to validate computational models and extrapolate beyond the scale and parameter space that can be tested in the NHERI wind facilities), to allow researchers to consider more realistic conditions from field studies, and assist in the creation of surrogate models for regional simulations. Two-way fully coupled fluid–structure interaction (FSI) is currently under development.

Hydro-UQ

This is the SimCenter's Hydrodynamic loading with Uncertainty Quantification (*HydroUQ* [4]) application to assess the response of structures to fluid flows from storm surge, tsunami, or other hazards. The current version (V0.9.0-alpha) allows two-dimensional shallow water solutions obtained from far-from-coast calculations with GeoClaw *GEOCLAW* [3] to be used as input to a three-dimensional CFD solver (*OpenFOAM* [5]). This facilitates a multi-scale coupling by resolving areas of interest by coupling shallow-water solvers with CFD solvers through an interchangeable workflow. As a part of the inputs, the tool allows the researchers to consider: (a) bathymetry and topography of the ocean floor and (b) initiation conditions due to tsunami and storm surge events. Upcoming features will include the ability to use *ADCIRC* [1] runs for studying hydrodynamic loads during hurricanes.

PBE

The Performance-Based Engineering (*PBE* [13]) application is an extensible workflow application to evaluate the performance of buildings or other assets to natural hazards. The current (V2.0.0) release provides researchers with a tool to assess the performance of a building subjected to earthquake ground motions. The application focuses on quantifying nonlinear building response and damage through decision variables. *PBE* builds upon the *EE-UQ* tool using the estimates of structural response to assess the damage to building components and the consequences of such damage. The user defines the simulation model, the damage and loss models of the structure, and the seismic hazard model in the *PBE* tool. The tool incorporates an underlying workflow application *PELICUN*, which is modeled after the FEMA P-58 framework for earthquake loss assessment but with a broader vision to address alternate hazards (wind, water inundation, etc.) and facilities beyond buildings. Upcoming features will extend PBE to handle storm wind hazards to buildings as well as the performance assessment of other infrastructure elements such as buried pipelines.

R2D

The Regional Resilience Determination Tool (*R2DTool* [8]) is a research application that focuses on running regional simulations and interpreting their results. The tool integrates the workflow components from other research tools developed for individual building assessment (e.g., *EE-UQ*, *PBE*) and extends them to consider multiple assets and a regional characterization of hazard scenarios. The first release of the *R2DTool* provides features for seismic risk assessment. Additional features planned for 2021 will enable hurricane risk studies including the simulation of both wind and storm surge effects. The calculations are performed by an extensible command line workflow application (*rWHALE*) that integrates the entire framework of backend applications developed by the SimCenter. Besides several small examples provided to help users get started, the SimCenter is developing a small number of detailed regional studies to illustrate the potential in regional simulations and provide researchers several templates of workflows with various levels of complexity.

1.4 Concluding Remarks

In addition to developing and releasing the computational workflow tools and training modules, the SimCenter is engaging with researchers to extend the simulation capabilities through collaboration with NHERI researchers. Collaboration opportunities include: (1) development and implementation of new computational simulation models, metadata standards, and software; (2) application studies to apply and enhance the simulation tools across a spectrum of scales, from individual components through to regional studies of the impact of natural hazards on the built-environment; and (3) development of educational resources, including curricula materials that utilize advanced simulation tools, along with webinars, papers, and other means of documentation.

This report is an important component of the SimCenter's workplan to identify and incorporate state-of-the-art simulation methods and software into the computational workflow applications. It also identifies areas where further research and development is needed. Thus, this report serves not only as a report on the state of the art for the NHERI community but also as a guiding document for the SimCenter. As seen in Figure 1.5, for example, there is currently a major gap in computational models for simulating disaster recovery, which represents a major challenge to the NHERI community.

Beyond incorporating existing and emerging simulation tools into the computational workflows, an important component of the SimCenter's mission is to overcome computational challenges associated with scaling up the simulations to allow higher fidelity and higher resolution models. These computational aspects of the software development involve collaboration and coordination with NHERI cyber-infrastructure available through DesignSafe and other organizations.

Part I
Hazard Characterization

Characterization of natural hazards for engineering applications aims to quantify the severity of a natural hazard at a particular location or over a pre-defined region of interest. The time histories that provide a detailed description of natural-hazard effects—such as severe ground shaking or high-speed winds—are often summarized by so-called intensity measures (IMs) that represent their most important characteristics. Peak ground acceleration, permanent ground deformation, average one-minute wind speed, and peak inundation depth are a few examples of such IMs for various natural hazards. Using IMs facilitates the development of a stochastic hazard model that defines the hazard severity at the site(s) of interest using one more more random variables or random fields. The uncertainty in the hazard that is captured by these random entities shall be propagated through engineering simulation.

High-fidelity approaches simulate the time-history of structural response using dynamic analyses (see Part II for details). These simulations require a time-dependent load function that represents the hazard characterized by IMs. An acceleration time history of a ground motion is an example of such a load function, which is often used for seismic response estimation. These load functions are either selected from historical data (e.g., ground-motion records) or generated using a stochastic process (e.g., local wind inflow conditions for a CFD simulation). The procedures and best practices available for this task will be discussed for each natural hazard below.

Three types of natural hazards are examined in the following sections: earthquake, hurricane, and tsunami. They present several fundamentally different threats to the built environment, such as ground shaking and liquefaction under earthquakes, or wind and storm surge under hurricanes. Each chapter in this part discusses one of those threats.

Chapter 2
Earthquake—Ground Shaking

Adam Zsarnóczay with contributions by Wael Elhaddad,
along with review comments and suggestions by Jack W. Baker and David McCallen

The simulation methods and the software tools presented in this section characterize the ground-shaking intensity due to earthquakes at a specific site or over a group of sites that cover a region. Although the amount of historical earthquake data at any particular site is small, the improvements in the field since the publication of the seminal paper on earthquake hazard by Cornell (1968) allows engineers to combine the available information from several sites and create a seismic hazard model that can quantify the expected ground-shaking hazard and the corresponding uncertainty.

Probabilistic Seismic Hazard Assessment (PSHA) and disaggregation of the calculated hazard are the most popular methods to characterize ground shaking at a site of interest (Bazzurro and Cornell, 1999). The earthquake engineering community is fortunate to have access to a large number of free—and often open-source—tools available for this task. Besides PSHA tools, this chapter also covers tools that perform scenario-based, deterministic analysis. Most probabilistic and deterministic analyses use empirical ground-motion models (GMMs) that describe the attenuation of shaking intensity with increasing distance from the hypocenter to characterize the ground shaking at a site from fault rupture. [The empirical GMM denomination is preferred over the conventional GMPE (ground-motion prediction equation) in several recent publications to emphasize that modern attenuation relationships are substantially more complex than a single equation.] Other approaches, such as physics-based GMMs and the corresponding simulations, are also becoming sufficiently robust to be widely applicable for risk assessment, and they are likely to be used more widely in the near future.

This chapter reviews the above methods, the data they use, and the tools that have implemented them. The recent book by Baker et al. (2021) provides more details about the characterization of ground shaking and the methods available for probabilistic seismic hazard assessment.

2.1 Input and Output Data

2.1.1 Input Data

Ground-motion hazard assessment requires information about the site and the seismic source(s) in its vicinity. These data can be classified as follows:

Site location(s)

These are latitude and longitude pairs for each site of interest. For regional analyses, ground shaking is either characterized directly at the location of each asset or a carefully designed intermediate grid is used, and the site-specific results are determined by interpolation between the grid nodes. The direct approach is used when the number of assets is relatively small (e.g., Padgett et al., 2010), while the intermediate grid is used in studies with millions of assets (e.g., Deierlein et al., 2020).

Site data

Local soil conditions have significant influence on the ground motion at the surface at a particular site. Two neighboring sites with practically identical bedrock hazard might experience fundamentally different surface ground motions if their soil characteristics are different. If the soil profile above bedrock is available, the propagation of ground shaking from bedrock to surface can be modeled using the methods described in Chapter 10 of this report. However, the bedrock is often at a large depth and the absence of site-specific measurements makes it difficult to characterize the complete soil profile. This is especially the case for large, regional simulations with thousands or millions of sites. The lack of data translates into significant uncertainty in the amplification of ground motion from bedrock to surface and the resulting surface ground-motion estimate.

A pragmatic solution in the earthquake engineering community uses the average shear-wave velocity in the top 30 meters of the soil ($V_{S,30}$) as a proxy for soil conditions to estimate the site amplification at a site. Information about $V_{S,30}$ or at least about a broad soil class (e.g., rock, stiff soil, or soft clay) is either available or can be estimated for most sites. The USGS provides estimates of $V_{S,30}$ from topographic slope that can be used as an approximate solution when no other data is available (USGS, 2020).

Seismic sources

Ground motions are generated by seismic sources. Depending on the available historical information about the earthquakes in the region, sources might be described as faults, points, or areas with homogeneous seismicity. The abundant information about earthquakes in California allows researchers to develop a detailed map of faults for the state (Field et al., 2014), while the Central and Eastern United States (CEUS) is covered by area sources (Mueller et al., 2015).

Scenario-based analysis typically requires a hypocenter location, earthquake magnitude, and information about the rupture surface and style of faulting. Probabilistic assessments consider all sources that might affect the region along with a stochastic description of those sources using magnitude occurrence rates, hypocenter depth distributions, etc. These stochastic models are usually based on historical ground-motion data. The Uniform California Earthquake Rupture Forecast version 3.0 (UCERF3, Field et al., 2014) is an example of such a stochastic seismic-source model. It is published jointly by the United States Geological Survey (USGS), the California Geological Survey (CGS), and the Southern California Earthquake Center (SCEC). Seismic-source models for other non-U.S. regions have been prepared and made publicly available by the Global Earthquake Model (GEM) initiative (https://www.globalquakemodel.org/). These include Europe (Giardini et al., 2014), the Middle East (Danciu et al., 2017), and South America (Garcia et al., 2018).

Ground-motion model (GMM)

The ground-motion model describes the propagation of ground shaking from the earthquake rupture surface to the sites of interest. The widely used approaches are empirical, physics-based, and stochastic GMMs:

- Empirical GMMs estimate the severity of ground shaking in the form of intensity measures (IMs). These estimates are typically based on regression to historical IM data from recorded earthquake ground motions. Depending on the data and the functional form used for the regression, one might arrive at various models. There are hundreds of empirical GMMs available (Douglas, 2021), and it is important to select the one that is based on data and assumptions matching the seismicity in the region of interest.
- Physics-based GMMs describe the propagation of seismic waves from the location of the rupture to the surface at the investigated sites. They require a three-dimensional model of the local geology (i.e., the upper layers of the Earth's crust) and simulate the behavior of the seismic sources in the area within this environment. Even though these models are challenging to build and computationally expensive to run, they are becoming more and more popular, and are used in a variety of applications (Bradley et al., 2017).
- Stochastic ground motions are artificially generated accelerograms either from white noise that is modified to match target IMs (e.g., Rezaeian and Kiureghian, 2012) or by modifying historical ground-motion recordings (e.g., Atkinson and Goda, 2010; Seifried and Baker, 2016).

Logic tree

Logic trees have become popular means to consider the epistemic uncertainty in the ground-shaking hazard. Branches of the trees are populated with various modeling assumptions (e.g., GMMs, seismic-source models, maximum magnitudes, site data, etc.), and a set of weights are defined so that the branches and weights represent a probability distribution on the uncertain issue. Notwithstanding the problems inherent in such a strategy for UQ (Bommer and Scherbaum, 2008), recent research has shown several examples where the logic-tree approach provides additional insight that would otherwise not be available (e.g., Goulet et al., 2017).

2.1.2 Output Data

One or more of the following outputs are produced to describe the ground-shaking hazard:

Seismogram

A plot of ground motion versus time, which would be recorded by a seismometer or other instrument in a real event. Seismograms are also known as ground-motion records (GMRs) and are typically expressed in terms of ground acceleration, which are integrated to obtain ground-motion velocity or displacement.

Intensity measure (IM)

A measure of the intensity of shaking associated with a particular seismogram. The peak ground acceleration (PGA) and spectral acceleration at a given vibration period [$Sa(T)$] are the most commonly used IMs.

Response spectra

A response spectrum is often used to describe the intensity of a ground motion and to provide a proxy for the complete acceleration time history. It is a collection of IMs that describe the response of single-degree-of-freedom oscillators to the ground-motion record of interest; for example, acceleration response spectra are defined through a set of $Sa(T)$ values. The larger the number of vibration periods considered, the more detailed the resulting spectrum becomes. In empirical GMM-based simulations, the resolution of the response spectrum is typically limited by the vibration-period discretization used in the attenuation model. In physics-based simulations, the response spectrum is determined from the simulated GMR.

Hazard curve

Rather than focusing on ground motions from a single event, probabilistic assessments characterize the hazard through the annual exceedance rate of various IMs at the site of interest. This information is represented by a hazard curve. Each IM has its corresponding hazard curve. Studies typically focus on obtaining hazard curves for a set of $Sa(T)$ IMs.

Hazard spectrum

Given a set of hazard curves corresponding to $Sa(T_i)$ for T_i in a sufficiently wide range of vibration periods, it is possible to collect the $Sa(T_i)$ that correspond to a pre-defined annual exceedance rate. These $Sa(T_i)$ values describe the so-called uniform hazard spectrum (UHS), which is the collection of spectral accelerations that have identical (uniform) probability of exceedance. A popular alternative to the UHS is the so-called Conditional Spectrum (CS), where the spectra are conditioned on the probability of exceedance of response at a pre-defined (conditioning) period T (Baker and Lee, 2018; Lin et al., 2013). The UHS and CS are often used to describe the hazard in a probabilistic framework.

Hazard map

Given a particular annual exceedance rate (or return period or exceedance probability over a pre-defined time period) and corresponding hazard curves at various sites in a region, one can create maps of IM levels that describe the intensity of expected ground shaking. The engineering community uses a small set of pre-defined return periods (such as 475 years, which is equivalent to 10% probability of exceedance over 50 years) to describe the hazard for structural design and performance assessment purposes. Using the same return periods within the community facilitates the comparison of hazard maps among different regions and within different parts of the same region.

Disaggregation of the hazard

Probabilistic seismic hazard analysis aggregates the contributions of several sources to produce a hazard curve for a site. Disaggregation provides a break-down of the contribution of various seismic sources to the total seismic hazard. This allows researchers to estimate the characteristic features of the earthquake scenarios (typically magnitude and source-to-site distance) that are the main contributors to the seismic hazard at the site. Information about such features complements the estimated IMs and provides a more detailed understanding of the seismic hazard at the site.

2.2 Modeling Approaches

The two main approaches used in the research community for ground-shaking hazard characterization are as follows:

Estimate IMs using an empirical GMM

This type of methodology describes the hazard using IMs estimated based on historical earthquake data. The advantage of using empirical GMMs is the computational efficiency of the calculation; these models typically describe IMs as random variables. This approach allows engineers to estimate the probability of exceeding a pre-defined IM level given the characteristics of the earthquake scenario, the location of the site, and other parameters (soil conditions, damping, etc.). By aggregating these exceedance probabilities and the occurrence rates of corresponding earthquake scenarios over a region, engineers can arrive at the total probability of exceedance of a pre-defined IM level at the site of interest. Performing such a calculation for multiple IM levels produces the hazard curve for the site. The ground-shaking hazard is commonly described using a set of hazard curves that correspond to the spectral acceleration at various vibration periods. These hazard curves can serve as the basis of a UHS or CS for structural response estimation.

The choice of IM has been a subject of a large number of studies in recent decades (e.g., Luco and Cornell, 2019; Shome et al., 1998). There are three widely-used criteria when IMs are discussed: (1) *practicality* refers to the complexity of the calculation and if tools are already available to perform it; (2) *efficiency* describes the predicting power of the IM for the important characteristics of structural response; and (3) *sufficiency* corresponds to the uniqueness of the hazard description provided by the IM (i.e., a unique description means that GMRs with identical IM values yield identical structural responses). Besides the popular PGA and $Sa(T_1)$, the average spectral acceleration Sa_{avg} and significant duration are also used and assessed in several studies (e.g., Bijelić et al., 2018). There are more complex IMs that have been shown to perform better in terms of efficiency and sufficiency, and can become superior to conventional choices once widely applicable GMMs become available for them (e.g., Dávalos and Miranda, 2019).

In studies that use empirical ground-motion data, the selection of historical GMRs for dynamic analyses can be challenging. One can either use a generic suite of GMRs produced and vetted by experts (e.g., Baker et al., 2011) or perform the selection of GMRs from a database (e.g., Ancheta et al., 2014) based on a site-specific description of the hazard. As the number of records in ground-motion databases increases, the set of selected GMRs can often provide a good representation of the probabilistic hazard at the site, but rare events and unconventional hazard characteristics can still prove difficult to represent with empirical GMRs. If matching historical ground motions are not available, stochastic ground-motion generation is also an option to consider.

Estimate ground-motion records using a physics-based GMM

This type of methodology relies on a physical model of the crust and propagation of seismic waves in that model. It requires a significant amount of information about local geology to arrive at reliable results. Furthermore, the calculations are computationally expensive and usually require a high performance computing (HPC) environment. To the extent that the physics-based models are validated and based on reliable model parameters (geologic data), they can represent local geologic effects (such as deep geologic basins) that are not captured as well by empirical GMMs. The earthquake simulations provide GMRs directly as opposed to the IM proxies used in empirical approaches. These records can be applied directly in response estimation, which removes part of the uncertainty and ambiguity associated with GMR selection to match IM targets in empirical studies.

There are computational and modeling challenges before this approach becomes commonplace, but early adopters in the research community (such as SCEC `https://www.scec.org/` and Lawrence Livermore National Laboratory, `https://www.llnl.gov`) are already providing physics-based simulations that are being applied for performance and risk assessment (e.g., Frankel et al., 2018; Rodgers et al., 2019b). The SCEC Broadband Platform (Maechling et al., 2015) provides open-source access to such models and simulation tools; similar initiatives are available in Italy (D'Amico et al., 2017) and in New Zealand (Bradley et al., 2017). A recent special issue of Earthquake Engineering and Structural Dynamics also provides a selection of relevant research (e.g. Kato and Wang, 2021; Kusakabe et al., 2021; Paolucci et al., 2021; Seylabi et al., 2021; Zhang et al., 2021).

Concerns about the reliability of simulated ground motions have been addressed by recent studies that have shown similar demands and responses from real and simulated ground motion records (e.g., Figure 2.1, Galasso et al., 2013; Rodgers et al., 2019a). SCEC has a group of researchers focusing on testing and rating methodologies to build confidence in the use of these simulated acceleration time histories. As the gap between empirical and simulated ground motions is closing, the community will be able to take advantage of synthetic seismograms that can represent rare hazards and special site conditions.

2.3 Research Gaps and Opportunities

Conventional, empirical GMMs are expected to be replaced by non-ergodic models that can consider local site and path information when available (e.g., Abrahamson et al., 2019). In areas with abundant information, such models are expected to reduce the variability in the ground motion and provide a more realistic description of the seismic hazard. Because such detailed information is not available in every location, the models need to account for site-specific aleatory and epistemic uncertainty, thus acknowledging that the uncertainty in the estimated hazard is not uniform in space. This enhanced treatment of uncertainty will also require an expansion of existing logic trees to represent the center, body, and range of the input parameters (Gerstenberger et al., 2020).

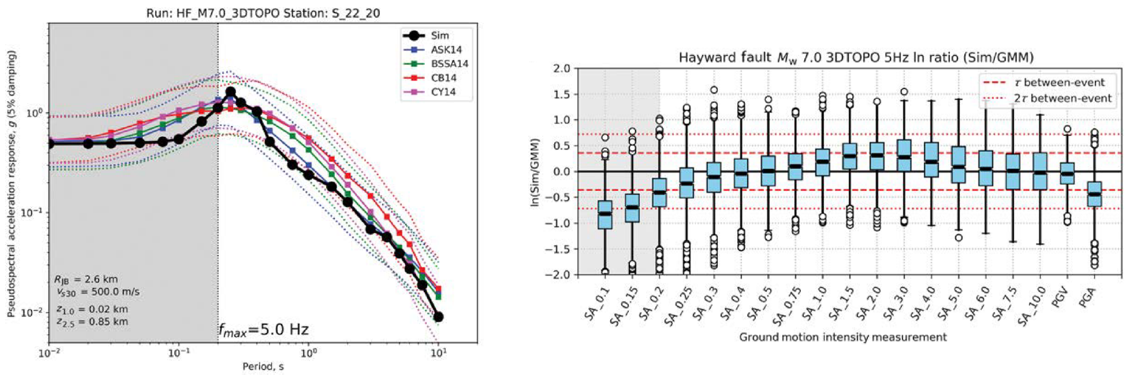


Fig. 2.1 Illustrative example of the comparison between empirical and physics-based GMMs from (Rodgers et al., 2019a): Left: RotD50 acceleration response spectra for a site in Oakland, California, predicted by four empirical GMMs (squares in color) and by a three-dimensional ground-motion simulation for the San Francisco Bay Area (circles in black). Right: Distribution of residuals between the simulated and empirical IMs over the entire simulation region. The thick black line indicates the median, the boxes show the interquartile range (IQR) (i.e., central 50% around the median), and the whiskers extend until 1.5 IQR. Outliers are shown as circles. Dashed and dotted lines show between-event uncertainties corresponding to the empirical GMM.

The rigorous combination of multiple empirical GMMs (e.g., Goulet et al., 2017) is also a promising direction that would allow the consideration of model uncertainty in the estimated hazard. Other sources of uncertainty that affect the seismic source model—or the physical model of the crust that is used to estimate soil amplification—are also important to quantify and propagate through the analyses.

The research community recognizes that there is long-term variability in the rate of earthquakes, and some nations have already adopted time-dependent, non-Poissonian models to have a more realistic estimate of the seismic hazard. More work is needed in this area to improve the corresponding models and to expand their use to other areas, including the hazard maps of the U.S.

When it comes to physics-based models, the continual increase in computational resources makes simulations that resolve the ground-motion time-histories up to 10 Hz and include softer soil layers in the analyses a feasible goal for the near future. As our ability to compute ground motions to ever higher frequencies increases, we are outstripping our knowledge of the subsurface geology at a fine scale. Addressing these geologic model uncertainties is one of the challenges for the community.

The next step for physics-based models would be to expand to probabilistic simulations that produce multiple plausible realizations of the ground shaking considering various sources of uncertainty in the generation and propagation of the waves. Such calculations require orders of magnitude greater computation ability than what is currently available. The challenge is to improve the physical models and frameworks to make such probabilistic analyses more feasible.

2.4 Software and Systems

The following is a list of software that is commonly used for characterizing earthquake ground shaking.

AWP-ODC

AWP-ODC [14] is an elastic wave propagation program (AWP-ODC, Cui et al., 2010) that performs a parallel finite-difference wave-propagation simulation. The software can simulate the dynamic rupture and wave propagation that occurs during an earthquake. It was originally written in Fortran and supports parallel computation using the message passing interface (MPI). A version of the software written in C and CUDA is also available to run on graphics processing units (GPUs).

BBP

The *The Broadband Platform* [29] Platform (Maechling et al., 2015) is a software system developed by SCEC that can be used to generate synthetic ground motions using wave-propagation models. The BBP is distributed with data products (velocity models and Green's functions packages) that allows for the generation of seismograms for simulating historical or hypothetical earthquake scenarios in California, the northeast of the U.S., and Japan. The software runs on Linux systems and provides different seismogram generation models.

CyberShake

CyberShake [15] is a computational simulation project on physics-based PSHA, developed and hosted by SCEC. CyberShake simulations have been created from studies that define the inputs, computational software, and the outputs. Outputs from studies done using CyberShake are stored in publicly accessible databases that includes studies performed for southern and central California. Data products of CyberShake include seismograms, hazard curves, disaggregation, duration results, and hazard maps.

HAZ

HAZ [18] is a probabilistic seismic hazard analysis tool written and maintained by Norman Abrahamson. It is written in FORTRAN and it is not heavily documented, but it still is a popular tool for several bridge, dam, and nuclear projects.

HAZUS 4.2

The Federal Emergency Management Agency (FEMA) has been supporting the development of *Hazus 4.2* [17] for more than two decades. It is publicly available and provides a convenient way to perform regional risk assessment following the HAZUS Multi-hazard Loss Estimation Methodology 2.1 (FEMA, 2011a,b,c, 2017). The methodology covers earthquake, hurricane, tsunami, and flood hazards. Researchers and agencies in the U.S. can download input data with the tool that provides information about the hazard, the exposure (i.e., building locations and characteristics), and the vulnerability (i.e., building fragility and consequence functions) of the region. These inputs are prepared in the standard format required by the software and provide exposure data (building inventories, etc.) at a census-tract-level resolution. The software runs on Microsoft's Windows operating system and has a GUI.

Hercules

Hercules (Tu et al., 2006) is a parallel finite-element wave-propagation software that can be used to simulate earthquake ruptures. It was originally developed by the Quake group at Carnegie Mellon University in collaboration with SCEC. The software is designed to be memory-efficient and highly scalable to run large-scale simulations in an HPC environment (Taborda et al., 2010).

NSHMP-Haz

NSHMP-Haz [20] is a Java-based library for PSHA that has been developed as part of the National Seismic Hazard Mapping Project (NSHMP) within the USGS Earthquake Hazards Program (EHP). The library is the engine driving different USGS web services and applications, which enables high-performance seismic hazard calculations required for generating hazard maps over large regions using different ground-motion models. A legacy Fortran version of this library is also available, although it is deprecated at the time of writing this report.

OpenSHA

OpenSHA [22] (Field et al., 2003) is an open-source platform for seismic hazard analysis (SHA) that was developed by the SCEC in collaboration with USGS. The platform is comprised of Java libraries and a suite of applications that are suitable for different SHA applications. For instance, OpenSHA provides graphical applications for calculating hazard spectra, hazard curves, hazard maps, hazard disaggregation, and querying site data. In addition, all the features provided by the graphical applications are available programmatically through the OpenSHA Java libraries.

OpenQuake Engine

OpenQuake [21] (Pagani et al., 2014) is an open-source library for seismic hazard and seismic risk computations. The library was developed using Python and is cross platform. The library uses data, methods, and guidelines outlined by GEM.

PEER Ground-Motion Database

The PEER ground-motion database (NGA-West2, Ancheta et al., 2014) is a comprehensive set of ground-motion records from shallow crustal earthquakes in active seismic regions around the world. The database includes 21,336 records from 599 earthquake events. In addition to the ground-motion records, the database stores detailed metadata that includes different source-site distance measures, site, and rupture characterization. A web service that can perform ground-motion record selection and scaling using the records in database is also provided.

R-CRISIS

R-CRISIS [25] is the latest version of the CRISIS software that has been developed by Ordaz et al., 2013 and supported by the National Autonomous University of Mexico and the Italian Department of Civil Protection. The latest version of the software is free and publicly available. It is designed to work with a GUI in a Windows environment. The software is designed to perform PSHA calculations with a large number of GMPEs built in and seismic-source models available in the literature.

SW4

Seismic waves, 4th order (*SW4* [23], Petersson and Sjogreen, 2017) is a software originally developed at the Lawrence Livermore National Lab (LLNL) and currently jointly developed by the LLNL and the Lawrence Berkeley National Lab under the U.S. DOE Exascale Computing Program EQSIM application framework. It can solve three-dimensional seismic wave-propagation problems. The software was developed using Fortran and C++ and makes use of a distributed memory-programming model using MPI. The software is suitable for running on HPC and is capable of producing synthetic seismograms in different formats.

UCVM

The Unified Community Velocity Model (UCVM, Small et al., 2017) is a software framework developed by SCEC that provides a common interface to query different three-dimensional seismic velocity models for the State of California. The software allows the use of alternative models to query and visualize seismic-wave velocities. The software provides query scripts to obtain the seismic-wave velocities and density visualized on a horizontal slice, cross section, and depth profile, and can also provide basin depth and $V_{s,30}$ maps. The properties provided by the velocity models included with UCVM are crucial for many wave-propagation software presented in this section.

UGMS MCER

UGMS-MCER (Crouse et al., 2018) is a web-based tool developed by the SCEC Committee for Utilization of Ground Motion Simulations (UGMS) to provide a site-specific maximum considered earthquake (MCE) response spectra for the Los Angeles region according to the site-specific seismic hazard analysis procedure outlined in ASCE 7-16. The tool is user-friendly and is oriented towards practitioners, and only requires the location (latitude and longitude) and site-soil classification (site class or V_{s30}).

2.4.1 Relevant SimCenter Tools

The SimCenter supports empirical ground motion modeling with a ground motion utility (GMU) that is integrated in research tools such as *EE-UQ* [2], *PBE* [13], and *R2DTool* [8]. These research tools also provide a standardized ground motion input feature that enables importing intensity measures and IM fields as well as ground motion acceleration time histories that were prepared in external tools. Such external tools include physics-based ground motion simulations. There are simulation examples provided that use data from *SW4* [23] to encourage researchers to take advantage of such data sources.

GMU

The Ground Motion Utility (*GMU*) is currently a backend application that interfaces with *OpenSHA* [22] to characterize the seismic hazard. Given the hazard, the GMU has several spatial correlation models (e.g., Jayaram and Baker, 2009; Markhvida et al., 2018) implemented to simulate spatially correlated ground motion intensity measure fields for a regional analysis. Finally, to support high-fidelity structural response estimation, the GMU can connect to the

PEER NGA-West2 ground motion record database (Ancheta et al., 2014) and select ground motion records from there that match the intensity measures (i.e., target spectrum) at each location of interest. These features are available for the analysis of individual buildings in *EE-UQ* [2], and *PBE* [13], and for regional analyses in *R2DTool* [8].

QS3HARK

The Site-Specific Seismic Hazard Analysis and Research Kit with Uncertainty Quantification (*QS3HARK*) simulates wave propagation through soil layers. The simulations use the finite element method as implemented in *OpenSees* [6] to perform the calculations. Uncertainties in both the soil properties and the bedrock ground motion inputs can be characterized and propagated throughout the simulations to arrive at a probabilistic description of the ground shaking. QS3HARK is integrated in *EE-UQ* [2], and *PBE* [13] to enable the automatic propagation of ground shaking from bedrock to surface and application of the simulated surface shaking in a structural analysis. This workflow will be integrated into *R2D* to enable such high-fidelity analyses at a regional scale.

smelt

The Stochastic, Modular, and Extensible Library for Time histories (*Smelt* [27]) is a C++ library for stochastically generating time histories, including acceleration time histories to represent ground shaking.

Educational Tools

The effect of ground shaking is illustrated in several educational tools developed by the SimCenter. The Multiple Degrees of Freedom Application (*MDOF* [19]) allows students to explore the effects of different building parameters on the time-varying response of a building under transient loads, including ground shaking effects. The building is represented by a shear column.

The Earthquake versus Wind Application (*EvW* [16]) focuses on comparing the response of buildings subjected to earthquake and wind loading, using the same shear model that is applied in MDOF.

The Site-Specific Seismic Hazard Analysis and Research Kit (*S3HARK* [26]) is the educational version of QS3HARK that provides the same features and versatile set of material models but without uncertainty quantification. Removing UQ supports educational needs by streamlining the user interface and facilitating the setup of simulations.

The Pile Group Tool (*PGT* [24]) supports studies on the behavior of a pile or a pile-group in layered soil under ground shaking. Its user interface allows students to interactively observe the response of the system to changes in the soil characteristics, the pile configuration, and the pile design.

The Transfer Function Tool (*TFT* [28]) focuses on calculating the transfer function that maps a given bedrock motion to a surface motion. The tool allows students to define the characteristics of layered soil profiles and examine how the input motion is affected by the soil deposit.

Chapter 3
Earthquake—Surface Fault Rupture

Michael Gardner with contributions by Jonathan D. Bray,
along with review comments and suggestions by Pedro Arduino, Chaofeng Wang

Surface fault rupture is a manifestation of subsurface fault displacement through the overlying earth—including soil deposits—resulting in permanent ground surface deformation that can damage engineered systems. The characteristics of the surface deformation depend on the type of fault movement, the inclination of the fault plane, the amount of displacement on the fault, the depth and geometry of the materials overlying the bedrock fault, the nature of the overlying earth materials and definition of the fault, and the structure and its foundation (Bray, 2001). The subsurface movement of the fault may be expressed as a distinct rupture plane or as distributed distortion of the ground surface. Additionally, extensional movement of the fault can cause tensile strains and cracking at the ground surface.

3.1 Input and Output Data

3.1.1 Input Data

Input data for analyses assessing surface fault rupture describe the characteristics of the fault, the overlying materials, and in some cases the structures overlying the fault. These inputs can be classified as follows:

Depth of overlying soil

The depth of the overlying soil affects how subsurface fault deformations manifest as surface fault rupture. In closed-form solutions, the depth of soil is an input into the analytical equation. In pseudo-static analyses, the depth of overlying soil is defined by the boundary conditions in the numerical model.

Angle of dilation

Some closed-form solutions take the angle of dilation as input, while soil constitutive models used in pseudo-static analyses account for soil dilatancy in their formulation. The angle of dilation will depend on the type and characteristics of the soil overlying the fault. “Dense” sand will tend to increase in volume during shearing, which is described by a larger angle of dilation. Conversely, “loose” sand may contract during shearing such that the dilation angle is often near zero or negative. Normally consolidated to slightly over-consolidated clay is characterized by low dilatancy, while heavily over-consolidated clay will respond dilatively.

Fault characteristics

The type of fault, slip-type, and fault geometry influence the likelihood and amount of surface fault rupture that may occur during an earthquake. Closed-form solutions are only applicable for the fault type for which they were developed, so care must be taken when applying these methods. Pseudo-static analyses explicitly model the fault type and geometry by specifying boundary conditions and boundary displacements in the numerical model. Some probabilistic models, such as the model developed by Moss and Ross (2011), are specific to a particular type of fault and slip-type, while other methods, such as the Hecker et al. (2013) model, can be applied more generally.

Moment magnitude

Moment magnitude is a quantitative measure of the earthquake size or magnitude. It is the only magnitude scale that is not subject to saturation as it is based on seismic moment as opposed to the ground-shaking level. Probabilistic fault displacement hazard assessments take magnitude as an input and condition the probability of surface fault rupture occurring and the probability of rupture past the site on the input magnitude.

Numerical method and soil constitutive model

In pseudo-static analyses, soil is modeled using both continuum and granular methods. Both finite-difference and finite-element methods have been applied when modeling the soil as a continuous medium. Constitutive models employed in these methods have ranged from the elastoplastic Mohr-Coulomb model to more advanced models, such as UBCSAND (Byrne et al., 2004), that can capture nonlinear stress–strain response, contractive and dilative volumetric response, and dependence on confining pressure. The discrete element method (DEM) has been used to explicitly model the granular nature of soil. In this approach, the particles are modeled as rigid bodies, and all nonlinear behavior is captured in the model by describing contacts between particles. Contact models range from as simple as linear elastic contacts to nonlinear Hertz-Mindlin type contact models.

3.1.2 Output Data

Depending on the type of analytical procedure used, one or more of the following outputs can be produced:

Shape and location of failure surfaces

Closed-form solutions can provide estimates of the shape and location of the failure surface, and possible failure modes associated with shallow foundations. Pseudo-static analyses can provide a more complete description of the anticipated location, shape, width, and extent of the failure surface and its dependence on soil conditions at the site.

Foundation-rupture interaction

Pseudo-static analyses can be employed to investigate how different foundation systems and soil improvement can influence how subsurface fault displacement propagates through the overlying soil deposits and manifests at the surface. This requires more knowledge about the conditions at the site being analyzed such that constitutive models can be calibrated to provide meaningful results.

Probability of surface rupture

Probabilistic fault displacement hazard assessments can provide estimates of the probability of surface rupture occurring at a site and the probability that the rupture will fall within an estimated range of displacements.

3.2 Procedures for Evaluating Surface Ruptures

In the event that surface fault rupture is anticipated to occur at a site, the following procedures can be applied:

Closed-form solutions

Closed-form solutions for evaluating surface fault rupture and its interaction with structures are not typically used in research or practice because they are oversimplified and not well validated by field case histories. For free-field analyses, the method presented by Cole and Lade (1984) provides estimates of the shape and location of failure surfaces in soil. The required inputs for this procedure are the depth of the overlying soil, the angle of dilation of the soil, and the dip angle of the fault; however, this method is restricted to dry, cohesionless soils above dip–slip faults. Note: this procedure was developed based on small-scale experiments and has not been validated by field case histories. Another approach, presented by Berrill (1983), provides analytical solutions for assessing various failure modes for shallow foundations across strike–slip faults. Similarly, this procedure is not widely used in practice.

Probabilistic assessment of fault-displacement hazard

Probabilistic fault displacement hazard assessments provide a means to evaluate the probability of some amount of fault displacement occurring at a site. Generally, these methods provide an estimate of the probability of some level of fault displacement being exceeded. This is analogous to the approach used in PSHA for ground shaking based on a given set of input parameters that characterize the type of event and location of the site relative to that event. Examples of such methodologies are Hecker et al. (2013), Moss and Ross (2011), Petersen et al. (2011), and Youngs et al. (2003).

Pseudo-static analysis

Pseudo-static numerical analyses can provide estimates of not only the amount of surface fault displacement that may occur at a site, but also the characteristics of the deformation at the site and how structures might interact with the deforming soil. Continuum-based methods (such as finite-element and finite-difference methods) and discontinuous methods (such as the DEM) have been implemented to model surface fault rupture. These methods can capture how fault and soil material properties affect surface manifestations of subsurface fault displacement, providing insight into potential hazards at a site. These methods require more knowledge of site conditions and soil properties such that constitutive model parameters can be calibrated to provide meaningful results for a particular site. For pseudo-static analyses, the dynamics of fault rupture are ignored. Instead, the fault displacement is specified while the displacement rate is kept slow enough to avoid dynamic effects. Some researchers have investigated dynamic surface fault rupture (Oettle et al., 2015) and have demonstrated that ignoring dynamic effects results in insignificant differences in the results; therefore, most analyses are implemented in a pseudo-static manner (Anastasopoulos and Gazetas, 2007; Anastasopoulos et al., 2008; Bransby et al., 2008a; Bransby et al., 2008b; Garcia and Bray, 2018a,b; Oettle and Bray, 2017; Oettle and Bray, 2013).

3.3 Research Gaps and Opportunities

Recent advances in probabilistic fault rupture assessment methods allow for hazard-based evaluation of surface fault rupture and are amenable to being applied at a regional scale; however, they do not currently incorporate soil conditions in evaluating surface fault rupture. Comparatively, pseudo-static simulations of surface fault rupture have been used to assess how local soil conditions and the characteristics of foundations overlying the fault affect the rupture path and how it manifests at the surface. Unfortunately, the computational demand associated with these analyses is prohibitive at the regional scale. The challenge of assessing surface fault rupture can be attributed to the nature of the phenomenon, i.e., displacements occur across a narrow shear band along significantly longer lengths of rupture, posing unique challenges to the research community.

When considering numerical simulations of surface fault rupture, a major difficulty is ensuring sufficient numerical resolution while also minimizing computational cost. Given that the area of interest is highly localized—even in "loose" soil deposits where deformation is more distributed, the shear band is relatively narrow compared to the rest of the simulation domain—adaptive meshing and refinement techniques could help alleviate some of the computational burden while maintaining sufficient resolution where it is needed. Additionally, currently simulations do not consider the layered and heterogeneous nature of natural soils, which potentially could have a significant influence on the propagation of subsurface rupture to the ground surface. To implement and validate numerical models capable of performing these simulations in HPC environments, open-source software is needed. In addition, there is a gap in the amount of high-quality experimental data that is available to validate numerical capabilities. Available experimental datasets focus primarily on homogeneous, cohesionless soils, so it is not possible to calibrate and validate numerical models that potentially could capture the influence of heterogeneity in overlying soil deposits.

On a regional scale, probabilistic assessment of fault displacement hazard has great potential for broad application. Current methods consider the probability that surface fault rupture will occur at a site conditioned on the earthquake magnitude being large enough to cause rupture and that sufficient subsurface rupture occurs to manifest as surface rupture. Developing models that are capable of incorporating additional data that describes soil conditions and explicitly consider different fault and slip-types would provide insight into how more localized conditions could affect regional response.

3.4 Software and Systems

The following list is a compilation of software commonly used in assessing earthquake surface fault rupture. Currently, there are no software packages available for the closed-form procedures. Although probabilistic fault displacement hazard assessment software has been developed by consultants that perform this type of analysis (Wells and Kulkarni, 2014), it is not available publicly.

OpenSees

The Open System for Earthquake Engineering Simulation (*OpenSees* [6]) is an open-source software framework capable of performing pseudo-static and dynamic analyses with the finite-element method. OpenSees is maintained by the Pacific Earthquake Engineering Research (PEER) Center and actively developed by researchers at UC Berkeley and various research institutions. Several commonly used soil constitutive models have been implemented in OpenSees, and additional models can be added based on user needs. The framework is capable of running on HPC systems and supports MacOS, Linux, and Windows operating systems.

YADE

YADE [38] is an extensible open-source framework focused on the DEM (Šmilauer, 2015) that can be used to perform pseudo-static and dynamic analyses. Yade is capable of performing three-dimensional simulations with various particle shapes and contact models. Since it is open-source, it is possible to add different particle shapes and contact models as needed. Currently Yade supports Linux operating systems. In terms of parallel-computing capability, shared memory parallelism using OpenMP implemented though distributed memory capability using MPI is under development. More information, including the source code, can be found on the Yade homepage.

LIGGGHTS

LIGGGHTS-PUBLIC [33], an open-source (at least partially) DEM package, is capable of performing both pseudo-static and dynamic analyses. LIGGGHTS originated as an expansion of the granular package in *LAMMPS* [32], an open-source molecular dynamics framework developed and maintained by Sandia National Laboratories. Some functionality within LIGGGHTS is not available in the public version. The source code for the public version is available at `https://github.com/CFDEMproject/LIGGGHTS-PUBLIC`.

LMGC90

LMGC90 [34] is an open-source framework developed and maintained by the Mechanical and Civil Engineering Laboratory (LMGC), a research laboratory of the University of Montpellier and of the French National Center for Scientific Research (CNRS). The software implements the DEM with non-smooth contact dynamics. More information is available on the LMGC90 homepage.

FLAC

Fast Lagrangian Analysis of Continua (*FLAC* [31]), developed by the Itasca Consulting Group, has been used to perform pseudo-static and dynamic surface fault rupture analyses. FLAC implements the finite-difference method and models the soil as a continuum. In addition to the pre-programmed soil constitutive models available in FLAC, users can provide customized soil constitutive models either as pre-compiled dynamic libraries or by using the scripting language FISH. This software is proprietary, closed-source, and does not support HPC deployment. Currently, FLAC supports only Windows-based operating systems.

PFC

Particle Flow Code (*PFC* [36]) is a general-purpose DEM framework. The PFC can model the granular nature of soil and has been used for pseudo-static analyses of surface fault rupture in sand; it is capable of performing either two-dimensional or three-dimensional analyses using various contact models. User-defined contact models can be input using either FISH scripts or pre-compiled dynamic libraries. Currently, PFC supports only Windows-based operating systems and is not HPC capable. The software is proprietary and closed-source.

PLAXIS

PLAXIS [37], now part of Bentley Systems, is a finite-element method software package that can be used to perform pseudo-static and dynamic analyses. Custom soil constitutive models can be implemented within this platform. PLAXIS is proprietary and closed-source. Currently, it is not HPC capable and supports only Windows-based operating systems.

General FEM solvers

LS-DYNA [35] and *ABAQUS* [30], both proprietary, closed-source general finite-element methods solvers, have been used successfully for large-scale pseudo-static and dynamic analyses. Custom material models, such as UBCSAND, can be implemented in these frameworks. Depending on the license purchased, LS-Dyna and ABAQUS are capable of running on HPC systems. LS-Dyna supports Unix, Linux, and Windows-based operating systems and is currently available on DesignSafe. ABAQUS currently supports Linux and Windows-based operating systems.

3.4.1 Relevant SimCenter Tools

The SimCenter supports the application of advanced uncertainty quantification techniques in the field of numerical simulation of fault rupture.

quoFEM

The Quantified Uncertainty with Optimization for the Finite-Element Method (*quoFEM* [7]) tool facilitates model calibration, optimization, uncertainty propagation, reliability analysis, surrogate modeling, and sensitivity analyses of numerical materials, components, and systems by combining existing simulation environments with state-of-the-art uncertainty quantification applications. The graphical user interface currently supports finite-element software (OpenSees and FEAP) and can also interface with custom analysis packages, including, but not limited to those based on the discrete element and finite difference method and other commercial software that cannot be bundled with the open-source SimCenter application (e.g., LS-DYNA, ABAQUS). These features provide users instant uncertainty analysis and optimization capabilities for numerical models. Furthermore, quoFEM provides an opportunity for researchers working with experimental facilities to use advanced UQ methods and tools to design experiments and calibrate numerical models.

Chapter 4
Earthquake—Soil Liquefaction

Chaofeng Wang with contributions by Jonathan D. Bray,
along with review comments and suggestions by Pedro Arduino, Brady Cox, and Michael Gardner

Soil liquefaction has caused much damage in recent earthquakes (e.g, Bray et al., 2017; Cubrinovski et al., 2011; Cubrinovski et al., 2017). In fluid-saturated, geologically unconsolidated soil, liquefaction is a phenomenon caused by a sudden change in stress due to a rapid earthquake loading, during which the pore-water pressure increases and the effective stress reduces so that the soil loses much of its stiffness and strength and behaves like a liquid. The liquefied soil may lose its ability to support overlying structures or buried utilities.

As summarized in the Kavazanjian et al. (2016) report, the consequences of liquefaction may include vertically or laterally displaced ground, landslides, slumped embankments, foundation failures, and mixtures of soil and water erupting at the ground surface. In turn, these effects may lead to settlement, distortion, and the collapse of buildings; the disruption of roadways; the failure of earth-retaining structures; the cracking, sliding, and over-topping of dams, highway embankments, and other earth structures; the rupture or severing of sewer, water, fuel, and other lifeline infrastructure; the lateral displacement and shear failure of piles supporting bridges and waterfront structures; and the uplift of underground structures.

4.1 Input and Output Data

Input data for assessing the liquefaction hazard describe the earthquake intensity measures (IMs), the characteristics of geologic and technical site conditions, and the topography of the site.

4.1.1 Input Data

Ground motion and intensity measures

Mechanics-based numerical simulation of liquefaction requires ground motions as input data. Simplified empirical methods take earthquake moment magnitude and IMs as input data that include peak ground acceleration (PGA), spectral acceleration ($Sa(T)$), Arias intensity (A_I), etc. Which IM to use depends on the selected analytical models.

Site characteristics

Site characteristics include geologic and geotechnical site conditions, water table, slope, and topography.

Geologic characteristics

Regional liquefaction assessment depends on geologic information. Youd and Perkins (1987) proposed a method for classifying the liquefaction susceptibility of numerous geologic units. This requires the mapping of geologic units, which are generally characterized by their depositional environment, physical characteristics, and age. The depth to the groundwater table is also required.

Geotechnical characteristics

Geotechnical characterization of the site consists primarily of identifying soil properties, such as soil type, shear strength, density, fines content, water saturation, etc. These parameters can be estimated by *in situ* tests, such as the cone penetration test (CPT), standard penetration test (SPT), and shear-wave velocity (V_s) measurement, or laboratory testing of soil specimens.

Topography

Ground topographic parameters (e.g., ground slope, free face height, and the distance to a free face) define the boundary conditions of a site and are input data required for a liquefaction assessment.

4.1.2 Output Data

Depending on the modeling approach used, one or more of the following outputs can be produced:

Liquefaction indices at a site

Based on input data collected at a site, various liquefaction indices can be calculated, including liquefaction potential index (LPI), liquefaction severity number (LSN), etc.

Induced ground displacement at a site

Liquefaction in the soil can lead to the deformation of the ground surface, such as vertical settlement and lateral spreading.

Liquefaction maps

Maps of liquefaction susceptibility or liquefaction-induced ground damage can be the outputs of a regional liquefaction assessment.

4.2 Modeling Approaches

Analysis of liquefaction and its consequences is an active area of research and development in geotechnical engineering. Methods for estimating liquefaction triggering and its consequences vary. They fall into two categories: simplified methods and mechanics-based numerical methods.

Simplified methods

In 1998, a consensus was reached within the geotechnical community on the use of an empirical stress-based approach for liquefaction triggering assessment called the "simplified method," first developed by Seed and Idriss (1971). This method is still commonly used in practice today (Kavazanjian et al., 2016; Youd and Idriss, 2001).

In a simplified method, a factor of safety (FS) against liquefaction triggering, defined as the ratio between the seismic loading required to trigger liquefaction (i.e., the liquefaction resistance) and the seismic loading expected from the earthquake (i.e., the seismic demand), is computed. Both the seismic demand and the liquefaction resistance are characterized as cyclic stress ratios, defined as the ratio of the equivalent cyclic shear stress to the initial vertical effective stress. The seismic demand is the earthquake-induced cyclic stress ratio (CSR), and the liquefaction resistance is the cyclic resistance ratio (CRR): that is, the cyclic stress ratio required to trigger liquefaction.

Seed and Idriss (1971) proposed a simplified equation, based on Newton's second law, to compute a representative CSR for a given earthquake magnitude. This model was later revised by Boulanger and Idriss (2014), Cetin and Seed (2004), Idriss (1999), and Idriss and Boulanger (2008).

The most common approaches used in practice to compute CRR are based on geotechnical field data, e.g., CPT, SPT, and V_s. The most commonly used relationships to estimate CRR from a CPT profile are those developed by Idriss and Boulanger (2008), Moss et al. (2006), Robertson and Wride (1998), and Robertson (2009). The most commonly used relationships to estimate CRR from SPT blow count are those proposed by Boulanger and Idriss (2014), Cetin et al. (2018), and Youd and Idriss (2001). The most commonly used relationships to estimate CRR from a V_s profile were developed by Andrus and Stokoe II (2000) and Kayen et al. (2013).

Mechanics-based numerical simulation

The development and validation of numerical analysis tools and procedures for estimating the effects of liquefaction on the built environment is identified as an overarching research need (Bray et al., 2017). Numerical analysis is critical for several reasons, including obtaining insights on field mechanisms that cannot be discerned empirically, providing a rational basis for developing or constraining practice-oriented engineering models, and providing a tool for evaluating complex structures with unique characteristics that are outside the range of empirical observations.

Finite-element and finite-difference procedures are the most common procedures used in engineering practice. As pointed out in Bray et al. (2017), there are major challenges in developing robust validated numerical analysis procedures for evaluating the effects of liquefaction on civil infrastructure systems due to the variety of multi-scale, multi-physics coupled nonlinear interactions that come to the forefront in different scenarios where analytical capabilities for liquefaction effects have not been validated. Currently, research or commercial software platforms have not incorporated the best available solution techniques/options for these challenging problems, such as the coupled, large-deformation analysis of strain-softening, localizations, cracking, and interfaces in two or three dimensions with complex constitutive models.

4.3 Research Gaps and Opportunities

Liquefaction risk analyses has focused on assessing the likelihood of triggering of liquefaction, resulting in maps of susceptibility. The consequences of liquefaction, i.e., the induced damage to the ground, is not sufficiently studied. Well established and universally applicable methods for quantifying liquefaction-related damages to the ground are still to be developed. HAZUS provides a method derived from engineering experiences for evaluating liquefaction-induced permanent ground deformation (PGD) given PGA and site-specific liquefaction susceptibility; however, the HAZUS method was developed based on observations of relatively old events.

In recent years, with more liquefaction cases observed (Bray et al., 2017; Cubrinovski et al., 2017) and the creation of large liquefaction databases (Brandenberg et al., 2020), new regression-based ground damage models are being developed (Khoshnevisan et al., 2015; Stewart et al., 2016) and tested for different regions (Chen et al., 2016). New insights into the consequent damage to overlaying structures and their fragility are also being developed (Bray and Macedo, 2017; Fotopoulou et al., 2018). In regional simulations, large-scale assessment of liquefaction is needed. Traditionally, regional liquefaction can be coarsely assessed based on geological data (Holzer et al., 2006). In recent years, techniques such as random fields are proposed for regional-scale modeling of liquefaction hazard, which can account for spatial uncertainties while considering both geotechnical and geological information (Wang and Chen, 2018; Wang et al., 2017; Zhu et al., 2017a).

4.4 Software and Systems

Systems for liquefaction evaluation are divided into two categories according to the method used: simplified empirical methods and mechanics-based numerical methods.

Simplified methods

Simplified methods have been developed for rapid engineering evaluations of site-specific liquefaction. To date, no open-source software is available. *LiqIT* [40], *Cliq* [39], *NovoLIQ* [42], and *Liquefy-Pro* [41] are all Windows based. These tools provide a user interface that can let the user input the soil profiles and earthquake loading, and then visualize the liquefaction index for each soil layer.

Numerical methods

For mechanics-based numerical methods, creating a constitutive model that captures the soil's behavior under cyclic loads is crucial. Commercial software such as *PLAXIS* [37] and *FLAC* [31] are widely used by the geotechnical community. Both of them are Windows based. OpenSees is the only open-source software identified for dealing with liquefaction. Several well-known liquefaction-capable constitutive models are: PM4Sand, PM4Silt, PDMY02, UBCSAND, and DAFALIAS-MANZARI. Except for UBCSAND, they are all available in OpenSees.

4.4.1 Relevant SimCenter Tools

The SimCenter develops both research and educational tools to facilitate performing site-specific analysis of soil response to earthquakes. The tools currently available focus on the one-dimensional propagation of ground shaking from the bedrock to the free surface.

QS3HARK

The Site-Specific Seismic Hazard Analysis and Research Kit with Uncertainty Quantification (*QS3HARK*) performs site-specific analysis of ground shaking and liquefaction by simulating wave propagation through soil layers. The simulations use the finite element method as implemented in *OpenSees* [6] to perform the calculations. Several advanced material models are available in QS3HARK (e.g., PM4Sand, PM4Silt, PDMY, PDMY02, PDMY03, ManzariDafalias, Borja-Amies) to support advanced site-response analysis. Uncertainties in both the soil properties and the bedrock ground motion inputs can be characterized and propagated throughout the simulations to arrive at a probabilistic description of the ground shaking, ground deformation, and the liquefied soil layers.

S3HARK

The Site-Specific Seismic Hazard Analysis and Research Kit (*S3HARK*) is the educational version of QS3HARK that provides the same features and versatile set of material models but without uncertainty quantification. Removing UQ supports educational needs by streamlining the user interface and facilitating the setup of simulations.

Chapter 5
Earthquake—Slope Stability and Landslides

Michael Gardner with contributions by Jonathan D. Bray,
along with review comments and suggestions by Pedro Arduino, and Chaofeng Wang

Earth structures and natural slopes may experience deformation when subjected to seismic loading. When considering the response of these systems, it is important to first identify whether the materials considered may lose significant strength as a result of cyclic loading. If so, the system may be at risk of a flow slide, typically associated with liquefaction, which may lead to large deformations that can severely compromise an engineered system. Except for a dynamic nonlinear effective stress analysis, the methods presented in this section assume that liquefaction does not occur, and slopes will instead undergo some amount of deformation because of incremental displacements during seismic shaking due to inertial loading.

In the simplest case, a pseudo-static seismic slope stability analysis provides a factor of safety (FS) for a given system based on a specified seismic event or hazard, while more advanced methods provide an estimate of the range of seismic permanent displacement anticipated. Regardless of the analytical procedure employed, important aspects to capture in the analysis are the earthquake ground motion, the material properties of the system being considered and its foundation, its geometry, and the initial state of stress and pore-water pressure in the system and its foundation. Much depends on the intensity, frequency content, and duration of the earthquake ground motion, the dynamic resistance of the earth slope, which is defined by its yield coefficient, and the dynamic response characteristics of the earth or waste system being shaken.

5.1 Input and Output Data

5.1.1 Input Data

Whether employing a simplified method or performing a dynamic nonlinear effective stress analysis, the required inputs define (1) the characteristics of the seismic loading; and (2) the characteristics of the earth or waste system that have the greatest impact on the overall response. The input data can be classified as follows:

Moment magnitude

Moment magnitude is a quantitative measure of the earthquake size or magnitude. It is the only magnitude scale that is not subject to saturation, as it is based on seismic moment as opposed to the ground-shaking level.

Spectral acceleration at the degraded period of the sliding mass

Due to material nonlinearity, it has been shown that using the spectral acceleration at the degraded period instead of at the initial period of the sliding mass is an optimal IM across a range of fundamental periods for the sliding mass (Bray and Travasarou, 2007).

Arias intensity

The Arias intensity (A_I) is a ground-motion parameter that includes the effects of both amplitude and frequency content while also providing a good measure of the energy associated with a particular ground motion. The computation of AI is over the entire duration of the ground motion; as such, is not sensitive to how duration of strong motion is defined.

Peak ground acceleration

Peak ground acceleration (PGA), a measure of the ground-motion amplitude, is one of the most commonly used ground-motion parameters. The PGA of a motion is taken as the largest absolute value of the vector sum of orthogonal acceleration components.

Peak ground velocity

Similarly to PGA, the peak ground velocity (PGV) is a good measure of the ground-motion amplitude. Since PGV is less sensitive to higher-frequency components of a ground motion, it is likely a better measure of ground-motion amplitude at intermediate frequencies (Kramer, 1996).

Initial and degraded period of the sliding mass

In some idealized sliding mass models, the dynamic stiffness of the sliding mass is represented by the initial fundamental period, while the average reduction in the earth or waste slope being analyzed is captured by the degraded period.

Seismic yield coefficient

The seismic yield coefficient, k_y, is used to represent the slope's dynamic strength when using simplified sliding block procedures. Estimating the value of k_y requires careful consideration of the materials being analyzed as it is governed by the critical strata in the slope. Simplified procedures for estimating k_y can be found in Bray et al. (1998).

Soil constitutive model

For dynamic nonlinear effective stress analyses, a soil constitutive model is used to describe the evolution of stress and strain within the soil. These models can also capture the interaction between the soil and pore water by considering changes in pore-water pressure that depend on the soil type and boundary conditions in the numerical model. Examples of constitutive models employed in dynamic analyses can be found in Boulanger and Ziotopoulou (2017, 2018), Byrne et al. (2004), and Yang et al. (2003).

5.1.2 Output Data

Depending on the type of analytical procedure used, one or more of the following outputs can be produced:

Factor of safety

Pseudo-static stability analyses generally provide results in terms of an FS similar to what would be attained from a static limit equilibrium analysis. With an appropriately calibrated analysis, the FS gives an indication of magnitude of potential displacement.

Seismic displacement

Sliding block-type analyses generally provide output in terms of an estimated range of seismic displacement. Additionally, some methods provide probabilistic seismic displacement results as either the probability of a range of displacement occurring or the probability of exceeding a specified displacement threshold.

Full Description of displacement, stress, and pore-water pressure fields

When performing dynamic nonlinear effective stress analyses, simulations can provide the full time histories of the displacement, stress, and pore-water pressure fields estimated by the numerical model. These results provide insight into the site-specific response and can highlight localized phenomena that might not be captured by simplified methods.

5.2 Procedures for Evaluating Seismic Slope Displacement

There are three primary approaches employed currently in estimating seismic slope displacements, which are listed in order of increasing complexity:

Pseudo-Static stability analyses

This class of seismic slope stability analysis is analogous to a static limit equilibrium analysis where the earthquake loading is represented as an additional constant horizontal load applied to the slope. This horizontal seismic coefficient is a function of the characteristics of earthquake shaking and the dynamic response characteristics of the slope. The seismic coefficient is estimated as a percentage of the maximum value of the summation of the differential masses of the sliding blocks, each multiplied by the acceleration acting on them over time divided by the total weight of the sliding mass, which produces the maximum seismic coefficient. The percentage of the maximum coefficient used in the pseudo-static slope stability analysis is a function of the allowable seismically induced permanent displacement (Bray and Travasarou, 2009). For this type of analysis, the required inputs are soil-strength parameters, slope geometry, water pressures, and the pseudo-static seismic coefficient. Results are provided in terms of an FS that, when appropriately calibrated, gives an indication of the level of potential displacement. Prevalent pseudo-static methods can be found in Bray and Travasarou (2009), Bray and Macedo (2019), Hynes-Griffin and Franklin (1984), Macedo et al. (2018), and Seed (1979).

Sliding block analyses

Newmark-type sliding block analyses provide a range of anticipated seismically induced permanent displacements that serve as an index of seismic performance of a system. These procedures consider the dynamic response of the sliding mass if assumed to be non-rigid and calculates the sliding displacement. Methods that consider the dynamic response of the sliding mass consider this response as either decoupled or fully coupled. Typical inputs for these procedures provide information about the characteristics of the earthquake shaking being considered—moment magnitude, spectral acceleration at the degraded period of the sliding mass, A_I, PGA, and PGV—as well as dynamic properties of the sliding mass—the initial and degraded fundamental period of the sliding mass, and the seismic coefficient at which the sliding mass will yield, which is called the yield coefficient. From these inputs, the analysis provides estimates of the seismic slope displacement and the probability of some displacement occurring, or, in some cases, the probability of exceeding an allowable displacement. These methods are semi-empirical and are applicable primarily to events exhibiting similar features to those contained in the dataset used to develop a procedure. Commonly used procedures can be found in Bray and Travasarou (2007), Bray and Macedo (2019), Jibson (2007), Makdisi and Seed (1978), Rathje et al. (2014), and Saygili and Rathje (2008) for shallow crustal earthquakes and Bray et al. (2018) for subduction zone earthquakes.

Dynamic nonlinear effective stress analyses

Continuum-based methods, such as finite-element or finite-difference methods, are employed with soil constitutive models to analyze the dynamic response of the system to earthquake loading. This type of analysis requires greater effort computationally as the partial differential equations describing the mechanical response of the soil are numerically integrated over the full time history of earthquake shaking. Additionally, extensive information about the soil conditions at the site is required such that constitutive models can be sufficiently calibrated to attain meaningful results. Unlike the pseudo-static and simplified methods, this type of analysis is still applicable in the event that liquefaction is anticipated to occur at the site. It is the state-of-practice to employ dynamic nonlinear effective stress analyses in the evaluation of critical earth systems, such as dams, tailing dams, ports, and large earth-retention systems. Examples of constitutive models employed for dynamic analyses can be found in Boulanger and Ziotopoulou (2017, 2018), Byrne et al. (2004), and Yang et al. (2003).

5.3 Research Gaps and Opportunities

The vast majority of seismic slope displacement methods focus on analyzing a single slope; the resolution at which this slope is analyzed varies greatly between different methods. Simplified methods, while not capable of fully capturing the site-specific response of individual slopes, provide reasonable estimates of seismic slope displacement at negligible computational cost. Comparatively, dynamic nonlinear numerical analyses can be meticulously calibrated to provide insight into localized response, but require detailed knowledge of the site being analyzed, additional computational resources, and necessitate a greater level of skill from the end-user. The limitations of these methods will be dependent on the application and scale at which they are to be applied. Many engineering applications do not require a fully nonlinear analysis, while it also is not possible to perform high-fidelity, full-physics numerical simulations at a regional scale. The varied application of seismic slope stability methods provides many opportunities to advance the field (e.g., Bray et al., 2017).

For site-specific, high-resolution simulations, continued research is required to better resolve grain-level dynamics and fluid-solid interaction. Much progress has been made in continuum simulations of soils, and several models are available that are capable of describing the nonlinear, plastic behavior of soil during seismic loading, while also considering the impact of excess pore-water pressure generation during earthquake shaking. At the grain-level, however, there remains opportunity for exploring the interaction between water and soil particles, and how material type and fabric interplay with transient pore-water pressure within the soil matrix. Beyond the constitutive and numerical models describing soil response, there is a need to implement, validate, and calibrate these models in open-source software that is capable of leveraging high-performance computing (HPC) resources. This ultimately will broaden their impact and accessibility to the natural hazards community.

In terms of regional scale seismic slope stability, the opposing demands of detailed response models and capturing large regions pose unique challenges and provide opportunities for further development. Most regional-scale co-seismic landslide hazard models are based on an infinite slope analysis that largely ignores local geology and the associated failure modes. Research by Grant et al. (2016) presents a multi-modal landslide hazard assessment tool that accounts for local geological as well as topographical conditions that may contribute to the expected failure mode and corresponding hazard. There is opportunity to build upon this work by leveraging co-seismic landslide databases for developing tools that run more sophisticated models in regions where more data is available, with the goal of providing insight into how these results could be extrapolated to regions where data is sparse. Additionally, advances in remote sensing provide exciting opportunities to dynamically inform hazard models such that updated predictions could be made from real-time observations to help guide emergency response.

5.4 Software and Systems

The following list of software is commonly used in assessing the potential for seismic slope displacement:

SLAMMER

SLAMMER [43] (Jibson et al., 2013) is capable of performing Newmark-type sliding block analyses. It allows users to choose from various simplified methods as well as running rigid block, decoupled sliding block, and fully coupled displacement calculations on time histories selected from an included catalog. Since SLAMMER is Java based, it is capable of running on any operating system through the Java Virtual Machine (JVM). The source code is available at on GitHub.

OpenSees

The Open System for Earthquake Engineering Simulation (*OpenSees* [6]) is an open-source software framework capable of performing fully nonlinear dynamic effective stress analyses. OpenSees is maintained by the Pacific Earthquake Engineering Research Center (PEER) and actively developed by researchers at UC Berkeley and various research institutions. Several commonly used soil constitutive models have been implemented in OpenSees, and additional models can be added based on user needs. The framework is capable of running on HPC systems and supports MacOS, Linux, and Windows operating systems.

Spreadsheet solutions

Spreadsheet solutions are routinely used for Newmark-type sliding block analyses, with some authors releasing pre-programmed spreadsheets that implement their methods. To a lesser extent, spreadsheets are also used for pseudo-static stability analyses. Spreadsheet solutions can be implemented readily on any operating system using either Microsoft Excel or LibreOffice Calc. Note: pre-programmed spreadsheet solutions tend to be available in Microsoft Excel, which cannot be guaranteed to operate correctly in LibreOffice Calc.

UTEXAS4

UTEXAS4, available from ENSOFT, is a two-dimensional limit equilibrium analysis program capable of performing pseudo-static stability analysis. This software is proprietary and only supports Windows-based operating systems.

Slide2 and Slide3

Slide2 and Slide3 are two- and three-dimensional limit equilibrium analyses programs developed by RocScience that are routinely used for pseudo-static analyses. These tools are proprietary and only support Windows-based operating systems.

Slope/W

Slope/W is a proprietary program developed by GEOSLOPE. Similar to Slide2, it is a two-dimensional limit equilibrium solver that is capable of performing pseudo-static analysis. Currently, only Windows-based operating systems are supported.

FLAC

Fast Lagrangian Analysis of Continua (*FLAC* [31]), developed by the Itasca Consulting Group, is a proprietary finite-difference based software package capable of performing dynamic nonlinear effective stress analyses. FLAC allows users to import custom soil constitutive models either as pre-compiled dynamic libraries or by using the scripting language FISH. FLAC does not run on HPC systems and is closed source. Currently, only Windows-based operating systems are supported.

PLAXIS

PLAXIS [37], now part of Bentley Systems, is a finite-element software package that can be used to perform dynamic nonlinear effective stress analyses. Custom soil constitutive models can be implemented within the platform. PLAXIS is proprietary and closed source. Currently, it is not HPC capable and supports only Windows-based operating systems.

General FEM solvers

LS-DYNA [35] and *ABAQUS* [30], both proprietary general finite-element method solvers, are capable of fully nonlinear dynamic effective stress analyses. Custom material models, such as those required for modeling dynamic soil response, can be implemented in these frameworks. Depending on the license purchased, LS-Dyna and ABAQUS are capable of running on HPC systems. LS-Dyna supports Unix, Linux, and Windows-based operating systems and is currently available on DesignSafe. ABAQUS currently supports Linux and Windows-based operating systems.

5.4.1 Relevant SimCenter Tools

The SimCenter supports the application of advanced uncertainty quantification techniques in the field of numerical simulation of landslides and similar problems in rock mechanics (e.g., rock avalanches, sediment transport).

quoFEM

The Quantified Uncertainty with Optimization for the Finite-Element Method (*quoFEM* [7]) tool facilitates model calibration, optimization, uncertainty propagation, reliability analysis, surrogate modeling, and sensitivity analyses of numerical materials, components, and systems by combining existing simulation environments with state-of-the-art uncertainty quantification applications. The graphical user interface currently supports finite-element software (OpenSees and FEAP) and can also interface with custom analysis packages, including, but not limited to those based on the discrete element and finite difference method and other commercial software that cannot be bundled with the open-source SimCenter application (e.g., LS-DYNA, ABAQUS). These features provide users instant uncertainty analysis and optimization capabilities for numerical models. Furthermore, quoFEM provides an opportunity for researchers working with experimental facilities to use advanced UQ methods and tools to design experiments and calibrate numerical models.

Chapter 6
Tropical Cyclone—Wind

Ahsan Kareem with contributions by Liang Hu,
along with review comments and suggestions by Arindam Chowdhury, Seung Jae Lee, Rick Luettich, Lance Manuel, Forrest Masters, and Chen Xinzhong

Extreme wind induced by tropical cyclones (TC–hurricane/typhoon/tropical storm) dominates the wind loading on structures in the U.S. coastal areas. To assess the damage, loss, and performance of buildings probabilistically under wind hazard as well as its secondary hazards (flood, rain, debris, storm surge, etc.), this section describes computational models and inputs available for estimating statistical characteristics of TC-induced wind speeds.

Typically, field measurements of TCs are limited and insufficient for estimating the probabilistic description of wind speeds; thus they are usually generated by Monte Carlo-based procedures. Such a simulation procedure starts from sampling input physical properties of a hurricane (e.g., intensity, track, and Holland B parameter) in terms of their probabilistic characteristics to simulate the wind field, by which the wind speeds at a specific site may be recorded and estimated (Russell, 1971). The simulation is carried out by employing phenomenological models of the hurricane wind field with random parameters. Other models based on meteorological aspects [e.g., MM5 (Liu et al., 1997) and WRF (Davis et al., 2008)] are beyond the scope of this section. Three types of TC wind-field models are currently available. The first two models aim to solve the governing equation of motion of the TC atmospheric system directly using the central difference method: (I) height-resolved models, which can resolve the vertical structure of a tropical cyclone; and (II) slab models, which include an average or integration over the height of the governing equations. In contrast, Type III physics-based models solve the intensity and radial profile equations instead. The input variables are dependent upon the type of model selected.

6.1 Input and Output Data

Measurements

Through the past two centuries, data from recorded TCs have been used by the wind engineering community to create and calibrate probabilistic models. The National Oceanic & Atmospheric Administration (NOAA) provides an extended and comprehensive TC database for the Atlantic and Northeast Pacific, which encompasses data from reconnaissance, microwave and dropsonde radar, as well as anemometer measurements (NOAA, 2018). Additional field measurements supplement this database (e.g., Li et al., 2015b; Wang et al., 2016). Many other measurement databases exist and may be publicly available, such as the extreme hurricane wind speed database by NIST (Batts et al., 1980).

Occurrence rate

This parameter describes the number of hurricanes that occur at a specific site. It is usually described by a Poisson or binomial distribution, whose parameters are obtained by statistics over the hurricane database (Li et al., 2016; Vickery et al., 2009c).

Track model: Initial location, Translation speed, and Heading

The track model describes the genesis point, heading direction, and translational speed of the center of a TC for simulation purposes. For a specific hurricane in the NOAA database, its best empirical track of the hurricane has already been synthesized by data fitting over various measurements. The database also describes how other TC parameters change along the track. For a specific site, the sub-region track model can be used, which only concerns the segment of TC tracks within a circle (often the radius is 500 km) centered at the site. This model is characterized by the perpendicular distance to the center and direction angle of the straight-line track (Georgiou, 1986; Xiao et al., 2011). Note: the full-track model is more popular in describing the genesis to the dissipation of a TC because it enables the simulation of extreme TC winds simultaneously for a large region rather than a specific site. The genesis location can be randomly selected from the historical record or generated based on its distribution function (Vickery et al., 2009c). Starting from the genesis location, the track is generated by Markov-type models, represented by auto-regressive functions in terms of TC parameters (latitude, translation speed, sea surface temperature, etc.) as well as a random error term (Vickery et al., 2000b) or by the Markovian transition probability function (Emanuel et al., 2006). The parameters of track models must be estimated from the hurricane database as well as other measurements (e.g., HadISST) (Li et al., 2016; Liu, 2014; Vickery et al., 2000b). Recent investigations usually apply the kernel method for modeling those parameters (Chen and Duan, 2018; Mudd and Vickery, 2015). Moreover, a dynamic track model (Beta-advection) has been developed based on isobaric wind speed measurements (Emanuel et al., 2006).

Intensity: Central pressure difference or Maximum wind speed

Type I and II hurricane models use the central pressure difference as a proxy for the TC intensity. Here, an auto-regressive model for the TC relative intensity (a function in terms of the pressure difference) has been established along with the track models. The Type III model employs the maximum mean wind speed as the intensity measure (IM), which may be predicted by a simple coupled ocean-atmosphere physical model CHIPS (Coupled Hurricane Intensity Prediction System) with its fast simulation algorithm (Emanuel, 2011, 2017; Emanuel et al., 2004) or by the historical record-free generator (Emanuel et al., 2008).

Size: Radius to maximum winds (RMW)

The Radius to Maximum Winds (RMW) denotes the size of a TC and is the only TC size parameter considered in Type I and II models. Type III models need additional parameters, e.g., the radius at the wind speed of 15.5 m/sec (Chavas and Lin, 2016). The probabilistic distribution of these size parameters can be estimated from the TC database. Note: an empirical model of RMW has been developed in terms of the location and intensity parameters as well as a random error term (Vickery and Wadhera, 2008; Vickery et al., 2009b).

Shape of radial pressure profile: Holland B parameter

Introduced by Holland (1980), the B parameter revises the radial pressure profile in Type I and II models to improve the goodness-of-fit of the maximum wind speed. From the TC database, this parameter can be estimated concerning the reconnaissance data, which evolves with time. Similar to RMW, statistical models are available for B as a function of RMW and latitude (Powell et al., 2005) or as a dimensionless function that also involves SST (Vickery and Wadhera, 2008). A physics-based pressure radial profile model has also been proposed by Holland (2008) and Holland et al. (2010).

Local terrain

The local topography at a specified site accounts for the boundary layer wind speed profile as well as the gust factor. A typical parameter of local terrain is the roughness length (or the equivalent shear velocity), which reflects the effects of upstream terrain within 3 km on the near-ground winds. Calculating this parameter is challenging, especially in consideration of the rapid change of wind azimuth during a TC (Vickery et al., 2009a). It can be adopted from existing design codes/specifications and augmented by additional computations by taking an average over various terrains along each wind direction. As long as field measurements of gust wind speeds are available at the specified site, the roughness length may also be estimated from the record (Masters et al., 2010). Furthermore, CFD-based methods are also available to estimate the local wind characteristics with detailed modeling of surrounding terrains. These are expected to yield more accurate results and are often the only reliable method for complex terrain but they are computationally expensive (Huang and Xu, 2013; Ishihara et al., 2005).

Landfall model parameters

After a hurricane makes landfall, the filling model starts to describe the weakening of the TC intensity, or, in other words, the decrease in the central pressure difference. This model is typically an exponential decay function, (Kaplan and DeMaria, 1995, 2001), whose decay constant is the filling rate as a statistical function in terms of the intensity, translational speed, and RMW (Vickery and Twisdale, 1995; Vickery, 2005; Vickery et al., 2009b). Moreover, both the mean wind speed vertical profile and radial profile are subject to notable changes after landfall, which may be captured by recently developed empirical models (Fang et al., 2018b; Snaiki and Wu, 2018; Zhao et al., 2013). A recent study points at slower decay of landfalling hurricanes when it strikes land, which is based on historical records potentially fueled by sea level rise, additional moisture, and climate change (Li and Chakraborty, 2020).

Output: Wind field

The main output of a TC simulation from an engineering perspective is the probabilistic model [i.e., Cumulative Distribution Function (CDF)] of mean wind speed in any specified target location/region. A single hurricane scenario results in a mean wind speed and direction time history, usually at the six-hour time interval. Additional effects of atmospheric turbulence may be reflected by gust factors as well as spectra. These results serve as the intensity measure (IM) for the ensuing performance-based wind engineering analysis (Barbato et al., 2013; Chuang and Spence, 2019; Liu, 2014; Spence and Kareem, 2014; Unnikrishnan and Barbato, 2016; Xiao et al., 2011; Yau et al., 2011).

6.2 Modeling Approaches

Provided the inputs stated above, all TC wind field models aim at solving the steady mean wind speed from the three-dimensional governing equation system describing atmospheric motion in a TC. Type I models solve the three-dimensional motion equation system without any dimensional reduction; Type II and III models are, per se, two-dimensional methods. Type II considers the equation system reduced from the original one, whereas the Type III model solves angular momentum equations derived by the physics-based mechanism of the TC rather than the original motion equation. Here, Type I models can solve wind speeds throughout the TC boundary layer height, whereas the other two models solve wind speeds at the gradient height, which are then converted to near-ground heights by the boundary layer wind speed profile. All the solved TC wind speeds need to be combined with the surface background wind speed, implying the use of the TC translational speed for Type I and II models. Eventually, the gust factor is applied to the mean wind speed to account for turbulence. Nonstationary effects associated with TC winds may also be considered.

Type I model

The basic atmospheric motion governing equation of TC is nonlinear and three dimensional, which can be solved numerically by the two-time-level time-split-based finite-difference scheme (Kepert and Wang, 2001; Kepert, 2011). It accounts for the salient height-related effects of both potential temperature and eddy viscosity (turbulent diffusivity represented by the vertical turbulent exchange coefficient K for momentum and heat) (Kepert and Wang, 2001; Kepert, 2010b). Linearization of the nonlinear equation has been carried out considering the gradient balance wind speed to yield the surface horizontal momentum equations (Kepert, 2001). The linearized equations are then solved by utilizing the perturbation method (Meng et al., 1995) or the Fourier series expansion (Kepert, 2001). Depending on the form of eddy viscosity (constant, height-dependent, or piece-wise linear or nonlinear) and the terms being neglected, various semi-analytical solutions are obtained (Fang et al., 2018a; Huang and Xu, 2013; Kepert, 2006; Meng et al., 1995, 1997; Snaiki and Wu, 2017). In comparison with the nonlinear solution, these linear solutions sacrifice accuracy to reduce computational costs (Kepert and Nolan, 2014).

Type II model

By integrating the three-dimensional equation over the vertical coordinate, a slab (or depth-averaged) model is derived (Kepert, 2010a). This model still involves the vertical turbulent diffusivity and is capable of calculating the vertical wind speed (Langousis, 2008; Smith, 1968; Smith and Vogl, 2008). Further simplification is achieved by removing both the advective and/or diffusive fluxes at the upper boundary, leading to the common category of TC models popular in the structural engineering community (Powell et al., 2005; Shapiro, 1983; Vickery et al., 2000a; Vickery et al., 2009b)). Chow (1971) was the first to develop a finite-difference scheme to solve the model. Since then, other issues in this model have been addressed to enhance its applicability, e.g., the boundary layer, drag coefficient, track model, and approximate fast algorithm. So far, the parameters of this model have been well-recognized probabilistically based on the TC database (Vickery and Wadhera, 2008). A review paper guiding application of this model is also available (Vickery et al., 2009a). Note: the TC intensity and track inside this model are being updated (Mudd et al., 2015; Vickery et al., 2010).

Type III model

The foundation of this approach is a physics-based intensity model derived by regarding the TC as a Carnot heat engine (Emanuel, 2004; Emanuel, 1988). The maximum wind speed-represented intensity can be calculated along the track (Emanuel, 2011). Although a simple formula was used as the radial profile at the gradient height (Emanuel et al., 2006; Lin and Chavas, 2012), a more reliable model has been proposed by dividing the profile into its inner and outer regions. Physics-based expressions for the two regions have been derived and then joined by a differential equation system to establish the whole profile (Emanuel, 2004; Emanuel and Rotunno, 2011). Given the input, only the equation system of the profile needs to be solved iteratively (Chavas and Lin, 2016; Chavas et al., 2015). The empirical models for converting the resulting gradient wind speeds to surface winds are different from the counterparts in the other two types of models.

Validation

All three models have been validated by comparing indicators (characteristics) obtained from the simulation results with those estimated from TCs in the database. The validation of the models consisted of taking input adopted from one or multiple TCs and determining if the indicators estimated over the output of a model match their target values (at least in the probabilistic sense). The appropriate indicator of validation may vary as it is dependent on the major characteristics of the specific type of models. Results of Type II models have been validated by almost all recent available TCs in the database in terms of the maximum wind speed as well as the time histories of both wind speed and direction (Li and Hong, 2016; Vickery et al., 2000a; Vickery et al., 2009b). The validation results suggest the Type II model by Vickery qualifies as a design tool in the ASCE specification (Vickery et al., 2009c). The indicators of Type I model include the pressure snapshot, vertical profile of mean wind speeds, and the radial profile, suggesting satisfactory validation. The radial profile using the Type III model also matched the target profiles well (Chavas et al., 2015; Emanuel, 2004; Emanuel et al., 2006). Finally, it is suggested that the CDF of wind speeds generated by all the models should be validated for the Type II and III models (e.g., citeemanuel2006statistical, li2016typhoon)

Comparison

An investigation benchmarked by the MM5 (Liu et al., 1997) suggests that, in general, the three-dimensional models may outperform the two-dimensional models, underscoring that the nonlinear solution is always superior (Kepert, 2010a,b; Kepert and Nolan, 2014). In addition, the investigation demonstrates that the Type II model is unable to replicate accurately the TC in the database due to the model neglecting many critical factors that are key for accurate results (Kepert, 2010a). Comparisons have also been carried out between specific models that belong to Type II and Type III class (Smith et al., 2008), or between models that belong to the same type class (Snaiki and Wu, 2017; Wills et al., 2000). Currently, a comprehensive comparison covering all three model types is not available.

Boundary layer wind speed profile

While a TC is still over the ocean, the marine wind speed profile in the boundary layer varies with model type. Type I models and height-resolved Type II models can generate the profile of the simulated wind field. Whether the generated profile can approximate well the ones estimated by dropsonde measurements in the TC database is still open for debate (Kepert and Wang, 2001; Kepert, 2011, 2013; Montgomery et al., 2014; Smith, 1968). For the remaining Type II models, an empirical profile formula has been proposed based on extensive statistics over the TC database and applied to the linearized three-dimensional model of Type I (Vickery et al., 2009b). Although such measurements may occasionally suggest the applicability of the power-law (Song et al., 2016), this formula is a deeply revised version of the logarithmic law. This profile, developed for the Type II model, may apply to the Type III model, but, so far, the latter model simply adopts a constant value of 0.85 to convert wind speeds from the gradient height to 10 m over the ground (Chavas et al., 2015). In contrast to the over-ocean case, the profile of a TC after landfall may be altered as described by the semi-empirical model by Snaiki and Wu (2018). Note: the vertical wind speed profile of a TC may resemble a nose-shape due to the formation of a low-level jet due to roll vortices, which is a contrast with non-TC winds (Li et al., 2019a, 2015b). Also the boundary layer may be perturbed by the presence of the mesoscale vortices and modify transient features in the wind field. Finally, for a specific land-based site, the wind speed profile of concern is heavily influenced by its surrounding terrain (Huang and Xu, 2013).

Drag coefficient

The surface drag coefficient is a common parameter shared by all three model types, which can influence significantly the final simulation results, especially the predicted maximum wind speed (Li and Hong, 2015; Powell et al., 2003). Currently, the velocity-dependent and constant models are extensively used for the over-ocean and over-land cases, respectively, but their appropriateness is still arguable (Smith et al., 2014).

Turbulence

Recent empirical data shows no significant difference between gust factors in TC and non-TC winds (Vickery et al., 2009a), although some exceptions do exist and are worthy of further investigation (Yu et al., 2008; Yu and Chowdhury, 2009). This implies that local terrain dominates turbulence effects even in winds generated by a TC, thus allowing for the use of gust factor models based on regular wind data (e.g., ESDU, 2008). In contrast, a recent study presented a different spectral model for the turbulence in TC winds, whereby the spectral content of TC winds at the high reduced frequency range is larger than the one of non-TC winds (Hu et al., 2017; Li et al., 2015a).

Nonstationarity

Typically, TC winds involve both short-term and long-term nonstationary properties of concern in performance-based wind engineering. These may arise from rolls in the boundary layer inducing jet type flows and mesoscale vortices that introduce periodic type perturbations in the wind field (Fernandez-Caban et al., 2019; Li et al., 2015a, 2019a; Wurman and Koshiba, 2017). The mean wind speed, direction, and spectral contents of a TC are all time-dependent, evolving within the lifetime of TC. Considering the short-term nonstationarity of winds, the nonstationary wind loading is induced on a target structure, whose effects on the structural response as well as performance have been investigated (Kareem et al., 2019; Kwon and Kareem, 2009; Yau et al., 2011). Long-term nonstationarity effects relate to the life-cycle of the target structure. Over the long term, the input of TC models, e.g., the occurrence rate and the intensity, may evolve with time because of climate change (Emanuel, 2005). These long-term nonstationary effects have been assessed by integrating the TC models with the current climate change models (Emanuel et al., 2008; Lauren et al., 2014; Lin, 2015; Liu, 2014).

6.3 Software and Systems

Currently, there is no exclusive software publicly available for generating the wind hazard IM for TC simulations; however, a module designed for such a task is included in both the HAZUS (Vickery et al., 2006a) and FCHLPM (Florida Commission on Hurricane Loss Projection Methodology (Hamid et al., 2010; Powell et al., 2005) software. Both programs are based on Type II TC models, although the technical details populating the programs are slightly different. The programs are Windows-based, publicly available, and controlled by a GUI. Such in-house software exists in research laboratories around the world.

6.3.1 Relevant SimCenter Tools

The SimCenter developed a C++ application that implements the linear height-resolving wind field model of Snaiki and Wu (2017). This application is planned to be released and documented to provide a standalone solution that can generate wind fields for the research community. The next update to the R2DTool in 2021 will enable regional hurricane risk assessment and provide convenient controls for the aforementioned wind field model in the user interface. It will also allow researchers to retrieve design wind speeds for various return periods from the ATC Hazards by Location website (ATC, 2020).

smelt

The Stochastic, Modular, and Extensible Library for Time histories (*Smelt* [27]) is a C++ library for stochastically generating time histories, including velocity time histories for wind loading.

Educational Tools

Wind effects are illustrated in two educational tools developed by the SimCenter. The Multiple Degrees of Freedom Application (*MDOF* [19]) allows students to explore the effects of different building parameters on the time-varying response of a building under transient loads, including wind. The building is represented by a shear column.

The Earthquake versus Wind Application (*EvW* [16]) focuses on comparing the response of buildings subjected to earthquake and wind loading, using the same shear model that is applied in MDOF.

Chapter 7
Tropical Cyclone—Storm Surge

Andrew Kennedy with contributions by Tracy Kijewski-Correa,
along with review comments and suggestions by George Deodatis, Ajay B. Harish, Rick Luettich, and Lance Manuel

Simulations of coastal storm surge are used for planning, forecasting, nowcasting, hindcasting, climatological studies, and risk evaluation; the need for surge studies has been continual over recent years, and there is an ongoing need for trained professionals. The largest surges occur from tropical cyclones, but strong winter storms may also generate high water levels.

Surge studies are in many ways broadly similar: a wind and pressure field forces a hydrodynamic model, potentially inundating areas of interest (NJcoast, 2018). Details of modeling differ, with numerics, resolution, bottom friction, and theoretical assumptions as noticeable differences. Some systems include additional components such as wave setup and runup, while these are neglected by others. Atmospheric forcing can either be raster-based, where large-scale wind and pressure fields force the modeling system, or may arise from a tropical or extra-tropical storm scenario described by a storm track and set of parameters describing strength and size. These simulations yield geospatially distributed estimates of storm surge (storm-induced rise in seawater levels, primarily caused by wind) for the purposes of direct and indirect loss assessment for coastal communities (Jacob et al., 2011). Estimates of storm-induced inundation due to combined effects of storm surge and waves driving water over land are important outputs from any simulation environment. These outputs help quantify damage to structures as well as above and below ground civil infrastructure.

Because surge models can be expensive to run, in general there is a need to manage the trade-off between model fidelity and computational efficiency. One method that has seen increasing adoption in recent years uses surrogate models. Given a database of high-fidelity model runs to be used as a training set, surrogate models can reduce CPU times of model runs from hundreds and even thousands of hours to minutes and enable computationally efficient means to characterize uncertainty in the hazard (e.g., the hurricane track) for the purposes of risk assessment (Kijewski-Correa et al., 2014). Note: these surrogate models require large-scale training sets that may not be straightforward to generate.

7.1 Common Modeling Approaches

This section examines the three classes of models commonly coupled to capture storm surge and accompanying wave effects nearshore and overland, as well as surrogate models that can be tailored to these coupled models for a computationally efficient simulation alternative. Note:

this is not an exhaustive presentation of the simulation tools available for coastal hazards but focuses only on those viewed as the industry standard.

7.1.1 Storm Surge Heights and Inundation

Numerical models for storm-surge simulations are typically based on single-layer (or sometimes multi-layer) depth-averaged shallow water equations describing fluid motion driven by storm winds and pressure. These simplifications are necessary as a full Navier-Stokes based approach is computationally unfeasible. The available numerical models differ in their computational solution strategies, with implications for the spatial and temporal resolution of the simulations, the required computational resources and runtimes, and the required input data and model parameters. Generally, these models capture the amplitude of long-period, long-gravity waves and do not simulate short-period wave effects, which are addressed in subsequent sections. Models described herein are as follows:

SLOSH

The National Weather Service (NWS) utilizes a storm-surge model called Sea, Lake and Overland Surges from Hurricanes (*SLOSH* [48]), which solves the shallow water equations using structured curvilinear grids (Jelesnianski et al., 1992). Because it was developed to provide real-time estimates of storm surge on a single computational core, the grid resolution and the resulting spatial resolution of the results are fairly coarse. As reported by Mandli and Dawson (2014), a primary limitation of SLOSH is "the limited domain size and extents allowed due to the grid mapping used and formulation of the equations." Nevertheless, SLOSH has continued to be updated since its initial development and it is used for real-time forecasts of surge for public advisories and to inform emergency responders. SLOSH is very computationally efficient, which allows it to perform probabilistic simulations of storm surge prior to a hurricane landfall using several thousand runs to obtain some measures of the potential surge if storm tracks and intensities change. Because SLOSH has been used for many years and does not contain some modern features included in other models, it may at some point be replaced by a different model, the most likely candidate being the Coastal and Estuarine Storm Tide model (CEST) (Zhang et al., 2017a).

ADCIRC

The ADvanced CIRCulation (*ADCIRC* [1]) methodology is commonly regarded as the state of the art in high-resolution coastal storm-surge simulation (Luettich et al., 1992), which is capable of providing significantly more accurate simulations than methods based on SLOSH (Resio and Westerink, 2008) in near-shore coastal regions. As such, ADCIRC is the preferred methodology for coastal storm-surge investigations by the U.S. Army Corps of Engineers (USACE) and is one of the two models certified for the generation of FEMA Digital Flood Insurance Rate Maps (DFIRMSs). ADCIRC solves the depth-averaged shallow-water equations describing on a rotating earth, formulated using the traditional hydrostatic pressure and Boussinesq approximations, and discretized in space using the finite-element method and in time using the finite-difference method. ADCIRC can be run either as a two-dimensional depth integrated (2DDI) model or as a three-dimensional model, with elevation resulting from the solution of the depth-integrated continuity equation in generalized wave-continuity equation (GWCE) form. Furthermore, velocity is obtained from the solution of either the 2DDI or three-dimensional momentum equations, retaining all nonlinear terms. ADCIRC simulations have been validated for major hurricanes such as Katrina, Ike, Gustav, and Iniki (Kennedy et al., 2011, 2012). ADCIRC has been parallelized efficiently, with linear speedups to hundreds or thousands of cores for large domains.

Delft3D

Delft3D [46]-Flow is the second model certified for FEMA DFIRM generation. It is based on shallow-water equations in either depth-averaged or multi-layer formulation, and is used widely among engineering consultants and researchers (Hu et al., 2015; Vousdoukas et al., 2016). Delft3D may be run in either serial or parallel modes, with typical parallel runs using tens of cores. The Delft3D-Flow surge model is a part of a larger suite of interrelated models that include spectral wave and coastal runup/morphological evolution.

FVCOM

FVCOM [47] is s finite volume-based model that has been used by numerous academic researchers to study storm surge (Kerr et al., 2013; Rego and Li, 2010). It is based on unstructured meshes and shows comparable results with other models when run on a similar grid. The use of FVCOM for storm-surge studies is in some ways a simplification of the full model, which includes momentum, continuity, temperature, salinity, and density. It was originally developed for coastal and estuarine circulation by the oceanographic community and is fully open source (Chen et al., 2003).

GEOCLAW

GEOCLAW [3] lies between SLOSH and ADCIRC in terms of modeling resolution and computational cost. Originally developed to simulate tsunami inundation, GEOCLAW has recently been adapted to simulate storm surge (Berger et al., 2011; Mandli et al., 2016). Based on the CLAWPACK software libraries (LeVeque, 2002), GEOCLAW is an open-source, finite-volume, wave-propagation numerical model used to estimate hurricane-induced storm surge along a coastline. For overland flooding, the model uses Manning's n to parameterize roughness due to objects such as trees and small-scale structures that cannot be resolved computationally. Adaptive mesh refinement allows GEOCLAW to place computational resources where and when they are needed during a simulation. Thus, the overall cost of the simulation is reduced, while retaining the same or similar accuracy characteristics to ADCIRC. Figure 7.1 compares results calculated using GEOCLAW versus ADCIRC.

7.1.2 Spectral Wave Models

The platforms described above simulate slowly-varying surge heights but do not capture local wave effects. To capture such effects requires a separate wave model, either run as a fully-coupled system where both models pass information to each other or as a one-way loosely coupled system. In two-way coupling, wave models pass radiation stresses to the surge model, while the surge model passes water levels and currents to the wave model. In one-way coupling, which is

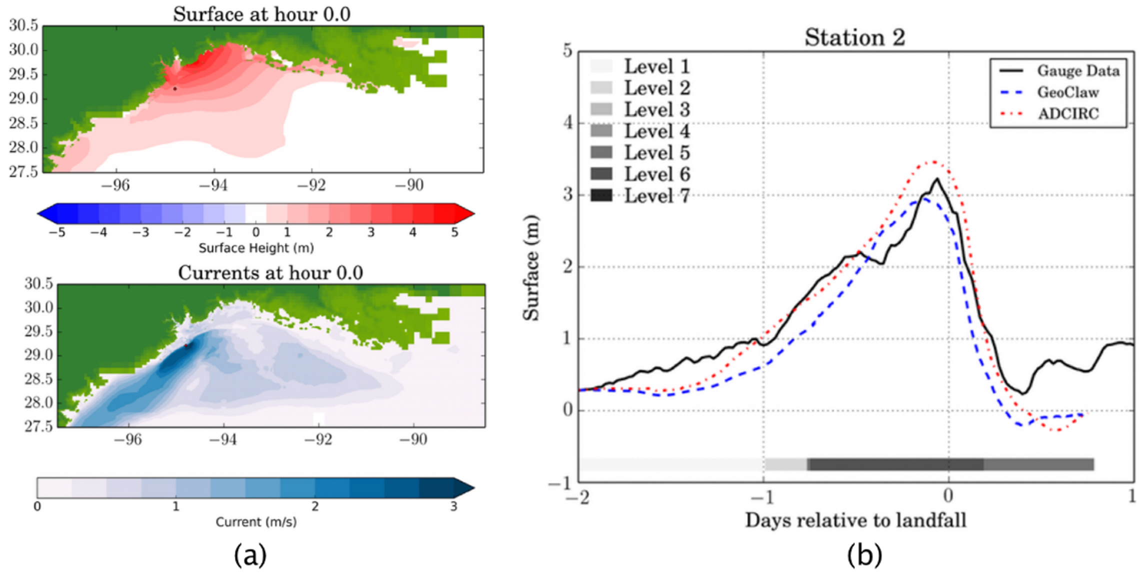


Fig. 7.1 (a) A snapshot of a GEOCLAW storm surge simulation of Hurricane Ike at landfall; and (b) tide gauge data computed from GEOCLAW and ADCIRC along with observed data at the same location (Mandli et al., 2016).

less accurate, the wave model is run at some given water level and radiation stresses are passed to the surge model.

The most common model used is Simulating WAves Nearshore (SWAN), which solves equations for wave spectral density in both frequency and direction (Zijlema, 2010). ADCIRC has been coupled previously with SWAN (Dietrich et al., 2011; Kennedy et al., 2012). The most recent North Atlantic Coastal Comprehensive Study (NACCS) (USACE, 2015) employs STWAVE, which is a steady-state, finite-difference spectral model for nearshore wind–wave growth and propagation based on the wave action balance equation (Smith et al., 2001). STWAVE simulates depth-induced wave refraction and shoaling, current-induced refraction and shoaling, depth- and steepness-induced wave breaking, diffraction, and wave growth because of wind input, and wave–wave interaction and white capping that redistributes and dissipates energy in a growing wave field. Figure 7.2 validates the coupled hydrodynamic models used in the NACCS by comparing the results to measurements across historical storms or tide predictions (Nadal-Caraballo et al., 2015). Additional wave models in use include WaveWatch III (Smith et al., 2018), which is NOAA's operational forecast model.

7.1.3 Wave Runup Overland

Even when coupled with an appropriate nearshore wave model, surge models simulate only the storm-surge elevation and not the additional impact of wave runup, which is particularly important for predicting losses to buildings and infrastructure in a storm event. Supplementary wave runup simulations are required to capture the interaction of the waves with the shoreline and any coastal protective features along coastal transects. Two types of models are common:

1. Wave-Group Envelope models, where the effects of unsteady wave groups on long-wave surge and runup drive time-varying water levels in the nearshore and at the moving shoreline. These

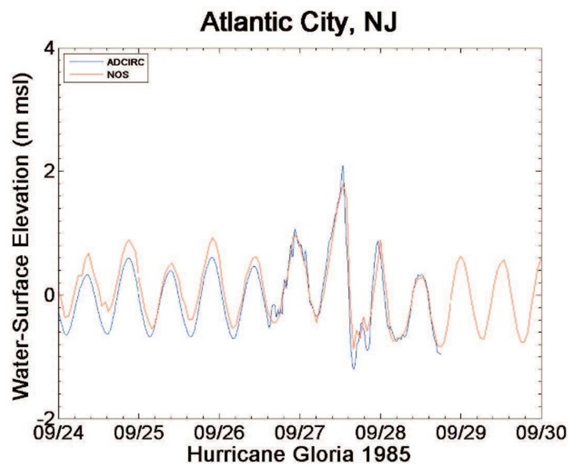


Fig. 7.2 Validation of surge simulation in Atlantic City using coupled ADCIRC-STWAVE for historical storm Hurricane Gloria, courtesy of USACE (Nadal-Caraballo et al., 2015).

models do not model individual wave runup, which can be important in certain instances. By far the most common model of this type is XBeach (Roelvink et al., 2009), which is also commonly used to estimate morphological evolution over short time periods. Models of this type require O(10m) resolution to resolve important processes, requiring more computational resources than both spectral wave and surge models for a similar domain. Thus, they are generally limited to km-to-tens of km-scales for simulations.

2. Wave-resolving models define individual points on the water surface to model the evolution of the detailed wave shape over arbitrary bathymetry. The most common models of this type use different versions of Boussinesq models (Kennedy et al., 2000; Lynett et al., 2002; Nwogu and Demirbilek, 2010), which are derived from Taylor series expansions about the long wave limit. Wave-resolving models can simulate both wave group runup and runup from individual waves, but may require resolution of O(5m) or finer in the nearshore. Although these models may be used to simulate nearshore behavior of entire storms, they are computationally very expensive (far more so than wave-group envelope models), and often one-dimensional transects are chosen for representative simulations. Transect locations are generally selected by segmenting the defined coastline in the areas of interest and then selecting the transect density proportional to computational demand. Each transect is then discretized to capture the site-specific bathymetry (offshore) and topography (onshore) along its length. Moreover, transects must accurately capture the current condition of coastal protective features, e.g., dunes, in order to effectively predict the total runup inland. To estimate the wave runup overland, inputs from the surge and spectral wave models are fed into a one-dimensional Boussinesq model executed at the pre-selected transects (Demirbilek et al., 2009).

7.1.4 Surrogate Modeling Approach

Given the high degree of sophistication and large amount of computational resources required to execute just one high-fidelity simulation (e.g., an ADCIRC+STWAVE/SWAN run), alternative simulation tools have been developed recently to enable a wider range of users to employ these models for hazard characterization, risk assessment, and design of coastal protective strategies. Most notably, surrogate modeling approaches can efficiently evaluate hurricane wave and surge responses by leveraging databases of existing high-fidelity simulations normally driven by a collection of historical and synthetic hurricane tracks (USACE, 2015). This is made possible by formulating a simplified description of a storm scenario by a small number of model parameters corresponding to its characteristics at landfall. The scenarios in the database are then parameterized with respect to this model parameter vector and ultimately provide an input–output dataset. Because the geospatial representation often covers a regional coastline (typically represented by a large number of nodes) and resolves the coastal hazards at different times during the hurricane's history, the dataset is often high dimensional. After correcting for any dry nodes at inland locations, the surrogate model is then built to approximate this input–output relationship.

Although the initial implementations of the surrogate modeling approach relied upon a moving least-squares-response surface methodology, more recent implementations for natural hazard risk assessment now employ a Kriging metamodel for this purpose (Jia and Taflanidis, 2013). To further reduce the computational burden pertaining to both speed of execution—and more importantly memory requirements—this approach is coupled with principal component analysis (PCA) as a dimensional reduction technique. The metamodel is then developed in this low-dimensional latent space (in this case below 100), with the predictions transformed back to the original space for visualization purposes. This PCA implementation results in very large computational savings, which is necessary to enable the evaluation of a large ensemble of scenarios as required for a probabilistic evaluation while circumventing the need for HPC resources (Jia and Taflanidis, 2013). Validation of these surrogate models using leave-one-out cross validation (Taflanidis et al., 2017) suggested high accuracy, with coefficient of determination close to 0.96 and a correlation coefficient close to 98%. By permitting rapid evaluation of alternate storm scenarios, surrogate models offer an effective way to communicate simulation results to urban planners and emergency managers. One such implementation is a software system developed to assess storm surge risks on the coast of New Jersey (NJcoast, 2018).

7.2 Required Inputs and Resulting Outputs

High-fidelity computational simulations of coastal hazards require: (1) storm track information, including the relevant description of the hurricane wind and pressure fields to drive the model; (2) the topography and bathymetry along the coastline; and (3) the land use/land cover data for the simulation of wave runup on shore. The simulations are inherently sensitive to assumptions made regarding tides at the time of landfall. The coupling of a storm surge + nearshore wave + wave runup model will yield geospatially distributed, time-dependent responses, i.e., the mean water elevation, maximum water elevation, maximum water depth, and significant wave height (or limit of moderate wave action). Such responses can be generated either by the coupling of the aforementioned high-fidelity models or a surrogate model tuned to a database of results from these models. A brief summary of specific inputs required for storm surge models, the wave runup models, and the related surrogate models are as follows:

Storm surge models

All storm-surge models require variations of the same inputs, potentially in much different forms. All models require:

- Spatial and temporal information about wind fields and pressure. This may be in the form of gridded data or in the form of parameterized wind and pressure fields;
- Bathymetry and topography over the entire domain;
- Frictional information, whether in the form of direct frictional coefficients or roughness, or land use/land cover information that is converted to frictional resistance; and
- Boundary conditions at the domain limits.

Many models will also require:

- Information on tidal forcing when real dates are being simulated; and
- Computational settings, particularly for parallel systems.

Wave runup models

In addition to the topography and bathymetry data at each identified transect, and potentially frictional information, the wave runup model must receive wave and water level inputs from the coupled wave-storm surge model.

Surrogate models

Inputs to the surrogate model are twofold: the primary input required to develop the surrogate model itself is the aforementioned database of high-fidelity simulations for a family of storm tracks that may include tropical and extra-tropical storms. Once developed, users of the surrogate model input only a collection of parameters necessary to describe the storm scenario based on its characteristics at landfall:

1. Reference location (latitude, longitude);
2. Track heading (angle);
3. Central pressure (or pressure difference);
4. Forward speed; and
5. Radius of maximum winds.

More recently, this implementation was further simplified to enable simulation based on only reference location and storm strength (Category 1-5) (NJcoast, 2018). Note: once the surrogate model is tuned to high-fidelity simulation data for a specific geographic location, it can efficiently provide predictions for storm scenarios of varying characteristics, even if that scenario does not match any of those within the original database of high-fidelity simulations.

7.3 Primary Software Environments

The execution environments are briefly summarized below, but only for models included in the NHERI DesignSafe suite.

ADCIRC and coupled models

ADCIRC [1] has been optimized by unrolling loops for enhanced performance on multiple computer architectures and can be executed on any operating system with a working FORTRAN compiler. These include large commercial Unix systems (IBM Power & Blue Gene, Cray, SGI, and Sun), Linux- and FreeBSD-based clusters, and personal workstations running Windows or Mac OSX. ADCIRC includes MPI library calls to allow it to operate at high efficiency on parallel computer architectures, which is often preferable for simulations over large domains where a single hurricane realization can require thousands of CPU hours. Coupled ADCIRC+SWAN models are available on all of the aforementioned platforms (with the exception of Windows), while the coupled ADCIRC+STWAVE model is available on all the platforms including Windows PCs as part of the Coastal Storm Modeling System (CSTORM-MS). ADCIRC and its parallel implementation, PADCIRC, along with the coupled ADCIRC+SWAN software, are available on DesignSafe.

CLAWPACK/GEOCLAW

Clawpack [45] ("Conservation Laws Package") is a collection of finite-volume methods for linear and nonlinear hyperbolic systems of conservation laws. Clawpack employs high-resolution Godunov-type methods with limiters in a general framework applicable to many kinds of waves. *GEOCLAW* [3] is an open-source, finite-volume, wave-propagation software implemented in CLAWPACK that is capable of estimating hurricane-induced storm surge with adaptive mesh refinement. The CLAWPACK 5.4.0 suite and the GEOCLAW tools are available through DesignSafe.

SLOSH

SLOSH [48] (Sea, Lake and Overland Surges from Hurricanes) is a computerized numerical model developed by the National Weather Service (NWS) to estimate storm-surge heights determined from historical, hypothetical, or predicted hurricanes by taking into account the atmospheric pressure, size, forward speed, and track data. These parameters are used to create a model of the wind field that drives the storm surge. The SLOSH model consists of a set of physics equations that are applied to a specific locale's shoreline to incorporate the unique bay and river configurations, water depths, bridges, roads, levees, and other physical features. Storm-surge forecasts developed using SLOSH are available at `https://www.nhc.noaa.gov/surge/slosh.php`.

7.3.1 Relevant SimCenter Tools

The SimCenter develops both research and education tools to facilitate the entry for new researchers into the field of storm surge simulation.

Hydro-UQ

The Hydrodynamic loading with Uncertainty Quantification Tool *HydroUQ* [4] manages three-dimensional CFD simulations using *OpenFOAM* [5] and uses a universal interpreter to interface with two-dimensional, far-from-coast simulations performed by shallow water solvers (e.g., *GEOCLAW* [3], *ADCIRC* [1]). The shallow water simulation results are used as inputs for simulations in OpenFOAM. The bathymetry and topography of the ocean floor, the meshing of the model, and other simulation parameters can be conveniently adjusted through the user interface. Simulations can run remotely on the High-Performance Computing clusters linked to DesignSafe.

Educational Tools

The *CFD Notebooks* [44] (CFDN) prepare students for CFD-based research work by providing a basic working knowledge of *OpenFOAM* [5], including mesh preparation and the generation of boundary conditions. CFDN is a series of Jupyter notebooks hosted on DesignSafe. It leverages DesignSafe's High-Performance Computing platform to provide an interactive interface for students or instructors that can demonstrate running OpenFOAM simulations without any software installation overhead.

7.4 Major Research Gaps

Although many research topics regarding storm-surge models remain to be solved, the major issue is that the fast models are less accurate, while accurate models require enormous amounts of computation time. Thus, it remains impossible to run the most accurate models for the hundreds or thousands of simulations required to obtain surge probabilities prior to a landfalling hurricane or to simulate very long climatological records. Three methodologies hold the potential to improve the accuracy/speed trade-off:

- Surrogate or reduced models that make use of previous high-fidelity model runs to develop simpler and faster models for new cases. This was discussed earlier; AI also falls into this broad category;
- Improved computational schemes that improve parallel performance for slower models, or improve accuracy for faster models; and
- Improved theoretical schemes to increase the accuracy on coarse grids. The subgrid model corrections fall into this category and have been shown to increase accuracy greatly (Kennedy et al., 2019).

The next major research gap is difficult to address but it is extremely important as a future research goal: large-scale surge models that account for morphological evolution during storms. Dune or beach erosion and levee failure are two examples of morphological feedbacks that may have a significant effect on surge inundation; estimates of post-storm erosion are also greatly desired. This has been a long-term goal with little progress.

In conclusion, whether employing these high-fidelity models or a companion surrogate model, the resulting time-evolving water depth and velocity must translate into loads on buildings and infrastructure. In this regard, these models face similar limitations as wind-field models given the complexity of interactions with their surroundings. Accurately capturing the physics of the flow overland and the effect of its interaction with the built environment on the load description remains a challenging problem, even without further accounting for the effects of debris transported in the flow. Identifying means to reasonably determine the impact of these interactions on the load description—without having to support an intensive

CFD investigation—will enable a wider range of researchers to evaluate the impacts of coastal hazards.

Chapter 8
Tsunami—Inundation

Michael Motley with contributions by Andrew Winter,
along with review comments and suggestions by Ajay B. Harish, Andrew Kennedy, and Rick Luettich

The simulation tools used to model tsunami inundation can generally be categorized as either two-dimensional or three-dimensional models. Three-dimensional models solve Reynolds average Navier-Stokes (RANS) or Large Eddy Simulation (LES) equations numerically using the CFD techniques introduced in Chapter 11. Two-dimensional models often solve a different category of governing equations derived from the three-dimensional Navier-Stokes (NS) equation by integrating in the vertical dimension, e.g., shallow water equations and Boussinesq wave equations where the two dimensions can be characterized as latitude and longitude, with additional techniques available in some applications to consider variations in the vertical direction. Because such equations are computationally much easier to solve than the RANS and LES equations, they are broadly used in large-scale modeling of geophysical flows, e.g. tsunami, storm surge, and flooding. Two-dimensional models are used in those cases where computational efficiency is a factor. Examples include building an early warning system, which requires tsunami modeling to be done as quickly as possible after an earthquake, versus a probabilistic assessment that often requires thousands of computational simulations.

8.1 Input and Output Data

Both two-dimensional and three-dimensional models need boundaries for the simulation and boundary conditions as input. In two-dimensional models, buildings and bridges cannot be described directly. Buildings, because they come into direct contact with the ground, are often incorporated as part of the ground topography and represented as an elevation field that varies in horizontal space, or by simply removing a volume of the water column in the shape of the building footprint from the computational domain. Bridges, on the other hand, are much more difficult to represent because of the three-dimensional complexities of the bridge geometry and the surrounding area. To define the computational domain, a finite region in the horizontal plane must be specified, inside of which the flows are modeled. The boundary conditions on the boundary of this finite region must be specified, e.g., flows are allowed to flow out of the region freely on one side, and/or are reflected on the other. The topography (or bathymetry) data that describe the shape of the ground (or sea floor) must also be specified as input, although these are not interpreted as boundaries since the vertical dimension vanishes in a two-dimensional model, and the topography data are treated as field variables that directly affect other field variables (like velocities) in the solver.

Generally for three-dimensional models, flows must also be bounded in the vertical direction where the top boundary often represents the atmosphere and the bottom boundary represents the ground. Additionally, the simulation incorporates buildings and bridges into the simulation by subtracting volumes that describe the geometry of those structures from the domain. The surface of these volumes thus becomes boundaries of the simulation domain as well, and their boundary conditions must be specified. Thus, the geometry of the structures must be provided as input if one wants to model them as well.

Both types of models also need input of initial conditions: namely, the state of the fluids before the simulation starts. For instance, the initial conditions for some nearshore regions might have the fluid at rest at sea level, while somewhere far from shore, a large volume of water is placed above sea level to represent a tsunami wave. Some two-dimensional models will also incorporate seismically-induced sea floor displacement profiles or other submarine tsunamigenic phenomena to be used as initial conditions at the ocean surface above where they occur. Different initial conditions will result in different states later in time.

The output quantities from both two-dimensional and three-dimensional models include water surface and flow velocity; however, three-dimensional models are able to output quantities that vary in the vertical direction. The two-dimensional models generally do not depend on the vertical direction; therefore, its output quantities are generally not a function of positions in the vertical direction. Furthermore, the three-dimensional models can usually output more quantities of interest, e.g., water pressure, which can be integrated to obtain fluid loading on structures.

8.2 Models and Software Systems

In general, tsunami simulation requires modeling at a wide range of spatial scales, including (from large- to small-scale) offshore propagation, beach run-up, inland inundation, and impact on individual structures.

For modeling that focuses on the large-scale phases, two-dimensional models are still the most prevalent choices for their simplicity and computational efficiency. Two major variants in this category are based on the shallow-water equations and Boussinesq wave equations, respectively. Models that are based on shallow-water equations have been applied broadly to ocean-scale tsunami modeling and local flooding as well (Berger et al., 2011; George, 2008; George, 2004; Hu et al., 2000; Hubbard and Dodd, 2002; Popinet, 2012; Qin et al., 2018; Wei et al., 2013). Mathematically, the shallow-water equations do not model the dispersion in water waves directly, while the Boussinesq wave equations include an explicit dispersive term. Thus, many models based on Boussinesq wave equations have also been used (Kim et al., 2009; Kim et al., 2017; Lynett et al., 2010; Madsen and Sørensen, 1992; Madsen et al., 2003; Shi et al., 2012).

As computational power has grown, three-dimensional models based on RANS and LES equations have been applied for modeling of near-shore waves and floods, and, in particular, for fluid impact on coastal structures like bridges and buildings, which are relatively smaller in scales (Biscarini, 2010; Choi et al., 2007; Larsen et al., 2017; Mayer and Madsen, 2000; Montagna et al., 2011; Williams and Fuhrman, 2016). In addition, three-dimensional models output the pressure field directly, which can be integrated to obtain fluid forces on structures. In contrast, two-dimensional models rely on a simplified approach to convert their output to fluid forces on structures (Motley et al., 2016; Qin et al., 2018, 2016; Sarfaraz and Pak, 2017).

Many of these models are built into mostly open-source software packages that are broadly used by the NHE community and maintained by researchers at research institutes. Examples include *GEOCLAW* [3] (Berger et al., 2011), MOST (Titov and Gonzalez, 1997), and *Tsunami-HySEA* [49] (Macías et al., 2016).

8.2.1 Relevant SimCenter Tools

The SimCenter develops both research and education tools to facilitate the entry for new researchers into the field of tsunami simulation.

Hydro-UQ

The Hydrodynamic loading with Uncertainty Quantification Tool *HydroUQ* [4] manages three-dimensional CFD simulations using *OpenFOAM* [5] and uses a universal interpreter to interface with two-dimensional, far-from-coast simulations performed by shallow water solvers (e.g., *GEOCLAW* [3], *ADCIRC* [1]). The shallow water simulation results are used as inputs for simulations in OpenFOAM. The bathymetry and topography of the ocean floor, the meshing of the model, and other simulation parameters can be conveniently adjusted through the user interface. The tool can also be used to run virtual experiments that help with the design of laboratory tests and validate CFD models against existing measurements in wave tanks such as those in the O.H. Hinsdale Wave Research Laboratory in Oregon State University. Simulations can run remotely on the High-Performance Computing clusters linked to DesignSafe.

Educational Tools

The *CFD Notebooks* [44] (CFDN) prepare students for CFD-based research work by providing a basic working knowledge of *OpenFOAM* [5], including mesh preparation and the generation of boundary conditions. CFDN is a series of Jupyter notebooks hosted on DesignSafe. It leverages DesignSafe's High-Performance Computing platform to provide an interactive interface for students or instructors that can demonstrate running OpenFOAM simulations without any software installation overhead.

8.3 Major Research Gaps and Needs

One challenge in tsunami modeling is to develop models of different fidelity to satisfy different needs. For instance, site-specific inundation modeling and analysis often need to be performed in the design of vertical evacuation structures (Ash, 2015; González et al., 2013). In this case, a more accurate but time-consuming three-dimensional model is desired. On the other hand, compiling tsunami hazard maps—where typically thousands of runs are needed—might require using a faster but less accurate two-dimensional model. Because ASCE 7 requires site specific analysis to predict local flow characteristics for critical structures, a more formal methodology for proper probabilistic tsunami hazard analysis over large areas is a critical research gap.

Another demand in the area is to update or even re-design the relevant software to capitalize on the rapidly growing computational power. These computational resources often require running code on clusters or newer machines with graphics processing units (GPUs); thus, there is a need to adapt these software packages to take advantage of these high-performance computing (HPC) machines. Increased use of three-dimensional models is directly associated with increased computational power; unfortunately, three-dimensional analysis is still not computationally practical at larger scales. This requires the development of complex coupling mechanisms between the two-dimensional and three-dimensional solvers. Similar coupling mechanisms between the inundation models and the built environment, thus enabling both load prediction and structural response and potential debris flows, are also a necessary step in streamlining the analysis process across the various scales.

Part II
Response Estimation

Response estimation entails computational finite-element and other analysis methods to simulate the physical response of solids and fluids related to natural hazards engineering (NHE). The section on structural systems describes simulation technologies to analyze the response of constructed facilities (buildings, bridges, and other facilities) to the loading effects of gravity, earthquakes, storms (wind and storm-surge flows), and tsunami inundation. The section on geotechnical systems describes methods to explicitly simulate the detailed response of soil and soil–structure interaction under input ground motions. The simulation results are used to determine ground deformations, liquefaction, soil–structure interaction, and ground instabilities due to other phenomena (e.g., changes in ground water levels, scour, etc.). The sections on computational fluid dynamics address methods to simulate wind and water flows due to water inundation and tsunami.

Chapter 9
Structural Systems

Gregory G. Deierlein with contributions by Joel P. Conte and Ertugrul Taciroglu, along with review comments and suggestions by David McCallen and Vesna Terzic

Response simulation of structural systems is an essential component of natural hazards engineering (NHE) to quantify the effects of gravity loads, earthquake ground motions, wind and water flows, and other loads on buildings, bridges, piers, pipelines, and other constructed facilities. Founded on the principles of structural mechanics, structural response simulation methods encompass a broad range of computational approaches, ranging from simplified phenomenological models to detailed continuum finite-element methods. The required simulations encompass a broad range of structural materials, systems, and scales. Construction materials include wood, masonry, concrete, steel, and other materials configured in multiple ways. The scale of simulations ranges from detailed finite-element models of structural components and connections up through complex three-dimensional structural systems and, in the case of regional simulations, large inventories or networks of structures.

The field of structural and finite-element analysis is well established and documented in academic research papers and textbooks, and it is complimented by a multitude of research and commercial software of varied capabilities. This review is limited in scope to the subset of structural simulation methods and software technologies that are most directly relevant to NHE, particularly those that are well suited to the research objectives and questions in the NHERI Science Plan.

9.1 Input and Output Data

In the context of NHE, structural response simulations entail the development and analysis of idealized structural models to assess the structural responses necessary to evaluate damage and resulting consequences (life-safety risks, economic loss, downtime, etc.) to constructed facilities and systems. In developing structural response models, it is important to clearly define the objectives and scope of the model, specifically with regard to how the hazard loading effects will be incorporated and how the results of the analyses will be used. At one extreme, structural response analyses may involve high-resolution models to interrogate local (pointwise) response of structural materials and components. At the other extreme, highly idealized models of building systems may be used to evaluate economic losses and downtimes for regional assessments of large building inventories. Obviously, the goals of the simulation will dictate the type and resolution of the model employed, including how the input hazard is characterized and how the simulation output will inform downstream calculations.

In earthquake engineering applications, the loading input for structural simulations is usually earthquake ground shaking, which is described in terms of one or more intensity measures (IMs) (e.g., spectral acceleration, spectral displacement, duration, etc.) or ground-motion seismograms. In some cases, the earthquake input may be characterized by input ground deformations, such as for buried pipelines and tunnels or structural foundations. In wind engineering, the loading input is typically equivalent static wind pressures or response histories of wind pressures, the latter being more important for flexible structures that interact dynamically with the wind. For assessment of storm surge and tsunami inundation, the loading input is usually equivalent static water pressures or debris flow forces.

Traditionally, structural response simulation has focused on structural framing components and systems; more holistic risk assessments require modeling of so-called nonstructural components that can affect the structural response and final damage state. For wind and water inundation flows, the interaction between the wind/water flows and the architectural cladding, partition walls, and other surfaces is particularly important. For earthquake engineering, architectural cladding and partition walls are important to model for certain types of light-frame construction because these components can provide significant strength and stiffness (e.g., wood-frame residential houses).

9.2 Modeling Approaches

As illustrated in Figure 9.1, models for nonlinear analysis of structures can range from uniaxial spring or hinge models, to more fundamental fiber section and continuum finite-element models. In general, all models are phenomenological in that they rely on empirical calibration to observed behavior at some level of idealization. The concentrated models (see Figure 9.1a-b) are highly phenomenological in that the underlying functions that describe the structural behavior are based on semi-empirical calibration to overall component behavior (e.g., Do and Filippou, 2018; Folz and Filiatrault, 2001; Ibarra et al., 2005; Lowes and Altoontash, 2003). While Figure 9.1 illustrates these as moment-rotation hinge models, the concentrated springs can apply to any univariate response quantity, e.g., axial or shear springs. At the other extreme, the continuum finite-element models (see Figure 9.1e) are calibrated at the material level (e.g., Dettmer and Reese, 2004; Lee and Fenves, 1998; Lemaitre and Chaboche, 1990; Maekawa et al., 2003), where the kinematics and equilibrium of the components are represented more directly by the model formulation. As such, the continuum models are more adaptable to different geometries and loading regimes; however, to the extent possible, the models should be validated against test data that represents the governing phenomena in the structural components being modeled.

In between the concentrated hinge and continuum models are fiber section or fiber hinge models (see Figure 9.1c-d), where kinematic assumptions (such as plane sections remain plane) are used to relate uniaxial material response to generalized strains and stress resultants (e.g., moment-curvature) at member cross sections. The uniaxial material models that comprise fiber models can be calibrated based on the uniaxial material stress-strain behavior (e.g., Carreño et al., 2020; Dodd and Restrepo-Posada, 1995; Mander et al., 1988; Menegotto and Pinto, 1973) or alternatively on quasi stress–strain, where the properties are adjusted to account for phenomena such as steel reinforcing bar buckling (e.g., Dhakal and Maekawa, 2002; Kunnath et al., 2009).In between fiber section beam–column elements and continuum finite-element models are beam–truss models, which are capable of capturing local member softening and system softening in a robust and computationally efficient way (Álvarez et al., 2020; Lu and Panagiotou, 2014). Computationally efficient beam–truss models have been shown to capture the softening behavior induced by flexure–shear interaction, which is a very challenging task for computationally intensive continuum finite-element models. As an illustration, Figure 9.2 shows a beam–truss model (developed in OpenSees) of the Alto Rio building, which collapsed in the 2010 Mw 8.8 Maule earthquake in Chile (Zhang et al., 2017b).

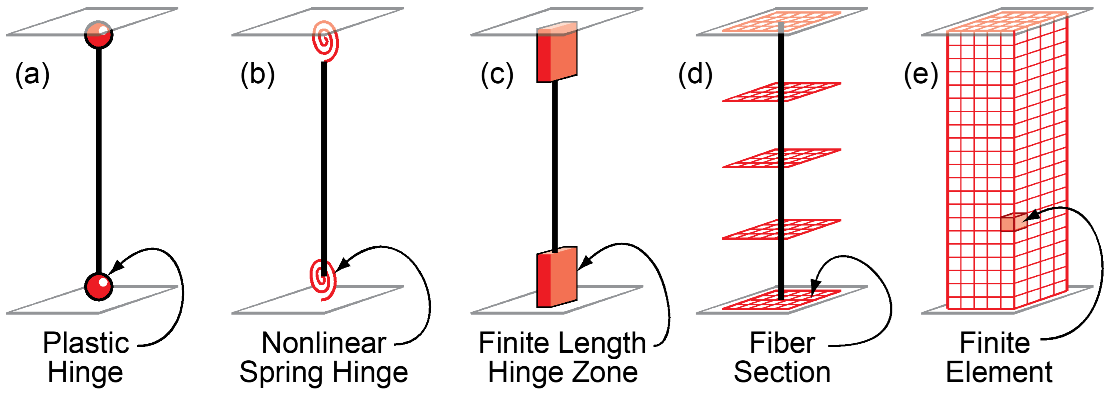


Fig. 9.1 Range of structural model types (Deierlein et al., 2010).

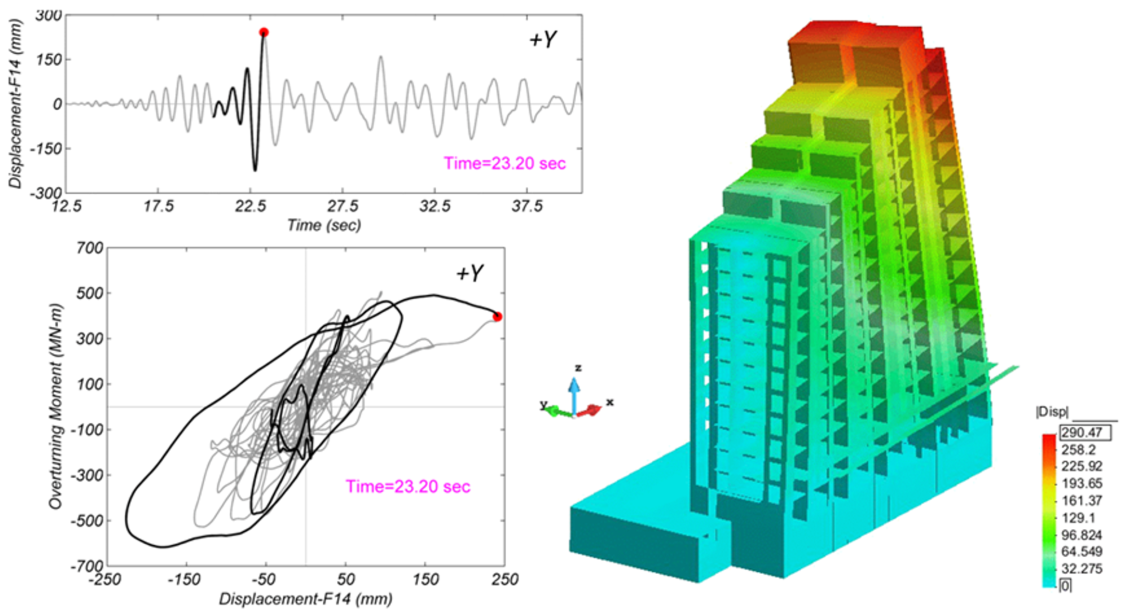


Fig. 9.2 OpenSees Beam-truss model of Alto Rio Building subjected to three components of 2010 Mw 8.8 Maule Chile earthquake recorded at the CONC station (Zhang et al., 2017b).

The choice of model type for a given application involves a balance between reliability, practicality, and computational efficiency, subject to the capabilities of available software and computational resources. The optimal model type depends on many factors, including the structural system and materials, governing modes of behavior, the expected amount of nonlinearity, and the level of detail available for the input and output data. The reliability of the model comes from its ability to capture the critical types of deformation that are of interest to the modeler and control the response.

In recent years, applications to performance-based earthquake engineering have led to major advancements in the development and calibration of nonlinear structural analysis models to simulate the response of buildings, bridges, and other structures from the onset of damage up through collapse. Several recent NEHRP publications have reviewed structural models and modeling parameters for nonlinear analysis to support seismic evaluation, retrofit, and design of buildings (N.I.S.T., 2017a,b,c). These NIST documents summarize models and parameters, along with references to many of the underlying research publications, for concrete and steel moment frames, steel concentrically braced frames, concrete shear walls, reinforced masonry walls, and light-frame wood shear walls. A NIST technical brief (Deierlein et al., 2010) provides a broader review of nonlinear analysis methods with a summary of proposed research and development needs for performance-based seismic engineering of buildings. Other resources on nonlinear modeling and analysis include: PEER/ATC report on tall buildings (Malley et al., 2010), Spacone and El-Tawil (2004) on composite steel-concrete structures, and Nurbaiah et al. (0017) on masonry infilled RC frames.

A detailed performance-based modeling and analysis guidelines for bridges is described in a PEER report by Aviram et al. (2008), which targets reinforced concrete (single- or multi-span) bridges common in California (NBI, 2016). An example of the components involved in modeling of a typical bridge is shown in Figure 9.3. Research cited in the Aviram report and publications since then address structural modeling details for bridges related to: (1) straight and skew angled abutment backfill models (Shamsabadi et al., 2010): (2) abutment kinematic interaction models (Zhang and Makris, 2002): (3) shear key models (e.g., Silva et al., 2009); (4) pile-soil interaction models for conventional (Hutchinson et al., 2001; Taciroglu et al., 2006), group (Lemnitzer et al., 2010) and large-diameter (Khalili-Tehrani et al., 2014) piles; (5) in-span hinge models (Hube and Mosalam, 2008); and (6) column models (Terzic et al., 2015; Xu and Zhang, 2011). The aforementioned models have been used in studies that have furthered the state of the art, which include work by Kaviani et al. (2014), who targeted skew bridges, Omrani et al. (2015), who comprehensively examined and improved upon the bridge PBSA guidelines by Aviram et al. (2008), and Omrani et al. (2017), who examined fragility sensitivities to abutment modeling uncertainties. In all these studies, the analysis tool of choice has been OpenSees (McKenna, 2011) wherein most, if not all, of the aforementioned models are publicly available.

Most natural hazards research on nonlinear response simulation of structures is related to earthquake engineering where addressing inelastic response has long been recognized as a necessity under design ground motions. In contrast, inelastic structural effects tend to be less pronounced for evaluation of gravity, wind, and other loading effects. In the case of storm-driven wind and wave loading or tsunami inundation, the largest nonlinear behavior involves the loading due to the dynamic fluid (air or water) flows and their interaction with the structure. Examples of recent research to study the response of structures to fluid flows include Ataei and Padgett, 2015; Attary et al., 2016; Madurapperuma and Wijeyewickrema, 2013; Minjie et al., 2018; Minjie and Scott, 2014; Petrone et al., 2017.

Repeated nonlinear response history analyses for constructing seismic fragility curves or for performing simulations of regionally distributed systems typically require large-scale computational resources. Due to the granular nature of each structural analysis, the required computations are embarrassingly parallel (i.e., perfectly scalable in a parallel computing sense). Apart from the computational requirements, analyses of buildings, bridges, or other distributed

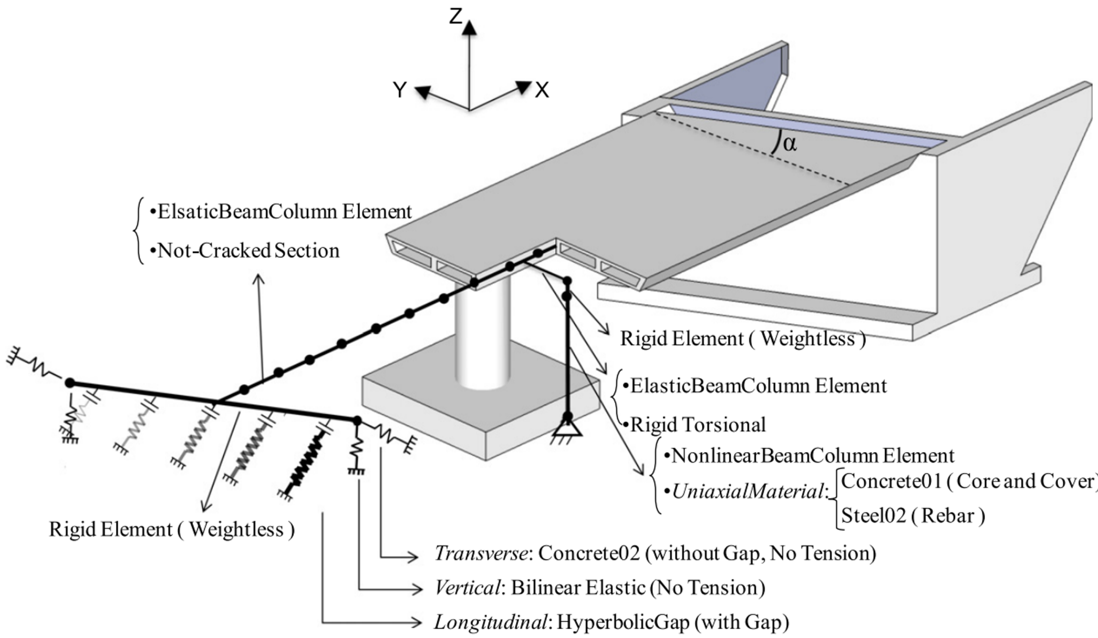


Fig. 9.3 Schematic view of a generic bridge numerical model in OpenSees (Kaviani et al., 2012).

infrastructure requires consideration of correlations in the hazard demands (e.g., earthquake ground motions) across the region along with correlations of the structural system response. Such regional-scale analyses are uncommon and not standard, but various attempts have been made (e.g., Miller et al., 2015).

9.3 Software and Sytems

While there are a large number of available software systems with various capabilities, this summary focuses on software programs that are well-suited and widely used in research related to NHE. Emphasis is on open-source software currently available and supported on the NHERI DesignSafe computing platform along with a few widely used commercial codes.

OpenSees

The Open System for Earthquake Engineering Simulation (*OpenSees* [6]) is an open-source, object-oriented software framework for simulating the seismic response of structural and geotechnical systems. OpenSees was developed and is maintained by the Pacific Earthquake Engineering Research (PEER) Center for research in performance-based earthquake engineering and is widely used and contributed to by researchers from around the world. OpenSees has advanced capabilities for modeling and analyzing the nonlinear response of structural systems using a wide range of material models, beam–column elements and continuum elements, and solution algorithms. The software is designed for parallel computing to allow scalable simulations on high-end computers or for parameter studies. The software is available on DesignSafe and can be downloaded to run on Linux, Windows, or Mac OS (http://opensees.berkeley.edu/)

LS-DYNA

LS-DYNA [35] is a general-purpose finite-element program capable of simulating complex real-world problems with primary users from the automobile, aerospace, construction, military, manufacturing, and bioengineering industries. It has nonlinear frame and continuum finite elements, with material models for steel, concrete, and soils along with fluids. LS-DYNA's origins lie in highly nonlinear, transient dynamic finite-element analysis using explicit time integration, and it is optimized for shared and distributed memory Unix, Linux, and Windows-based platforms. The software is maintained and marketed by Livermore Software Technology Corporation, with licensing available to both the commercial and academic markets. It is available on DesignSafe for users with an academic license. (http://www.lstc.com/products/ls-dyna)

FEAP

The Finite Element Analysis Program (*FEAP* [51] and *FEAPpv* [52]) is a general-purpose finite-element program for solving nonlinear, static, and transient partial differential equations. Its primary applications are directed to the solution of problems in solid mechanics; however, the system may be extended to solve problems in other subject areas by adding user developed modules to address problems in fluid dynamics, flow through porous media, thermo-electric fields, and others. The software is available to run on UNIX/Linux/Mac or Windows environments (see http://feap.berkeley.edu/)

Other Commercial Software

The following is a list of other commercial software, with simulation capabilities for NHE commonly used in both industrial and academic research. For details regarding the capabilities of the software, readers are referred to the websites of the software providers.

- SAP 2000, ETABS, PERFORM3D (https://www.csiamerica.com);
- ABAQUS Unified FEA (see https://www.3ds.com/products-services/simulia/products/abaqus/);
- LARSA (https://www.larsa4d.com/);
- Marc (http://www.mscsoftware.com/product/marc); and
- DIANA (https://dianafea.com)

9.3.1 Relevant SimCenter Tools

The SimCenter develops both research and educational tools to facilitate the calibration of numerical models and the simulation of structural response under earthquake and wind loading.

quoFEM

The Quantified Uncertainty with Optimization for the Finite-Element Method (*quoFEM* [7]) tool facilitates model calibration, optimization, uncertainty propagation, reliability analysis, surrogate modeling, and sensitivity analyses of numerical materials, components, and systems by combining existing simulation environments with state-of-the-art uncertainty quantification applications. The graphical user interface currently supports finite-element software (OpenSees and FEAP) and can also interface with custom analysis packages, including, but not limited to those based on the discrete element and finite difference method and other commercial software that cannot be bundled with the open-source SimCenter application (e.g., LS-DYNA, ABAQUS). These features provide users instant uncertainty analysis and optimization capabilities for numerical models. Furthermore, quoFEM provides an opportunity for researchers working with experimental facilities to use advanced UQ methods and tools to design experiments and calibrate numerical models.

EE-UQ

The Earthquake Engineering with Uncertainty Quantification (*EE-UQ* [2]) tool facilitates the assessment of structural response to earthquake events. Uncertainties in the properties of the ground motions and the structural system can be characterized and propagated through the simulations. Ground motions can be imported from external sources, or automatically selected from the PEER NGA-West2 database (Ancheta et al., 2014) to match a target seismic hazard description. The structural response simulations are run in the *OpenSees* [6] finite element code.

WE-UQ

The Wind Engineering with Uncertainty Quantification Tool (*WE-UQ* [11]) is designed to assess the response of buildings subjected to wind loading. Uncertainty Quantification refers to considering the uncertainty in the properties of the building and the wind loads and propagating such uncertainty through the simulations. It provides access to advanced CFD-based loading as well as other methods for specifying wind loads, such as online wind engineering databases (e.g., TPU, 2020) and the stochastic wind load generation available in *Smelt* [27]. The CFD simulations are run using *OpenFOAM* [5] and the calculated wind loads are applied on finite element models in *OpenSees* [6]. Two-way fully coupled fluid–structure interaction is currently under development.

R2DTool

The Regional Resilience Determination Tool (*R2DTool* [8]) is a research application that focuses on running regional simulations and interpreting their results. The tool integrates the workflow components from other research tools developed for individual building assessment (e.g., *EE-UQ*, *PBE*) and extends them to consider multiple assets and a regional characterization of hazard scenarios. The first release of the *R2DTool* provides features for seismic risk assessment. Additional features planned for 2021 will enable hurricane risk studies including the simulation of both wind and storm surge effects. The response of buildings in the regional simulation is modeled using the finite element method and the *OpenSees* [6] software. Models are either built with user-defined Tcl or Python scripts, or basic building information (e.g., number of stories, type of structural system) is used to automatically define an idealized building model.

Educational Tools

The response of structures to ground shaking and wind effects is illustrated in several educational tools developed by the SimCenter. The Multiple Degrees of Freedom Application (*MDOF*

[19]) allows students to explore the effects of different building parameters on the time-varying response of a building under transient loads. The building is represented by a shear column.

The Earthquake versus Wind Application (*EvW* [16]) focuses on comparing the response of buildings subjected to earthquake and wind loading, using the same shear model that is applied in MDOF.

The Braced Frame Modeling *BFM* [50] application focuses on the details of modeling braced frames by showing how various modeling assumptions affect the simulated response of a brace and its agreement with actual experimental data.

The Shear Wall Intelligent Modeling *SWIM* [53] application helps students explore the numerical modeling of shear walls. The application allows users to test various modeling assumptions and see how the simulated response compares to experimental data. Machine learning algorithms are used in the background to help students choose reasonable parameters for the model.

9.4 Research Gaps and Needs

While computational tools for simulation of structural materials and systems are fairly mature, there are still significant limitations in the modeling capabilities along with the continuing need for improved calibration and validation of existing models. The limitations and needs depend on the scale and resolution of the models, i.e., whether one is interested in detailed models of structural material and components to examine localized behavior or less detailed models that can reliably simulate the behavior of complete structural systems (buildings, bridges, etc.) or large inventories of systems (e.g., building inventories or geographically distributed infrastructure systems).

At the detailed level, there are continuing needs to develop, implement, and validate continuum finite-element models that can simulate nonlinear behavior and damage to structural materials and components under random cyclic loading, including interfaces and interaction between materials. Models for steel and other ductile materials are fairly well established for simulating large plastic strains and deformations (e.g., to simulate local and overall buckling (see N.I.S.T.-A.T.C., 2018), whereas methods to reliably capture fracture under cyclic inelastic loading are still evolving. For other structural materials, including reinforced concrete, wood-based materials, and masonry, many challenges remain to reliably simulate inelastic damage and degradation as seen in physical tests. In addition to the models themselves, further research and development are needed to implement and validate models in open-source software to run on high-performance computing (HPC) resources to broaden their impact in NHE.

At the large-scale system or distributed inventory/system level, there is a need for systematic approaches that develop, calibrate, and manage models computationally efficient enough to be deployed at scale, which also capture accurately the dominant behavioral effects. For such applications, many of the challenges are more related to supporting modeling and data management tools as much as the models themselves. Dimension reduction methods (DRM) may offer opportunities for coupling of physics-based hazard models (e.g., geophysics ground shaking or computational fluid dynamic wind or fluid flows) with models of structural systems. A related need is to develop inventory data with reliable descriptions of the systems that includes information on the uncertainties and correlations in those uncertainties.

Chapter 10
Geotechnical Systems

Pedro Arduino,
with review comments and suggestions by Jonathan D. Bray, Brady Cox, Michael Gardner, Boris Jeremic, David McCallen, Chaofeng Wang

Problems in geotechnical earthquake engineering often involve complex geometry and boundary conditions. Materials comprising geotechnical media behave almost always in a nonlinear fashion. Moreover, soil is made of three phases, and interactions between these phases play an important role in the global response, making theories even more complicated. Interaction of structural foundations (e.g., bridges, abutments, or buildings) with the surrounding soil is also a major aspect to consider in geotechnical earthquake analysis and design. Natural material inhomogeneity caused by soil deposition, as well as human influence, contributes to the complexity of the problem. In addition, the dynamic nature of earthquakes and their effects can rarely be considered in simplified models while preserving all their important aspects.

To address these problems, numerical analysis have become the most viable method for design and research purposes. In describing the state of the art in numerical modeling in geotechnical earthquake engineering, it is necessary to discuss each one of the aforementioned aspects; i.e., numerical methods, coupled formulations, constitutive models, interface elements, boundary and initial conditions, and corresponding verification and validation efforts. A list of common geotechnical codes used in geotechnical earthquake engineering is provided below. Although incomplete, this list identifies tools that address several common aspects. A few notes on research gaps and needs is included at the end to complete this section.

10.1 Numerical Methods

Among many other methods of analysis, the finite-element method (FEM), finite-difference method (FDM), the material-point method (MPM), smooth particle hydrodynamics (SPH), and discrete-element method (DEM) are used in geotechnical earthquake engineering. Of these, the FEM and FDM are most common in geotechnical practice and research. Commercial codes such as *PLAXIS* [37], *FLAC* [31], *LS-DYNA* [35], and *ABAQUS* [30] and open-source codes such as *OpenSees* [6], *FEAP* [51], and *Real-ESSI* [59] are examples of numerical frameworks that offer dedicated geotechnical capabilities for earthquake applications. For one-dimensional wave propagation analysis, equivalent linear methods continue to be a common choice, with "shake-like" tools, such as *ProShake* [58], *Strata* [60], and *DeepSoil* [57] (EL), being popular in practice. Most FEM tools offer one-dimensional, two-dimensional, and three-dimensional capabilities. Finite-element formulations that reduce computational demand via mesh accuracy, effective assimilation of nonlinear constitutive models, or general efficiency (McGann et al., 2015, 2012) are ideal in this context. Today, extensive research is devoted in establishing finite-element formulations for solid mechanics that are equally applicable to any arbitrarily-posed problem.

When considering problems dominated by large deformations, such as the case of debris flows or tailing-dam runouts, meshless techniques, such as MPM and SPH, provide the necessary functionality to account for these conditions (Mast et al., 2015). MPM codes commonly used in research and practice include *CB-Geo-MPM* [55], *Claymore* [56], *Uintah* [61], and *Anura3D* [54].

In recent years the discrete-element method (DEM) and discontinuous deformation analysis method (DDA) have gained applicability in geotechnical earthquake engineering, in particular for understanding phenomena at micro- and meso-scales and homogenization to the macro-scale (Kawamoto et al., 2018). Popular DEM and DDA tools include PFC, LIGGGHTS, and LS-DEM.

10.2 Coupled Fluid–Solid Formulations

Geotechnical earthquake engineering requires the evaluation of total and effective stresses. Total stress analysis is based on conventional single-phase formulations. Effective stress analysis requires a method to account for the interaction between the pore fluids and soil skeleton in saturated or partially saturated soil. Various approaches derived from the early work of Biot (1941, 1956, 1962) and others, including Borja (2006) and Ehlers (2002), have been developed and added to multiple numerical frameworks, each one adding fluid degrees-of-freedom to the system using different assumptions (Arduino, 2001). Three primary numerical approaches are discussed in Zienkiewicz and Shiomi (1984). These approaches include the $u - p - U$ formulation (which uses the full coupled system of equations developed for a saturated problem), the $u - U$ formulation (which assumes both media are incompressible), and the $u - p$ approach (which simplifies the system by assuming that the fluid acceleration can be neglected). The $u - p$ approach is most common in commercial codes such as *PLAXIS* [37] and *FLAC* [31], and is also available in *OpenSees* [6] and *Real-ESSI* [59]. These formulations have also found application in MPM codes, although at this level it is important to completely separate the phases. Extensive research is currently ongoing in this field.

10.3 Treatment of Soil–Foundation Interfaces

Interaction of structural components with the surrounding soil is of major concern in geotechnical earthquake engineering. This issue arises in many geotechnical problems whether related to retaining structures, foundation engineering, underground construction, or even soil improvement systems, and is one of the most important and challenging aspects of geotechnical numerical modeling since it is inherently nonlinear and complex. Different approaches have been proposed over the past forty years that range from simple interaction springs ($p - y$, $t - z$,and $Q - z$ springs) (API, 2007) to methods based on contact mechanics (thin layer and interface elements) (see Laursen, 2002). Simplified models rely heavily on empirical methods. Extrapolating these methods to more complicated and general cases requires extreme scrutiny of the problem-at-hand and method used. The more advanced the methods are, the more complex and costly they become in terms of computation. *PLAXIS* [37], *FLAC* [31], *ABAQUS* [30], and *Real-ESSI* [59] include interface elements, and *OpenSees* [6] offers a suite of elements, including nonlinear springs, interface elements, and contact elements to characterize beam–solid interaction (see Ghofrani, 2018; Petek, 2006). Coupling between structural systems and geotechnical domains rely on the appropriateness of these elements. Continued efforts and developments are underway in this field.

10.4 Soil Constitutive Modeling

Constitutive models play a vital role in geotechnical earthquake engineering. Accurate and reliable numerical analyses require constitutive models to represent the *in situ* soil response and different drainage and loading conditions. Over the years, soil constitutive models have ranged from relatively simple von Mises, Drucker-Prager, and Mohr-Coulomb plasticity models to sophisticated models that capture specific aspects of soil behavior; see Borja, 2013. Among them Cam-Clay and other critical-state-based plasticity models have been of particular value and significance in geotechnical engineering. Most of these models use isotropic hardening and are applicable to static and monotonic loading conditions. Most geotechnical FE codes (PLAXIS, OpenSees, Real-ESSI, etc.) include conventional implementations of these models. For dynamic analysis, however, kinematic hardening is required to capture the cyclic nature of the soil response. For this purpose, three families of models are commonly used: multi-yield surface models, bounding surface models, and multiple-strain mechanisms models. These models differ in the way kinematic hardening is treated. Multi-surface plasticity models were introduced for soils by Prevost (1977, 1985) and were extended to liquefiable sands by Elgamal et al. (2003). These models have been used to represent the constitutive behavior of both cohesive and cohesionless soils in total and effective stress analyses and are available in OpenSees. Bounding surface models were first introduced in geotechnical engineering by Dafalias (1986) and coworkers, and extended using critical-state concepts by Dafalias and Manzari (2004) to represent the response of liquefiable soils. This model is available in OpenSees, Real-ESSI, and FLAC. Variations of this model by Boulanger and Ziotopoulou (2017, 2018) (referred to as PM4Sand and PM4Silt) have been developed to better represent the undrained cyclic response of sands and silts. These models are available in FLAC, PLAXIS, and OpenSees. The multi-mechanisms approach is defined in strain space and has been used in Japan, most particularly through its implementation in the Cocktail model proposed by Iai et al. (2011, 2013).

10.5 Boundary and Loading Conditions

Boundary conditions in geotechnical problems require special attention to ensure appropriate results. At a minimum, boundaries must be fixed such that all rigid-body displacement modes are restricted. In static and pseudo-static analyses, the main concern is diminishing the effects of the boundary on the portions of the model that are of primary interest. For the analysis of a soil–foundation system, boundary effects can be controlled by extending the limits of the soil domain away from the location of the foundation elements. Minimizing boundary effects is also critical in dynamic analysis; however, devising proper boundary conditions is more difficult than for static or pseudo-static cases. The particular method used for this purpose depends upon the objective of the numerical model and originates from the fact that the assumption of a rigid boundary is typically not valid. Several strategies have been proposed to accommodate the effect of a semi-infinite subsurface in a numerical model of finite size. The use of periodic boundary conditions, in which the lateral extents of the model share translational degrees-of-freedom, is one such approach that attempts to appropriately account for the free-field response of the soil domain.

Lysmer and Kuhlemeyer (1969) introduced a technique to capture a transmitting boundary through the use of viscous dashpots. By defining the viscous response of the dashpots based on the density and shear-wave velocity of the material beyond the boundary, this approach appropriately captures the outward propagation of wave energy in the numerical model as long as the waves impinge in a near-normal orientation to the boundary. When defining transmitting boundaries using the Lysmer and Kuhlemeyer (1969) method, accelerations are not directly applied to the model. Instead, an effective force is applied using the technique developed by Joyner and Chen (1975). This effective force is proportional to the input velocity and the constitutive properties of the material beyond the boundary. This approach is commonly used in numerical analysis for geotechnical problems to account for the compliance between the soil domain of the model and the semi-infinite media outside of the considered domain.

Better results can be attained using a perfectly matched layer (PML), which is an artificial absorbing layer for wave equations commonly used to truncate computational regions in numerical methods to simulate problems with open boundaries, especially in finite-difference and finite-element methods (Zhang et al., 2019b). PML's are designed so that waves incident upon the PML do not reflect back to the medium at the interface. In general, PMLs have been shown to produce better results than LK dashpots.

Lastly, a technique to properly account for the differences in wave behavior inside the finite soil domain represented by the model and the wave behavior in the semi-infinite soil medium is the domain reduction method (Bielak et al., 2003; Yoshimura et al., 2003). The domain reduction method (DRM) consists of two phases. The initial phase involves a background geological model that includes both the source of the earthquake and the region of interest. This background model is used to compute the free-field displacement wave-field demands on the boundary of the smaller region of interest. The second phase involves only the reduced region of interest. In this phase, effective seismic forces are applied at the boundary of the local region. These effective forces are derived from the boundary displacement demand obtained in the initial phase. In general, these methods require coupling data from different codes or accessing databases with recorded or synthetic motions. This is of particular importance in geotechnical earthquake engineering. The propagation of waves in geologic media can be simulated using codes such as broad band platforms (BBP) based on Green's functions and stochastic analysis. In general, these codes cannot represent the extreme soil nonlinearity observed at the surface where finite-element methods are more appropriate. When the response of a basin is of interest, finite-element and finite-difference codes, like Hercules or SW4, can be used to simulate the propagation of waves in large heterogeneous geologic domains, but they require extensive high-performance computing (HPC) resources to run properly. Independent of the tool used, coupling between these codes and conventional finite-element analysis is required. Efforts are underway to facilitate these simulations by the NHERI SimCenter and DesignSafe.

10.6 Initial Conditions

Representation of the initial state of stress and initial stress history is of paramount importance in geotechnical simulations. The soil response (i.e., stress–strain) greatly depends on initial conditions. Several approaches can be used to create an appropriate initial state. A typical method is to apply gravitational body forces to the elements prior to any static or dynamic analysis steps. Most tools facilitate this step by using a staged modeling procedure in which gravitational stresses are first developed in a base soil mesh. The stress history of the the soil (i.e., its overconsolidation ratio) should also be specified so the soil constitutive model responds correctly when first loaded. After this stage is complete, soil elements can be removed or added and replaced by foundation or additional soil elements, and gravitational stresses are developed for the new configuration.

10.7 Verification and Validation

Over the years, as numerical formulations have become more refined they have also become more elaborate, adding complexity to their implementation and use. Therefore, before a newly proposed tool or model is used in practice or research, verification and validation (*V&V*) processes are necessary. *Verification* is meant to identify and remove programming errors in computer codes and verify numerical algorithms. *Validation* is meant to assess the accuracy at which a numerical model represents reality and includes the essential features of a real model. In contemporary numerical modeling, *V&V* has become an integral part of software development. Today, all numerical tools undergo exhaustive and continuous *V&V* processes. Recent comprehensive *V&V* efforts in geotechnical earthquake engineering include Prenolin, LEAP, and the NGL project.

10.8 Research Gaps and Needs

- Development and implementation of advanced constitutive models for geotechnical earthquake engineering applications continue to be a challenge. In addition to model formulation and functionality, robustness and implementation efficiency are of paramount importance;
- Formulations capable of representing multi-phase materials including mixing and separation and large deformations continue to limit the applicability of numerical tools to simplified scenarios and conditions. Recent developments in FEM and meshless techniques are promising, although extensive work is needed;
- Performing adequate soil–structure interaction (SSI) for major facilities continues to be a challenge and a gap in geotechnical earthquake engineering. In general, older codes (circa 1970s) continue to be the preferred option. Although very useful, these codes are based on simplifying assumptions, and do not offer real HPC capabilities; engineers are continually forced towards model-size-reduction compromises;
- It is still common to idealize incident ground motions as pure vertically propagating shear and compression waves: this is not correct. Although the research community has engaged

time-domain nonlinear SSI, there is still a lot of work to do to develop appropriate modeling solutions for regional simulations. This is really important for major infrastructure systems;

- Integration of capabilities to execute regional-scale simulations of hazard and risk continues to be a challenge. Software descriptions for earthquake simulations are pretty much stand-alone and do not discuss the end-to-end coupling needed for regional simulations. It is important to begin discussions on approaches, challenges, and gaps for effective regional-scale simulation. This should include computational workflow strategies for handling massive amounts of data (both input and output) and rigorous coupling of geophysics and structural models; and
- One of the important advancements in earthquake simulations has been the expansive availability of parallel platforms to the community. As a result, our ability to represent large geotechnical domains subject to static and dynamic loading conditions is improving at a rapid pace. In the particular case of geotechnical earthquake engineering, our capacity to compute ground motions to even higher frequencies is ever increasing. A challenge will be how to address geologic model uncertainties, i.e., how to select optimal subsurface models.

10.9 Software and Systems

The following list includes software mentioned in this section and commonly used in geotechnical earthquake engineering applications:

OpenSees

The Open System for Earthquake Engineering Simulation (*OpenSees* [6]) is an open-source software framework capable of performing fully nonlinear dynamic effective stress analyses (McKenna, 2011). OpenSees is maintained by the Pacific Earthquake Engineering Research (PEER) Center and actively developed by researchers at UC Berkeley and various research institutions. Several commonly used soil constitutive models have been implemented in OpenSees, and additional models can be added based on user needs. The framework is capable of running on HPC systems and supports MacOS, Linux, and Windows operating systems (see `https://opensees.berkeley.edu/`).

FLAC

Fast Lagrangian Analysis of Continua (*FLAC* [31]), developed by the Itasca Consulting Group, is a proprietary finite-difference based software package capable of performing dynamic nonlinear effective stress analyses. FLAC allows users to import custom soil constitutive models either as pre-compiled dynamic libraries or by using the scripting language FISH. FLAC is not capable of executing on HPC systems and is closed source. Currently only Windows-based operating systems are supported (see `https://www.itascacg.com/software/FLAC`).

PLAXIS

PLAXIS [37], now part of Bentley Systems, is a finite-element software package that can be used to perform dynamic nonlinear effective stress analyses. Custom soil constitutive models can be implemented in within the platform. PLAXIS is proprietary and closed source.

Currently, it is not HPC capable and supports only Windows-based operating systems (see https://www.bentley.com/en/products/brands/plaxis).

FEAP

The Finite Element Analysis Program (*FEAP* [51]) is a general-purpose finite-element program for solving nonlinear, static, and transient partial differential equations. Its primary applications are directed to the solution of problems in solid mechanics; however, the system may be extended to solve problems in other subject areas by adding user developed modules to address problems in fluid dynamics, flow through porous media, thermo-electric fields, and others. The software is available to run on UNIX/Linux/Mac or Windows environments (see http://feap.berkeley.edu/).

Real-ESSI

The *Real-ESSI* [59] Simulator (Realistic Modeling and Simulation of Earthquakes, Soils, and Structures and their Interaction) is a finite-element framework for high-performance (sequential or parallel) analysis of linear and nonlinear geotechnical and structural systems including soil structure interaction. This software, developed at the University of California, Davis, is available to run on UNIX/Linux/Mac or Windows environments (see http://real-essi.us/)

General FEM solvers

LS-DYNA [35] and *ABAQUS* [30] are proprietary general finite-element method solvers capable of fully nonlinear dynamic effective stress analyses. Custom material models, such as those required for modeling dynamic soil response, can be implemented in these frameworks. Depending on the license purchased, LS-Dyna and ABAQUS are capable of running on HPC systems. LS-Dyna supports Unix, Linux, and Windows-based operating systems, and is currently available on DesignSafe. ABAQUS currently supports Linux and Windows-based operating systems.

General 1D tools

Strata [60], *ProShake* [58], and *DeepSoil* [57] are well establish tools to perform one-dimensional linear-elastic and equivalent-linear (SHAKE-type) site response analyses. Deepsoil also includes nonlinear capabilities and pore-water pressure generation and dissipation models.

General MPM solvers

In recent years, several MPM codes have been proposed. Among them the *CB-Geo-MPM* [55], *Claymore* [56], *Uintah* [61], and *Anura3D* [54] are well established open-source MPM frameworks. CB-Geo MPM is a highly parallel distributed material point method for solving large-deformation problems in geotechnical engineering. The code supports isoparametric elements, multiphase materials, and photorealistic rendering (see https://github.com/cb-geo/mpm). Claymore is a massively parallel and scalable multi-GPU MPM framework for simulating physical behaviors of materials undergoing complex topological changes, self-collision, and large deformations (see https://github.com/penn-graphics-research/claymore). The Uintah software suite is a set of libraries and applications for solving partial differential equations on structured adaptive grids using hundreds to thousands of processors. MPM functionality has been added to the code and used for simulating granular flow, high-impact metal deformation, and fluid-structure interaction (see http://uintah.utah.edu/). The Anura3D Software is a three-dimensional implementation of the material point method developed and used alongside field and laboratory experiments for understanding the physics involved in soil–water–structure interaction (see http://www.mpm-dredge.eu/).

General DEM solvers

Several DEM codes are available. Among them *PFC* [36], *LIGGGHTS-PUBLIC* [33], and LS-DEM have been used in geotechnical and geological settings. *PFC* [36] is a general discrete-element method (DEM) framework developed by the Itasca Consulting group. Together with FLAC, this tool is commonly used for the analysis of geotechnical and geological problems. LIGGGHTS, an open-source (at least partially) DEM package, is capable of performing both pseudo-static and dynamic analyses. Some functionality within LIGGGHTS is not available in the public version (see https://github.com/CFDEMproject/LIGGGHTS-PUBLIC). LS-DEM is a variant of DEM that uses level set functions to represent the shapes of constituent particles (Kawamoto et al., 2018). When used to represent a particle, a level set function is an implicit function whose value at a given point is the signed distance from that point to the surface of the particle. In a DEM framework, this formulation is convenient because two of the most important ingredients in DEM contact detection—interparticle penetration distance and contact normal—are given. Using this methodology, the tool is able to handle real, complex particle morphologies, which enable reproduction and prediction of the bulk behavior of experimental specimens.

10.9.1 Relevant SimCenter Tools

The SimCenter develops both research and educational tools to facilitate performing geotechnical engineering simulations. The tools currently available focus on the analysis of individual sites and help with one-dimensional propagation of ground shaking from the bedrock to the free surface and calibration of numerical materials and models used in geotechnical earthquake engineering. These methods will be added to the R2DTool to enable the sophisticated simulation of soil behavior in regional-scale analyses.

quoFEM

The Quantified Uncertainty with Optimization for the Finite-Element Method (*quoFEM* [7]) tool facilitates model calibration, optimization, uncertainty propagation, reliability analysis, surrogate modeling, and sensitivity analyses of numerical materials, components, and systems by combining existing simulation environments with state-of-the-art uncertainty quantification applications. The graphical user interface currently supports finite-element software (OpenSees and FEAP) and can also interface with custom analysis packages, including, but not limited to those based on particle methods, the discrete element and finite difference method and other commercial software that cannot be bundled with the open-source SimCenter application (e.g., LS-DYNA, ABAQUS). These features provide instant uncertainty analysis and optimization capabilities for numerical models. Furthermore, quoFEM provides an opportunity for researchers working with experimental facilities to use advanced UQ methods and tools to design experiments and calibrate numerical models.

QS3HARK

The Site-Specific Seismic Hazard Analysis and Research Kit with Uncertainty Quantification (*QS3HARK*) performs site-specific analysis of ground shaking and liquefaction by simulating wave propagation through soil layers. The simulations use the finite element method as implemented in *OpenSees* [6] to perform the calculations. Several advanced material models are available in QS3HARK (e.g., PM4Sand, PM4Silt, PDMY, PDMY02, PDMY03, ManzariDafalias, and Borja-Amies) to support complex site-response analysis. Uncertainties in both the soil properties and the bedrock ground motion inputs can be characterized and propagated throughout the simulations to arrive at a probabilistic description of the ground shaking.

EE-UQ and PBE

The Earthquake Engineering with Uncertainty Quantification (*EE-UQ* [2]) and the Performance-Based Engineering (*PBE* [13]) tools facilitate the assessment of structural response and the expected damage and losses from earthquake events. QS3HARK is integrated in these tools to allow for propagation of ground shaking from the bedrock to the surface and apply the simulated surface ground motions to a building model. This allows sophisticated consideration of soil behavior for the performance assessment of buildings. The workflow used in these tools for individual buildings will be integrated into the R2DTool, the regional simulation tool of the SimCenter to enable such high-fidelity analyses at the regional scale.

Educational Tools

The Site-Specific Seismic Hazard Analysis and Research Kit (*S3HARK* [26]) is the educational version of QS3HARK that provides the same features and versatile set of material models but without uncertainty quantification. Removing UQ supports educational needs by streamlining the user interface and facilitating the setup of simulations.

The Pile Group Tool (*PGT* [24]) supports studies on the behavior of a pile or a pile-group in layered soil under ground shaking. Its user interface allows students to interactively observe the response of the system to changes in the soil characteristics, the pile configuration, and the pile design.

The Transfer Function Tool (*TFT* [28]) focuses on calculating the transfer function that maps a given bedrock motion to a surface motion. The tool allows students to define the characteristics of layered soil profiles and examine how the input motion is affected by the soil deposit.

Chapter 11
Computational Fluid Dynamics—Wind

Ahsan Kareem,
with review comments and suggestions by Arindam Chowdhury, Catherine Gorlé, Peter A. Irwin, Seung Jae Lee, Paneer Selvam, and Chen Xinzhong

Buildings exposed to wind undergo complex interactions, which preclude a simple functional relationship between wind and its load effects with the exception of buffeting effects, i.e., turbulence excited wind loads along the direction of the wind. Accordingly, wind tunnels have traditionally served as a means of quantifying wind loads that are combined with structural analysis codes based on finite-element analysis.

With burgeoning growth in computational resources and parallel advances in computational fluid dynamics (CFD), computational simulations are evolving with the promise of becoming versatile, convenient, and a reliable means of assessing wind-load effects. Figure 11.1 summarizes salient advantages and disadvantages of the wind-tunnel-based experimental methods and the computational CFD-based schemes. Despite the substantial improvements in the efficiency and fidelity of CFD-based simulation of wind effects, it is prudent to say that the simulation of wind-load effects using CFD still faces challenges; therefore, wind tunnels remain as an essential validation tool.

Experimental (Wind Tunnel)	Computational (CFD)
• Quantitative description of flow phenomenon using measurement • For limited quantities at a time • At a limited number of points and time • For a limited range of problem and operating conditions **Error sources** • measurement errors • flow disturbances by the probes	• Quantitative prediction of flow phenomenon using CFD • For all desired quantities • With high resolution in space and time • For virtually any problem and realistic operating condition **Error sources** • Modeling • Discretization • Iteration • Implementation

Fig. 11.1 Comparison between experimental and computational approaches.

11.1 Challenges of CFD

The computational grid of complex geometries and clusters of structures is fundamental to CFD as it represents the computational domain in which calculations are carried out at regular intervals to simulate the passage of time. The more compact the spatially discretized grid and the smaller the time step, the more accurate and realistic are the simulated results. Unfortunately, simply introducing initial and boundary conditions does not ensure a solution because the system being solved is nonlinear, and the interaction among terms of the governing equations leads to the generation of multiple scales. Accordingly, one of the primary challenges with CFD is the trade-off between accuracy and computational effort. The choice of turbulence modeling discussed in the following discussion plays a critical role in the level of accuracy obtained and the computational effort required.

In addition, the efficacy of CFD is still under debate, although it has been successfully implemented in aerospace engineering and wind tunnels to validate final designs. This is primarily due to the nature of structural shape in aerospace applications like an airfoil with a streamlined shape, resulting in a flow field around it that essentially stays attached to the surface, which can be numerically captured rather accurately. Figure 11.2 summarizes the flow field around a streamlined airfoil to a circular cylinder and progressing to a sharped-edged body representing a typical building or a bridge cross section. In contrast, as we move from an airfoil towards a circular cylinder and a rectangular cross section, the flow field around them gets progressively more complex as the flow cannot negotiate the sharp changes in direction as it moves around the body and hence jettisons away, creating separated flow characterized by flow reversal. Capturing these interacting features numerically poses challenges, which has led to slower progress in the application of CFD in wind-load assessments on structures. A basic overview of the issues surrounding flow features around structural configurations and the role of turbulence is presented below, including ensuing numerical challenges.

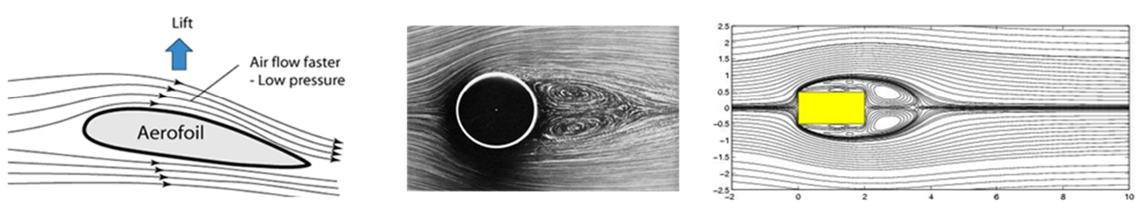


Fig. 11.2 Flow around cross-sections with increasing level of complexity (Ding et al., 2018).

The range of the size of eddies that manifest the turbulent flow around structures determines the grid size, which places demands on both the memory size and speed of the computational hardware. Ideally, the resolution of all scales in the flow from energetic low-frequency fluctuations to the smallest scale (the Kolmogorov Scale) in the viscous dissipation regime dependent on viscosity would be ideal. This approach is referred to as direct numerical simulation (DNS) and is computationally very intensive as the grid size for a required Reynolds number (Re) flow requires cells equal to Re9/4. Although highly desirable, such simulations are currently limited to address basic research in fluid dynamics using CFD.

To overcome this challenge, the Navier-Stokes (NS) equations of motion are filtered based on a length scale; thus, the motion of eddies smaller than the length scale is not calculated. Rather, the large eddy motion is computed, and the small-scale motions are modeled using ideas that range from enhanced coefficients of viscosity to an additional system of equations representing closure models. This results in a smoothing process, which helps to relax the number of grid points necessary to simulate the flow field. This scheme is known as the large eddy simulation (LES). As computer capacity increases, a broader range of eddies can be resolved, thus reducing the scales that need to be modeled.

An alternative schema involves time averaging or ensemble averaging of the NS equations (the Reynolds averaging are referred to as RANS) that result in obtaining only the mean and deviations from the mean of the computed quantities. It requires a coarser grid resolution compared to LES. RANS often has difficulty in capturing flow separation and reattachment as a consequence of averaging (Spalart, 2010). The performance of LES may also be impaired due to inadequate grid resolution and the treatment of the subgrid-scale turbulence. A hybrid combination of LES and RANS is referred to as detached eddy simulation (DES), composed of LES in regions for which the grid resolution can economically simulate the inertial subrange and reverts to RANS in near-wall regions where turbulence scale is smaller than the grid size (Hoarau et al., 2016).

That said, moving from the simulation of flow around isolated buildings to a cluster adds to the demand on computational resources; however, the flow patterns in the street canyons become more forgiving from the simulation perspective as sharply defined features become more unstructured due to mixing and can be resolved with less effort. Similar observations have been made in wind-tunnel studies when examining the influence of adjoining buildings in a cluster on the aerodynamic loads. This is akin to adding damping in structures and helps to dampen fluctuations in the flow field. LES nested in weather research and forecasting (WRF) models may be utilized to predict wind effects in a cluster of buildings in an urban setting under both extra-tropical and tropical systems.

11.2 Modeling of Flow around Structures

The CFD simulation process for modeling wind around structures involves the following main steps: problem statement; mathematical model; mesh generation; space and time discretization; inflow generation; boundary conditions; wall functions; simulation runs; fluid–structure interaction (aeroelastic effects); post-processing; verification/validation; and uncertainty quantification. Some of the salient aspects are presented schematically in Figure 11.3, with its primary focus on the choice of turbulence model, the mesh requirement especially near the boundaries of the structure, and inflow and boundary conditions (Ferziger and Peric, 2012). Generally, due to limitations in mesh resolution, it is essential to use a wall function. A wide variety of wall treatments for LES simulations of turbulent flows have been proposed (a recent overview is given in (Bose and Park, 2018), but the effect of the wall function formulation on the LES prediction of the turbulent pressure signal on a building has not been fully explored.

In computational wind engineering (CWE) applications, generation of inflow turbulence satisfying prescribed mean-velocity profiles, turbulence spectra, and spatial and temporal correlations is of great importance for accurate evaluation of wind effects on buildings and structures. Several methodologies have been proposed for this purpose, which can be classified into three general categories: precursor simulation methods, recycling methods, and synthetic methods. Compared with precursor simulation and recycling methods, in general, the synthetic methods offer a more practical and relatively efficient approach to generate inflow turbulence.

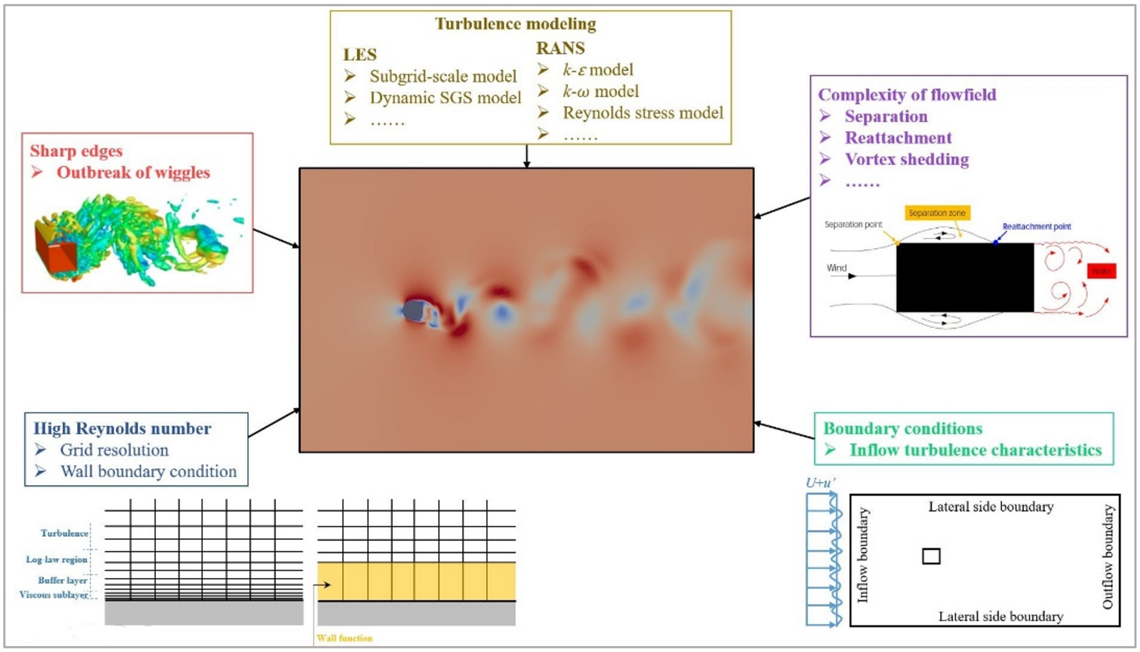


Fig. 11.3 Schematic of a digital analog of modeling flow around structures in a wind tunnel (Ding et al., 2018).

Research activities on synthetic turbulence generation have been vigorous over the past several decades and have branched out into several categories of techniques (Wu, 2017), including the synthetic random Fourier method (Hoshiya, 1972; Kraichnan, 1970), the synthetic digital filtering method (Klein et al., 2003), and the synthetic eddy methods (Jarrin et al., 2006). A comprehensive modeling approach for the neutral atmospheric boundary layer (ABL): consistent inflow conditions, a wall function, and turbulence model closure for a RANS based modeling are detailed in (Parente et al., 2011).

One of the challenges with inflow simulators is the decay of synthetic turbulence as we move from the inflow plane to the location of a building in the simulation domain (3, 4). One of the approaches involves an iterative approach through trial and error, or establishing a transfer function of the decay and embedding that in the simulation scheme. Alternatively, implementing an optimization to calibrate the inflow parameters is one way to circumvent this challenge and ensure that the correct turbulent statistics are obtained at the location of interest (Lamberti et al., 2018). In addition, there are continued efforts to develop improved inflow generation methods that could further reduce the decay (e.g., Bervida et al., 2020). Independent of the choice for the inflow generator, the need to first run an ABL simulation and verify whether the correct turbulence statistics are achieved at the location of interest—similar to the calibration of the flow in a wind tunnel—is important.

11.3 Computational Details and Post-Processing

The following discussion addresses computing time for simulation, and how it is influenced by several steps involved in the simulation process. For example, the computing time depends on the following: (1) the choice of numerical algorithm and data structure; (2) linear algebra solvers and criterion prescribed for interactive solvers; and (3) discretization parameters, such as mesh quality, mesh size, time step; hardware, vectorization, and parallelization. The quality of simulation results depends on: (1) the mathematical model and underlying assumptions; (2) types of approximations implied; and (3) stability of numerical scheme in terms of mesh, time step, error indicators, and iteration stopping criterion. Some of these features operate in isolation while others operate in combination, which influences both the quality and the time it takes to perform the simulation. These processes should be revisited when there is a need to enhance the quality of simulation and/or to reduce the time needed for simulations. Machine-learning tools—such as supervised, unsupervised learning, reinforcement learning, and deep learning—offer exciting avenues to learn from the simulations, help classify regions of similarity, and create predictions for future simulations (Kareem et al., 2019).

Once the simulations are complete, one needs to process data. This also entails the calculation of derived quantities, e.g., statistics of velocity or pressure fields; integral parameters, e.g., drag and lift coefficients, building response and their spectral characteristics; local zooming for a further look at a region of simulation exhibiting features of potential interest; visualization of data in space and time, a real-time portrait of flow features, digital version of analog flow visualization using smoke in wind tunnels, overall systematic analysis of data using statistical and signal processing tools and debugging, verification and validation of CFD models, and assessing the role of uncertainty.

11.4 Verification and Validation

Wind-tunnel validation of CFD-based simulations often serves as the final step in the process. The progressive reduction of uncertainty (Roache, 1998) is the only practical way to ensure any kind of confidence in a given CFD simulation. This calls for vigorous validation (AIAA, 1998), just as in any other complex numerical simulation. In particular, due to limited analytical solutions being available for simple flows only, CFD validation must be carried out through high-fidelity experimental testing. For this reason, experimental validation often becomes the essential step in ensuring the reliability of CFD simulations (Oberkampf and Roy, 2004; Oberkampf and Trucano, 2008; Roy and Oberkampf, 2011). This is particularly true in computational wind engineering, where the CFD simulation of a bluff body, like a tall building, immersed in an ABL is often validated through specific boundary-layer wind-tunnel tests (Yu et al., 2013; Yu and Kareem, 1998).

Note that many CFD studies seem to lack a thorough validation process, i.e., grid convergence studies are rarely carried out, and, in general, detailed flow field results are missing. The general lack of code verification, discretization scheme selection, turbulence modeling, mesh quality, and sampling time for statistical analysis, etc., adds more uncertainty. It should be observed, however, that this process is by no means simple and will, in general, be far more involved than the validation of channel or pipe flow, for instance, for a number of reasons including: (1) most experimental wind tunnel tests carried out on civil engineering structures are not exhaustive enough to allow a truly complete CFD validation; (2) the geometric configurations of the bluff bodies tested in wind tunnels are often too complex for an unsteady CFD analysis; and (3) the high Reynolds number in wind tunnel testing also adds difficulties in performing a systematic grid convergence study.

11.5 Software and Systems

While developments in CFD as applied to a host of topics in basic fluid dynamics, aerospace, automotive, and urban aerodynamics are evolving at a fast pace, there has been rather limited research focus on the development of CFD-based tools and schema to advance the computational modeling of wind effects on structures. Limited commercial software has been widely utilized by both researchers and industry (e.g. *ANSYS Fluent* [62]). The inherent nature of modeling and parametric sensitivities and the lack of flexibility to improvise has often led to simulations that reflect large variability and, on occasion, depart from experimental observations. This has fueled the misleading impression that CFD is currently inadequate to fully capture wind–structure interactions.

Yet, the current state of the art of CFD application in wind effects is defined by in-house tools wrapped around the popular open-source *OpenFOAM* [5] environment. CFD for wind simulation has advanced to the stage that the Architectural Institute of Japan (AIJ) now permits the use of CFD in place of other approaches, e.g., wind-tunnel testing, with the stipulation that the AIJ guidelines concerning three-dimensional LES and inflow simulation must be followed.

11.5.1 Relevant SimCenter Tools

The SimCenter aims to include CFD-based simulation of wind effects in its regional risk assessment workflow and R2DTool, the corresponding desktop application. The regional-scale CFD simulation capabilities need to build on top of a robust implementation of the analyses of individual buildings. Therefore, the SimCenter has been focusing on the analyses of individual buildings first.

TinF

The *Turbulent Inflow Tool* [63] application helps with the definition and parametrization of various turbulent inflow models and augments existing OpenFOAM model files with the respective parameter definitions.

WE-UQ

The Wind Engineering with Uncertainty Quantification Tool (*WE-UQ* [11]) is designed to assess the response of buildings subjected to wind loading. Uncertainty Quantification refers to considering the uncertainty in the properties of the building and the wind loads and propagating such uncertainty through the simulations. Besides the advanced features in TinF, it also provides access to other non-CFD-based methods for specifying wind loads, such as online wind engineering databases (e.g., TPU, 2020) and the stochastic wind load generation available in smelt. The wind simulations are run using *OpenFOAM* [5] and the calculated loads are applied on finite element models using OpenSees. Two-way fully coupled fluid–structure interaction is currently under development.

Educational Tools

The *CFD Notebooks* [44] (CFDN) prepare students for CFD-based research work by providing a basic working knowledge of *OpenFOAM* [5], including mesh preparation and the generation of boundary conditions. CFDN is a series of Jupyter notebooks hosted on DesignSafe. It leverages DesignSafe's High-Performance Computing platform to provide an interactive interface for students or instructors that can demonstrate running OpenFOAM simulations without any software installation overhead.

11.6 Future Directions

Uncertainty quantification in CFD modeling

Uncertainties in CFD modeling are primarily associated with the uncertain inflow boundary conditions representing the inherent variability of atmospheric flows and model-form uncertainties originating from the turbulence modeling assumptions applied to the unresolved small-scale turbulent eddies. These sources of uncertainties should be appropriately accounted for, and their impact on the predictive capabilities for the aerodynamic quantities need to be carefully examined since they may impact the aerodynamic loading characterization in CFD modeling. Uncertainty quantification (UQ) in CFD modeling involves the quantitative estimation of both the inflow and model-form uncertainties, and their resulting impact on the aerodynamic Quantities of Interest (QoIs). Techniques for UQ and uncertainty propagation including Monte Carlo simulations, polynomial chaos, and Gaussian process regression have been explored in many engineering problems as non-intrusive approaches that use solution samples to numerically estimate the output functions (Beran et al., 2017). An efficient UQ approach that quantifies the effect of coupled inflow and model-form uncertainties would allow propagation of uncertainties to the aerodynamic QoIs. Recent applications of UQ to CFD simulations can be found in (Gorlé et al., 2015) that utilizes an interval-based approach, while (Ding and Kareem, 2019) introduced a surrogate model-based scheme. Advances in data-driven approaches are leading to other schemes like deep neural networks (DNNs) for UQ (e.g., Ling et al., 2016b; Luo and Kareem, 2019)].

Multi-fidelity modeling

Computational fluid dynamics evaluations can feature both the high-fidelity models, which are accurate yet expensive and the low-fidelity models that are computationally efficient but can produce large modeling errors. RANS and its variants are currently the workhorse of CFD (Kareem, 2017) as the computational requirements are modest, but because its accuracy is compromised in separated flow regimes, it is viewed as low fidelity. LES solves the filtered NS equations at large energy-containing scales and relies on modeling to resolve the smaller more universal subgrid scales. The results thus offer a higher fidelity compared to RANS, but at an additional computational effort. Therefore, the simulation data may involve data sources of multiple fidelities with different computational costs.

In an attempt to blend the variable-fidelity information source, multi-fidelity surrogate modeling is an attractive avenue that utilizes hierarchical surrogate models relating low-fidelity (RANS) to high-fidelity (LES) models to obtain high-quality predictions with a computational effort comparable to RANS. Multi-fidelity surrogate modeling has been successfully applied to a host of engineering problems, including beam design, using finite-element analyses with variable mesh sizes (Leary et al., 2003), optimization of a transonic aircraft wing with two levels of CFD fidelity (Forrester et al., 2007), and rotor bade design based on the code with simplified aerodynamics, as well as high-fidelity numerical simulations (Collins, 2008), etc. Therefore, a multi-fidelity surrogate modeling approach in the aerodynamic shape-optimization framework that involves data from sources of both RANS and LES simulations would offer superior surrogates from the context of enhancing the model accuracy as well as maintaining low computational demand.

Fusion of machine learning and CFD

As discussed earlier in this section, despite recent advances in the computational resources, the CFD-based simulations are computationally very demanding, especially considering the desired level of fidelity. Recently, the focus in the CFD area is on the fusion of data-driven approaches to enhance the computational efficiency and accuracy of simulations (Kutz, 2017; Ling et al., 2016b; and Kareem, 2020). Using DNNs as a surrogate model to predict CFD simulation results is also a promising future direction. So far, relevant studies for Reynolds stress modeling using DNNs, convolutional neural networks (CNNs) for flow prediction, or physics-informed neural networks (PINN) (which have gained a considerable attention) have been applied to solve simple flow patterns at low or moderate Reynolds numbers. (e.g., Liu et al., 2020; Mao et al., 2020; Tompson et al., 2016). This deep-learning-based approach can be also based on experimental data or an integrated experimental and computational simulation framework (Luo and Kareem, 2019, 2020). Others have involved machine learning as a CFD closure model, whereby closure model parameters based on representative datasets are extracted and embedded in the flow solver to enhance the quality of simulations. Similarly, machine-learning models are being developed to model errors, e.g., RANS- or LES-based prediction compared to DNS data. (Ding and Kareem, 2018) used a similar surrogate model to account for the discrepancy between RANS and LES simulations of shape optimization of buildings; this approach also facilitates UQ in such an exercise (Ding and Kareem, 2019; Ding and Kareem, 2018). Furthermore, machine-learning approaches can be used as "wrappers" around existing toolsets to enhance predictive capabilities. Other applications involve invoking the concept of digital twins for the exploitation of computational physics data, consisting of using machine learning to enlarge the simulation databases to cover a wider spectrum of operational conditions and provide quick response directly on the field (Kareem, 2020; Molinaro et al., 2021). The resulting product from this hybrid physics-informed and data-driven modeling may be referred to as Simulation Digital Twin. A recent example of CFD, machine learning, sensing, and actuation of a dynamic building façade shows an example of how the fusion of these technologies can offer a viable platform to manage autonomously the profile of a building façade under varying wind environments (Ding and Kareem, 2020).

Chapter 12
Computational Fluid Dynamics—Water

Michael Motley with contributions by Ajay B. Harish and Andrew Winter,
along with review comments and suggestions by Arindam Chowdhury, Catherine Gorlé,
Andrew Kennedy, and Seung Jae Lee

Computational Fluid Dynamics (CFD) uses numerical methods to solve governing equations that arise in fluid mechanics. While the previous section focused on gaseous fluids (e.g., air), here we focus on applications of CFD for liquid fluids (e.g., water), although modeling of the water's free surface arises in many situations, especially those around natural hazard modeling as it requires modeling the air, the fluid, and the interface between the two. For water, the standard governing equations are the incompressible Navier–Stokes (NS) equations (Darrigol, 2005). These equations describe the motion of viscous fluid substances; their solution provides much of the useful information for natural hazards engineering (NHE) problems, e.g., the current speed of the flow and fluid pressures on built infrastructure.

Solving NS equations without the use of a turbulence model is often referred to as direct numerical simulation (DNS, Orszag, 1970), in which the whole range of spatial and temporal scales of the turbulence must be resolved. As a result, the expense of using extremely small grid sizes and time steps is unaffordable in many practical engineering systems, especially when the Reynolds number—which indicates the intensity of turbulence—is high. To accommodate these issues, some variants of NS equations are often used in practice. The two most popular approaches are Reynolds-averaged Navier–Stokes equations referred to as RANS equations (Chou, 1945; Reynolds, 1895) and large eddy simulation (LES, Deardorff, 1970)

The two models, while still able to give satisfactory approximations to the turbulence in the fluid, are much cheaper than DNS because they use new model equations to describe turbulent energy dissipation. These equations arise from the addition of new variables into the modified governing equations that result from the averaging and filtering processes to estimate turbulent phenomena. These unknown variables are typically related to known quantities such as the velocity gradient.

While the above methods use Eulerian methods, Lagrangian-based approaches such as Smooth Particle Hydrodynamics (SPH, Gingold and Monaghan, 1977; Lind et al., 2020; Lucy, 1977) have gained some popularity for solving flows around complex geometries. Other recent alternatives such as the Lattice Boltzmann Method (LBM, Chen and Doolen, 1998) or Immersed Boundary Method (IBM, Peskin, 1972, 1977, 2002), while less widely used, can be used to take advantage of specific physical phenomena (e.g., using IBM to consider flow around complex moving boundaries).

12.1 Input and Output Data

In all situations where CFD is used, the two basic inputs are the boundary conditions and initial conditions. The boundary conditions refer to the boundaries of the computational domain, which may include a wall where water cannot penetrate or an outlet where fluids flow out. For problems in NHE, such boundaries can include the ground over which the fluid flows, the outside walls of a building that will affect flow path of the water, or the complex geometry of a bridge hit by a tsunami or storm surge (e.g., Giles, 1990; Miquel et al., 2018).

The initial conditions refer to the state of the fluids before the simulation starts. For instance, in tsunami modeling, the initial conditions for some nearshore regions might have all water at rest at sea level while somewhere in the ocean, a large volume of water is placed above sea level that represents a tsunami wave. Implementation of these initial conditions is not trivial, especially along the inlet boundary, and care must be taken to maintain a stable solution as time marches forward; CFD solvers predict how the water volume and velocity evolve in time from their initial state. Different initial conditions will give different states later in time.

The output from CFD depends on the equations that are solved but generally includes water velocities, water pressure, and height of water surface (with extra treatment added to the NS equations, e.g., coupling the volume of fluid methods (Brackbill et al., 1992; Hirt and Nichols, 1981; Jasak, 1996; Ubbink, 2002; Ubbink, 1997) at any specified moment during the simulation and at any location within the domain. The pressure field can be further processed to obtain forces on structures.

12.2 Models and Software Systems

The implementation of CFD algorithms is often very complex. Many CFD software systems are developed and maintained by either commercial companies or large development teams with support from user communities. Some popular commercial software include: *S.T.A.R.-C.C.M.+* [68], *ANSYS Fluent* [62], and *COMSOL* [64]. Commercial software often provide the ability to customize solvers (to some extent) by allowing user-defined functions. Many researchers prefer the complete freedom of modifying the source code and use open-source CFD software, such as *OpenFOAM* [5] and *SU2* [69]. By far, OpenFOAM is the most widely used and provides very comprehensive functionality in all areas of CFD. The relevant research communities have also contributed many pre-processing and post-processing tools for OpenFOAM, e.g., wave-generation tools that are often required in hazard modeling. Customized versions of OpenFOAM for certain applications are also available. Some examples include *H.E.L.Y.X.* [65], *olaFlow* [67], and *IHFOAM* [66]. The latter two are specially designed to simulate coastal, offshore, and hydraulic-engineering processes (Higuera et al., 2013a,b, 2014a,b, 2015).

12.2.1 Relevant SimCenter Tools

The CFD-based analyses of water flow are primarily used to simulate large-scale, regional inundation sceanrios in the natural hazards engineering community. Two of such hazards were discussed in Chapters 7 and 8. The SimCenter first responds to this need in the community, but the tools are planned to be extended to allow more advanced structural response simulation in the future.

Hydro-UQ

The Hydrodynamic loading with Uncertainty Quantification Tool *HydroUQ* [4] manages three-dimensional CFD simulations using *OpenFOAM* [5] and uses a universal interpreter to interface with two-dimensional, far-from-coast simulations performed by shallow water solvers (e.g., *GEOCLAW* [3], *ADCIRC* [1]). The shallow water simulation results are used as inputs for simulations in OpenFOAM. The bathymetry and topography of the ocean floor, the meshing of the model, and other simulation parameters can be conveniently adjusted through the user interface. The results of CFD simulations are used to generate loads in a three-dimensional finite element environment (e.g., OpenSees). Uncertainty Quantification in the name of the tool refers to the ability to consider uncertainties in structural parameters and propagate them throughout the simulation using DAKOTA. Simulations can run remotely on the High-Performance Computing clusters linked to DesignSafe. The tool can be used to model a small portion of a regional study to perform high-resolution simulations around critical buildings, bridges, or other parts of the built environment. The results of such simulations can serve as training data for surrogate models that can provide more efficient response estimation for regional studies without sacrificing the fidelity of CFD simulations.

Educational Tools

The *CFD Notebooks* [44] (CFDN) prepare students for CFD-based research work by providing a basic working knowledge of *OpenFOAM* [5], including mesh preparation and the generation of boundary conditions. CFDN is a series of Jupyter notebooks hosted on DesignSafe. It leverages DesignSafe's High-Performance Computing platform to provide an interactive interface for students or instructors that can demonstrate running OpenFOAM simulations without any software installation overhead.

12.3 Major Research Gaps and Needs

Computational fluid dynamics is a broad concept that is used as a simulation approach in many industry and research fields. Although the general-purpose commercial or open-source CFD packages can provide a broad variety of requirements, cutting-edge research in a specific area often requires tackling very specialized problems. As a result, either in-house code must be developed, or heavy modification and customization must be added to CFD packages. Fortunately, the prevalence and maturity of open-source CFD software has provided a solid foundation or is, at the very least, a very helpful resource for researchers that focus on such software development. One drawback, however, is that there is a consistent lack of complete documentation for many of these software, creating obstacles for new users.

The lack of open-source meshing tools remains a significant challenge as CFD requires high-quality structured hexahedral grid for efficient computation; unfortunately, most of the available open-source meshing tools are better at constructing triangle / tetrahedra-based unstructured grids (Geuzaine and Remacle, 2009). Automated structured hex meshing tools are not available, in spite of the several citations in the literature (e.g., Gao et al., 2017;

Verhetsel et al., 2019; Yamakawa and Shimada, 2003). Thus, the users depend on commercial pre-processors like Hypermesh. OpenFOAM has two built-in meshing tools, namely blockMesh and snappyHexMes, but they fall short for problems of interest beyond academia.

Another challenge is the portability and scalability of CFD software, which allows the code to run on high-performance computing (HPC) facilities. The explosive growth of computing power in the past two decades has tremendously changed many areas, allowing for the performance of simulations that were impossible in the past. Unfortunately, CFD software, especially in-house code or customized solvers, may not run naturally on new machines. OpenFOAM specifically has been shown to have difficulty scaling to maximize performance on HPC clusters. Different implementations in the code must be taken and even new algorithms designed such that the code can run efficiently on a cluster that consists of thousands of computing nodes and a cluster that consists of new architectures like GPUs.

In terms of modeling physical processes, one significant research gap is in robust modeling of the air–fluid–structure interaction phenomena associated with wave impacts and fast moving flows around complex geometries. The effects of air compressibility and potential air entrapment are often either poorly considered or neglected altogether. Some loosely coupled one-way approaches for fluid–structure interaction response are available, but a more comprehensive two-way coupling approach to combine CFD with various structural analysis techniques is needed. Similar novel coupling mechanisms between CFD solvers and the two-dimensional approaches presented in Chapter 8 are also a notable research gap. Because of the computational expense of CFD approaches relative to the nonlinear shallow water or Boussinesq approaches used at very large scales, developing approaches that allow flow to move between these types of solvers is a significant challenge.

Part III
Performance Assessment

The built environment is a collection of various types of assets that affect the well-being and quality of life of residents in an urban area. The list of such assets includes residential and commercial buildings, bridges, networks of roads, railways, pipelines and power lines, and their supporting facilities. This part of the report focuses on evaluation of the damage and direct consequences that typically describe the immediate impact of the disaster and assign a performance measure to the various assets that make up the built environment. Part IV focuses on the simulation of recovery and consequences that consider interdependencies between infrastructure systems, the built environment, and local communities.

The performance of assets depends heavily on the description of the hazard and the simulation of asset response to one or more characteristic events that are consistent with the hazard at the asset location. Although this chapter focuses on performance assessment, some of the tools listed here have hazard and response estimation capabilities as well. Those features have been covered in Parts I and II, respectively.

This part is organized around the types of assets and asset-networks needed to arrive at a comprehensive description of the performance of an urban region subjected to a natural-hazard event. The content is divided into four chapters to facilitate navigation, but the importance of an integrated assessment is emphasized by highlighting the synergies across assets and hazards throughout the chapters.

Chapter 13
Buildings

Adam Zsarnóczay,
along with review comments and suggestions by Jack W. Baker, Paolo Gardoni, Thomas O'Rourke, Vesna Terzic, and Chaofeng Wang

Buildings are arguably the most important asset type when it comes to direct consequences of a natural disaster. A severely damaged or collapsed building may result in loss of life, injuries, and significant capital losses. Seismic performance assessment of buildings has received a lot of attention from the research community and funding agencies in the past few decades (Agency, 1997; ATC, 1985; Fajfar and Krawinkler, 2004; Kircher et al., 2006). Consequently, the most sophisticated and mature methods are available in that area (ATC, 2012). Several researchers have focused on adopting these methods for other asset types (Chmielewski et al., 2016; Werner et al., 2006) and for other types of hazards (Attary et al., 2017; Barbato et al., 2013; Bernardini et al., 2015; Lange et al., 2014; Vickery et al., 2006b). Although this has led to similar methods being used for various types of assets, some of the synergies between these methods remain un-utilized in research.

Historically, two different approaches have been developed for performance assessment of buildings. Until recently, the methods and models used in these approaches improved in parallel (Figure 13.1):

- Large-scale simulations of distributed building inventories required idealized, efficient models that provided sufficiently accurate performance estimates while limiting the computational workload to make the simulations feasible. The most popular example of such an approach is the HAZUS framework that has been developed for earthquake (FEMA, 2018a), hurricane (FEMA, 2018b), and tsunami hazards (FEMA, 2017). HAZUS and similar methods typically take path I or II in Figure 13.1 and estimate the consequences of a disaster using vulnerability or fragility functions that link the intensity of the natural hazard directly to measures of damage and losses at the building level; and
- The assessment of individual buildings has been moving from a holistic towards a component-based approach. Instead of trying to characterize the building damage as a whole, recent performance-based engineering (PBE) methods disaggregate buildings into sets of components and apply separate models (i.e., functions) to estimate the damage and losses for each component. These methods require a detailed description of the building and its behavior under the natural hazard event, necessitating the simulation of building response following path III in Figure 13.1. In return, they provide high-resolution information about the damage and losses that allow better understanding of the building's performance. FEMA P-58 (ATC, 2018a) represents the state of the art in high-fidelity seismic performance assessment for buildings. Researchers have recently been developing similar PBE methodologies for other hazards (e.g. Attary et al., 2017; Barbato et al., 2013; Ouyang and Spence, 2020).

The two approaches presented above were traditionally separated because neither the computational resources nor the detailed description of assets were available to apply the high-fidelity models and methods at a large, regional scale. Recent advances in computational resources, data harvesting, and processing (see Part V) are now bridging the gap between these methods, suggesting that integrated multi-fidelity performance assessment of large asset portfolios will become available for researchers in the near future (Deierlein et al., 2020).

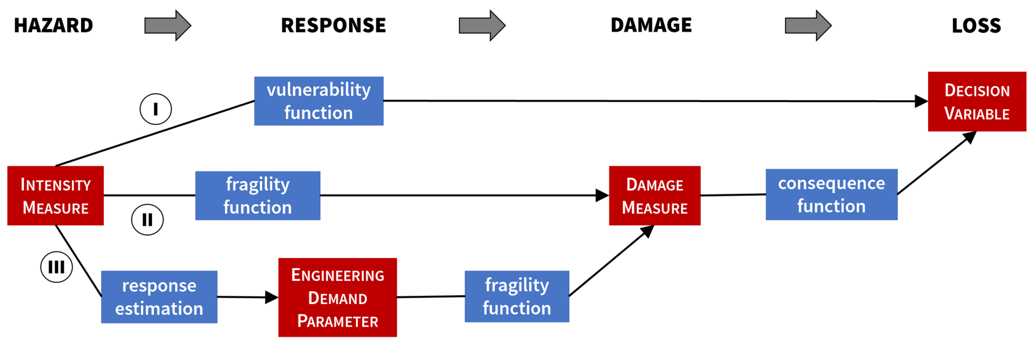


Fig. 13.1 Schematic workflows for asset performance assessment (Deierlein et al., 2020).

13.1 Input and Output Data

13.1.1 Input Data

The following types of data are required to evaluate the performance of a building:

Hazard characterization

When the building performance is not conditioned on a particular disaster scenario but is evaluated considering all possible scenarios within a time period, the likelihood of each possible scenario needs to be estimated [e.g., time-based assessment in FEMA P-58 (ATC, 2018a)]. The hazard curve describes the rate of exceeding various levels of an intensity measure (IM) over the time period of interest. More information about the description of the hazard is provided in Chapter 2.

Intensity measures

Efficient building performance assessment methods directly link IMs to damage measures (DMs) and decision variables (DVs) using fragility functions and vulnerability functions, respectively. For such methods, the inputs need to characterize the intensity of the event either through parameters of a distribution function (e.g., mean, standard deviation) or by directly providing samples of the IMs. More information about obtaining IM data is available in Part I.

Engineering demand parameters (EDPs)

High-fidelity building performance assessment uses EDPs as proxies for the detailed history of building response under a natural hazard event. Such EDPs should have high correlation with the building damage of interest and should be estimable with sufficiently high accuracy through numerical analysis. Estimation of EDPs first requires a building response model that is typically created in one of the environments listed in Chapter 9. Second, the building model needs to be excited with loads that correspond to a particular hazard event. The inputs required for these models and analysis have been described in previous parts of this report.

Engineering demand parameters are extracted from the structural response simulation. Seismic performance assessment often uses peak responses at every story such as peak story drift ratios and peak floor accelerations (ATC, 2018a). Other hazards result in different response histories and damage, and they are characterized by other EDPs, such as external pressures (Ouyang and Spence, 2020) or maximum inundation depth (Reese et al., 2011).

Component characteristics

Depending on the complexity of the performance assessment method and data availability, buildings are described as a system of components or component-groups. For example, the component-group-based approach followed by HAZUS (FEMA, 2011a) aggregates structural components, non-structural components, and contents into three groups. The FEMA P-58 method represents the other end of the spectrum; it disaggregates the building into units of components with identical behavior. The component-group-based method typically requires fewer and more generic inputs such as the type of structural system and the occupancy type to infer component behavior. The more detailed methods use the quantity, direction, and location of each component unit on each floor of the building to estimate their damage.

Fragility functions

Fragility functions describe the likelihood of exceeding a particular damage state as a function of IM or EDP magnitude; see Figure 13.1 and Baker et al. (2021). Many fragility functions are publicly available, and there is open discussion about their improvement for the seismic performance estimation of buildings (e.g., Silva et al., 2019). FEMA P-58 enables sophisticated analysis for seismic hazards by providing (ATC, 2012) and continually revising (ATC, 2018a) a database with detailed description of more than 700 types of components. The HAZUS platform includes fragility and vulnerability functions for component-groups for various hazards, but the development of publicly-available functions that would allow more detailed assessment under wind and water hazards is a topic of active research.

Vulnerability and consequence functions

Vulnerability and consequence functions describe losses from a disaster as a function of its intensity and the experienced structural damage, respectively. Vulnerability functions are more efficient because they do not require information about the damage incurred, but their estimates have more uncertainty. Vulnerability functions typically describe the consequences at a building-level (e.g., HAZUS), while consequence functions can use more detailed information (e.g., FEMA P-58) about the damage. Each damage state has its corresponding set of consequence functions. These functions are defined by additional input data such as repair cost per component unit, affected area for calculation of injuries, or the expected downtime until the building can be re-occupied. The description and propagation of uncertainty in these functions is an important part of the calculation method. Consequences that are primarily a function of damage within the building and not affected by the performance of other parts of the civil infrastructure are often referred to as direct consequences. Vulnerability and consequence functions can estimate such outcomes well.

13.1.2 Output Data

One or more of the following outputs are produced to describe building performance.

Damage measures

Damage in buildings is quantified through damage measures that identify the damage state (DS) of the investigated building or component. Component damages are classified into a finite number of damage states, so that each DS groups damage scenarios with similar consequences together. Performance assessment is typically executed in a stochastic framework; the DMs are considered random, and the raw results of the assessment are at least thousands of samples of each output variable. Therefore, interpretation and visualization of the results is an important part of the process. The majority of applications focus on mean or median values to describe central tendencies, with the 10th and 90th percentiles used to illustrate the variability of results. High-performance computing and the improvement in the quality of input data have created the incentive to improve estimates of the tails of the distributions and to look at the joint distribution of the variables. These analyses reveal details of complex systems that might be overlooked when focusing only at central tendencies.

Decision variables

Decision variables describe the losses due to the natural hazard and are used to characterize the performance of the building and meant to eventually drive decision- and policy-making. Each type of loss has its own DV, such as number of injuries, repair cost, business interruption time, etc.

Indirect consequences

The influence of building damage on surrounding buildings and infrastructure is challenging to model because of the scarcity of data that could be used for calibration and the substantial increase in the complexity of the analysis when dependencies between buildings needs to be considered. Decision variables in this group include non-immediate injuries and hospital demand, displaced households and short-term shelter needs, business interruption costs, demand surge, and its influence on reconstruction cost and downtime estimates. Modeling and simulation of these outcomes is discussed in Part IV of this report.

13.2 Modeling Approaches

The main assumption of the widely used stochastic model for building performance assessment is that the uncertainty in the DVs can be estimated through a series of independent calculations. This approach has been developed in the Pacific Earthquake Engineering Research Center (PEER); it is often referred to as the PEER performance assessment framework or simply the PEER "triple integral" (see Figure 1.1, Moehle and Deierlein, 2004, and Porter et al., 2001):

1. Describe a set of IM levels (e.g., spectral acceleration intensities) and corresponding likelihoods based on the hazard at the building location over a given time period;
2. Describe the building response through EDPs at each IM level;
3. Describe component or component-group DSs given the simulated EDP distributions;
4. Describe consequences using DVs given the estimated DS of each component or component-group; and
5. Aggregate DVs from all components or component-groups in the building.

Depending on which path is taken from Figure 13.1, one or more of the steps above can be merged. If calculations are performed independently, the models used for these calculations are decoupled (e.g., the DS for two different IM levels is assumed identical if the IMs generate identical EDPs). These steps are the basis of the widely used HAZUS models, and they were the foundation of the FEMA P-58 method that is currently considered the state of the art for seismic performance assessment of buildings.

Although sophisticated performance assessment methods promise more information about building performance, their veracity demands more detailed input data about the building and its components. Consideration of the uncertainty that stems from the limited amount of building information available is essential for a robust performance evaluation (Bradley, 2013). The methods available for quantification and propagation of such uncertainty are discussed in Chapter 21.

Under non-seismic hazards, there is no equivalent of the FEMA P-58 method that would enable high-fidelity building performance assessment. This partly stems from the lack of publicly available high-quality databases—which would drive more sophisticated model development—and from the different nature of the problem. The impact and disruption of earthquakes and hurricanes are very different in both spatial and temporal distribution, with hurricanes having a severe impact on a larger region over a longer time period. Therefore, the focus for hurricane and flood models have always tended to be more regional, and capturing the detailed response of individual structures receives less attention.

13.3 Research Gaps and Needs

The integration of multiple hazards and multiple asset types in a simulation framework is an essential step towards a comprehensive performance assessment for the built environment. It is important to recognize the difference between multiple hazard studies and multi-hazard studies. Following the naming convention suggested by Bruneau et al. (2017), the former studies consider multiple, independent hazards in an area, while the latter studies consider the interactions and cascading effects among those hazards as well. In a multi-hazard analysis, the majority of the resulting risk is not from concurrent extreme events because the probability of two of such events happening simultaneously is very low. The characterization and modeling of more frequent hazards becomes more important and influential to the results. There are already several examples of multi-hazard studies in the literature for a wide range of hazard and asset types: earthquake mainshock and aftershock (e.g., Nazari et al., 2015; Zhang et al., 2013); ground shaking, liquefaction, and landslides (e.g., Elgamal et al., 2008; Kojima et al., 2014); earthquake and tsunami (e.g., Akiyama and Frangopol, 2014; Carey et al., 2019); hurricane wind, wind-borne debris, storm surge (e.g., Lin et al., 2010; Park et al., 2014) and rainwater (e.g., Pita et al., 2012); and flood and sea level rise (e.g., Hinkel et al., 2014). It would also be important to model interactions not only at the hazard level (e.g., Gill and Malamud, 2014), but also include site effects, disruptions of systems, and system-level social and economic consequences. Analyses that model interactions beyond the hazard level are referred to as Level II interactions by Zaghi et al. (2016).

Consideration of the time-dependency of the hazard (e.g., non-Poissonian earthquake models, and the effect of climate change on wind and water hazards), the structural response and performance (e.g., the effect of aging, retrofitting, and maintenance in general) are gaps in the widely used frameworks that researchers are working to fill (e.g., Choe et al., 2008; Gavrilovic and Haukaas, 2020; Pitilakis et al., 2014). Note: bridges have traditionally received more attention than buildings.

The consideration of non-structural components has improved substantially for seismic hazards, but disaggregating their contribution from the structural ones would also enhance the performance assessment under other hazards and in a multi-hazard setting. Besides better characterization of losses due to non-structural damage, modeling the contribution of these building components to the strength and stiffness of buildings is also an important component of more realistic simulations (e.g., Filiatrault and Sullivan, 2014; Welch, 2016)

Constructing a performance model for high-fidelity analyses is also a significant challenge that has only been tackled by proprietary software such as *SP3* [74]. There is no publicly available rule set that could be used to populate a large inventory of buildings with the types, locations, and quantities of components based on the limited amount of building information available for regional-scale assessments. A similar, but distinct problem is the automated model definition for response estimation. That task has received more attention in recent years (e.g., Guan et al., 2020; Xiong et al., 2016) as well as methods that can produce high-fidelity results without the need to explicitly model and simulate building response (e.g., Zou et al., 2020).

Epistemic uncertainties (i.e., model-to-model variability) and the bias introduced by idealized models in performance assessment should be taken into consideration (e.g., Aslani and Miranda, 2005; Schotanus et al., 2004) as well as the influence of correlations between EDPs (Shome and Bazzurro, 2009) and damage and loss models within a building (Ramirez, 2009).

Many of the existing models and methods for performance assessment have not been validated, and new models are rarely compared to existing ones in the literature. Different approaches to model development lead to different results. Even if an identical building class is considered, there can be large variation in the predictions of these. For example, Crowley et al. (2014) shows 60% coefficient of variation in collapse probability among 24 different models for European reinforced concrete moment frames. This practice risks introducing bias in the performance assessment results and reduces the credibility of the methods. Silva et al. (2019) provides a set of recommendations to improve the reliability of these models.

13.4 Software and Systems

The following is a list of software that provides features required for state-of-the-art research in building performance assessment.

CAPRA

Development of the Comprehensive Approach to Probabilistic Risk Assessment (*CAPRA* [70]) platform was initially supported by the World Bank and the Inter-American Development Bank; it has been managed by Uniandes (Universidad de los Andes in Colombia) since 2017. CAPRA is designed to become a multi-hazard framework based on several modules that handle different tasks of the risk assessment workflow. The currently available modules allow risk assessment using vulnerability functions for several types of hazards (e.g., earthquake, hurricane, and flood). The open source CAPRA framework uses Visual Basic .NET and provides applications in a Windows environment.

MAEViz

Developed by the Mid-America Earthquake Center (MAE), *MAEViz* [71] is based on the HAZUS methodology for scenario risk assessment and it allows users to write their own extensions. Through these added modules, its functionality is not limited to building performance assessment and allows analysis of infrastructure and lifeline performance as well as indirect consequences in the region. It uses a Windows-based application with a user interface to guide the user through the analysis. MAEViz is open source and has been integrated into several platforms in the U.S. [e.g., ERGO, mHARP] and in Europe [e.g., SYNER-G (Pitilakis, 2014) and HAZturk (Karaman et al., 2008)].

HAZUS 4.2

The FEMA-supported *Hazus 4.2* [17] tool was already introduced in Chapter 2. The damage and loss assessment modules in the HAZUS earthquake methodology use a component-group-based approach and categorize components into structural, non-structural, and content groups. HAZUS methods for other hazards do not separate structural and non-structural components. They provide building-level estimates of decision variables. Decision variables cover a wide range of direct and indirect consequences of damage. The efficient use of vulnerability functions in this methodology allows simulations to be scaled to a regional level without having to resort to high-performance computing (HPC).

OpenQuake

OpenQuake [21] is developed and maintained by The GEM Foundation. The source code is written in Python; it is open source, and publicly available at a Github repository. OpenQuake provides a platform to perform regional disaster risk assessment. The Hazard part of the library has already been mentioned in Chapter 2. The Risk part of the library performs a component-group based performance assessment that is similar to the approach taken by HAZUS. Input data for the platform is collected and made publicly available in an online repository at platform.openquake.org. Currently, OpenQuake leans heavily towards seismic hazard and risk assessment, but there are developments that consider flood impacts, and the framework is sufficiently flexible to allow other extensions as well.

OpenSLAT

The Open Seismic Loss Assessment Tool (*OpenSLAT* [72])is an open-source library developed at the University of Canterbury and written in C++ and Python. It is publicly available and allows researchers to use the developed functions in their preferred environment. It implements the Magnitude-oriented Adaptive Quadrature (MAQ) algorithm developed by Bradley et al. (2010) to efficiently solve the integrals involved in performance-based engineering (PBE) calculations.

PACT

The Performance Assessment Calculation Tool (*PACT* [73]), published by the Applied Technology Council (ATC) is publicly available software that implements the performance assessment methodology from the FEMA P-58 document (ATC, 2018b). It is designed to describe the performance of a single building, not a region with a collection of buildings. The software is controlled by a GUI and is available for the Windows platform only. It does not perform hazard and structural response calculations, but rather requires researchers to provide the results of those calculations as inputs. All fragility and consequence functions developed in the FEMA P-58 project are conveniently available in PACT.

SP3

The Seismic Performance Prediction Program (*SP3* [74]) is proprietary software developed by the Haselton Baker Risk Group. It is widely considered the most reliable implementation of the FEMA P-58 methodology and ARUP's REDi framework for downtime estimation (ARUP, 2013). It is used by both practitioners and researchers. Besides the high-quality implementation, the software also provides valuable damage and loss databases and additional tools that facilitate building response estimation, and the creation of a performance model for damage and loss assessment. SP3 can be accessed through a web-based interface that guides the user through the steps of the performance assessment workflow. Researchers with programming skills can use it in batch mode that enables more powerful analyses. The calculations run on cloud computing servers, which allow users to run complex, demanding analyses within a reasonable timeframe.

13.4.1 Relevant SimCenter Tools

The SimCenter develops PELICUN, a performance assessment tool that integrates multiple conventional damage and loss assessment methods and allows researchers to take advantage of synergies between them when developing new approaches. PELICUN is available as a standalone Python library and it is the performance assessment engine behind the applications developed by the SimCenter.

PELICUN

The PELICUN library (*PELICUN* [12]) is an open-source Python package that implements the Probabilistic Estimation of Losses, Injuries, and Community resilience Under Natural Disasters

(PELICUN) framework developed by the SimCenter. The framework and the corresponding library is designed to provide a versatile, platform-independent and transparent loss-assessment tool for the research community. It integrates methods across hazards, resolutions, and asset types, and supports high-fidelity component-based as well as efficient building-level performance assessment (Zsarnóczay and Deierlein, 2020). Damage and loss model parameters (i.e., fragility, vulnerability, and consequence functions) for FEMA P-58, and the earthquake and hurricane methods from HAZUS are provided with the tool, and researchers can extend these with their own data. The PELICUN library is platform independent; it allows researchers to work in their preferred environment (e.g., MATLAB) and call its functions to perform loss assessment.

PBE Application

The Performance Based Engineering Application (*PBE* [13]) provides a convenient GUI-based tool for researchers interested in performance assessment. The GUI provides access to the versatile PBE workflow developed at the SimCenter and allows users to choose the tools and methods they wish to use for hazard estimation, response simulation, and loss assessment. Currently, the application is limited to seismic hazards, with wind and water hazard features under development. Seismic hazard assessment uses OpenSHA and the PEER ground-motion database (see Chapter 2), response estimation uses OpenSEES to simulate both structural and soil behavior (see Chapters 9 and 10), and loss assessment uses PELICUN to perform the calculations. Researchers can expand the set of tools supported by the application. If EDPs are already available from external tools, those can be imported, and the PBE application can perform the damage and loss assessment based on those EDPs.

R2DTool

The Regional Resilience Determination Tool (*R2DTool* [8]) is a research application that focuses on running regional simulations and interpreting their results. The tool integrates the workflow components from other research tools developed for individual building assessment (e.g., EE-UQ, PBE) and extends them to consider multiple assets and a regional characterization of hazard scenarios. The first release of the R2DTool provides features for seismic risk assessment. Additional features planned for 2021 will enable hurricane risk studies including the simulation of both wind and storm surge effects. Building performance is assessed using PELICUN to simulate the damage and losses for each building in a region. The tool supports efficient calculations using damage and loss models based on intensity measures, as well as complex analyses that require structural response estimation followed by high-resolution damage and loss assessment based on engineering demand parameters.

Chapter 14
Transportation Networks

Adam Zsarnóczay with contributions by Rodrigo Silva-Lopez and Ertugrul Taciroglu, along with review comments and suggestions by Jack W. Baker and Thomas O'Rourke

Transportation systems play an important role in regional response and recovery after a disaster. Roads, railways, and bridges and the interdependencies between these systems and other parts of the built environment must be considered in a comprehensive regional risk assessment. There are several challenges in the performance assessment of transportation networks, from the realistic representation of spatially correlated intensity measures (IMs), through collecting exposure data that describes the location, geometric, material, and design characteristics of the network components, to developing models for their response and damage estimation. Finally, the consequences of network damage are measured by evaluating the quality of service (e.g., travel times, trips made, etc.). These calculations introduce a set of additional challenges. Computing travel delays requires modeling the behavior of people, which is highly nonlinear and difficult to predict in a reliable manner in lieu of post-disaster travel data.

14.1 Input and Output Data

Performance of the transportation infrastructure requires inputs and provides outputs at a regional scale. Conceptually, some of the inputs are similar to those required for building performance assessment; however, the regional analysis introduces additional challenges, such as the necessity to consider spatial correlation in hazard severity and the significant increase in computational complexity of consequence estimation due to the need to model traffic on the damaged network. The following list focuses on the differences and the additional details required when compared to building performance assessment.

Hazard characterization

Regardless of the type of hazard considered, its severity needs to be described by one or more two-dimensional IM fields. Each field represents one hazard scenario and prescribes an IM map for the region. In earthquake engineering, these IMs are typically derived from probabilistic analyses, and researchers need to model the correlation between different locations and different IMs to ensure that the IM fields provide a realistic representation of a ground-motion scenario (e.g., Han and Davidson, 2012; Lee and Kiremidjian, 2007; Loth and Baker, 2013). The probabilistic description of wind and water flow characteristics under a hurricane or tsunami are considerably more challenging and not part of the typical research workflow. Although there are examples of probabilistic hazard assessment for non-seismic infrastructure risk studies (e.g., Kameshwar and Padgett, 2014), it is more common to investigate such risk based on scenario events; the IM field under each scenario is a result of a separate, physics-based hazard simulation (Bjarnadottir et al., 2014). These IM fields represent realistic scenarios; the challenge in this case is to efficiently capture the range of possible IMs with a finite number of hazard simulations.

Engineering demand parameters (EDPS)

Road and railroad track damage is usually estimated using fragility functions that link IMs directly to damage states (e.g., relationships between ground deformation and road damage; Argyroudis and Kaynia, 2014). In such cases, because performance assessment of these network components does not involve explicit simulation of the roadway (or railroad) components, it does not involve calculation of EDPs. Exceptions to this may include cases where empirical relationships do not apply (e.g., roadways along natural or engineered embankments; Lagaros et al., 2009; Yin et al., 2017) or to critical infrastructure (e.g., high-speed rail tracks).

Bridge damage can be estimated directly from IMs (e.g., FEMA, 2018a), but the high-fidelity performance assessment of bridges typically involves structural simulation to relate specific EDPs to critical damage states in structural components. Depending on the component, these are local deformations, internal forces, or a DM derived from these quantities (e.g., Park and Ang, 1985) that are well-correlated with the damage states of the particular component (Choi et al., 2004). Estimation of these EDPs with sufficient accuracy requires nonlinear response history analysis on reliable models; hence the computational resources available are an important factor when deciding the level of modeling fidelity.

Fragility functions

These functions describe the probability of exceeding a particular DS of the network component given an IM that describes the severity of the hazard at the site (e.g., Balomenos et al., 2020) or evaluates the damage to separate sub-assemblies of the component (e.g., Nielson and DesRoches, 2007; Simon and Vigh, 2016). Both approaches are based on laboratory tests and past experience in post-disaster inspection. Conceptually, they are similar to building fragility functions.

Consequence functions

The likelihood of direct loss of life and injury due to transportation network damage is significantly lower than the likelihood of such events due to building damage. Hence, studies focus more on estimating the cost of reconstruction and downtime for each component as a function of the damage severity expressed by the DS (Gidaris and Padgett, 2017; Stergiou and Kiremidjian, 2006). Losses estimated at the component level directly from component damages cannot consider system-level effects and interdependencies. These consequence functions need to be complemented with a system-level analysis of indirect consequences.

Traffic models

Network performance assessment and evaluation of the consequences of network component damage at a regional scale require a model of traffic flow with source and destination data. Development of a traffic model for a large urban area is a large undertaking. Such models are prepared and used by local transport authorities, and typically are not publicly available.

There are good examples of collaboration between academia and local authorities that allow researchers to take advantage of the mature models and vast data available at the authorities (Miller and Baker, 2015).

Decision variables

Transportation network performance is described by system-wide downtime, the change in traffic, or the change in network capacity given the traffic model described above. Probabilistic assessment of network performance requires a complex and computationally demanding analysis. Performance metrics that serve as decision variables are a topic of ongoing research (Miller-Hooks et al., 2012; Miller and Baker, 2015). Changes in travel time (either regional statistics or focusing on a particular route) and accessibility are two commonly used metrics.

14.2 Modeling Approaches

Natural disaster impact on a transportation network uses the assumption of independent calculation steps from building performance assessment (Chang, 2000; Kiremidjian et al., 2006; Miller and Baker, 2015). Hence, the hazard characterization, response estimation, damage estimation, and consequence estimation are performed by independent stochastic models. This allows for the following approach to regional simulation; see Figure 14.1:

- Characterize the hazard in the region using IM fields;
- Estimate the response and the corresponding damage in each network component given the IM at the location of the component; and
- Estimate the downtime and repair cost for each network component and assess the performance of the transportation network given the level of damage in network components.

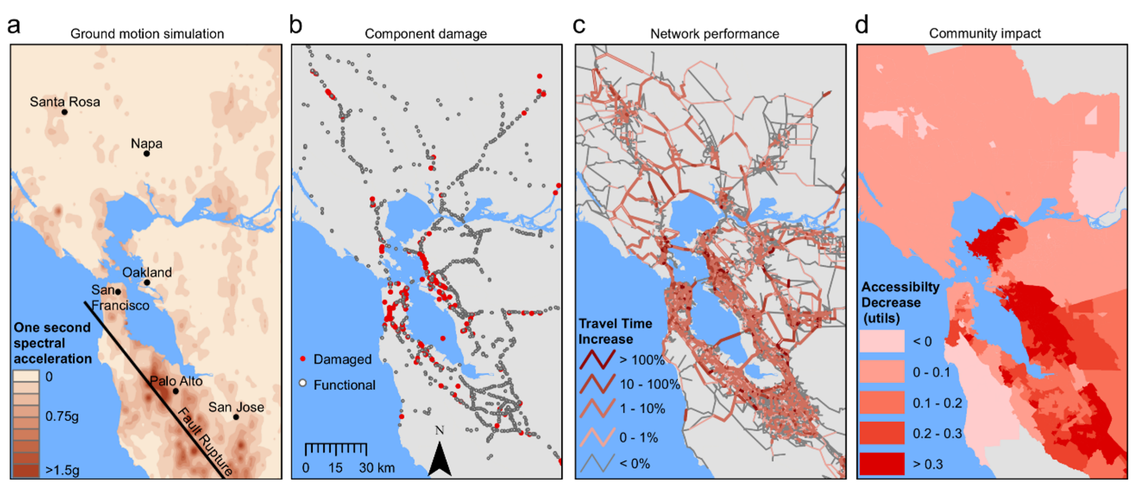


Fig. 14.1 Illustration of the transportation network risk assessment framework from Miller et al. (2015).

Structural response and damage (but not the consequences) in one network component is typically assumed to be independent of other components. This assumption enables more efficient simulation through parallel calculation of component damage in the region. It is expedient to note that this approach may overlook correlations in certain bridges that are designed and detailed in similar ways (e.g., bridges along major highways that may have been designed and constructed under one project). The spatially correlated IMs still ensure that similar components within a small area will experience similar demands and, consequently, similar damages.

If sufficiently detailed information of the transportation network is available, the cascading failure of components can be considered; for example, if one overpass fails, its collapse triggers the collapse of others in a complex highway interchange. Consideration of this type of interaction between network components prohibits independent, parallel assessment of network component damage.

A special but important case of transportation network analysis is the investigation of flood risk to the underground transport infrastructure. Such risk can be evaluated by computing the volume of water entering the tunnels based on the time history of flood height at each opening. The performance of the underground system can be evaluated based on the degree of flooding in each of its tunnels. This methodology is available in the GIS-based analysis tool of Jacob et al. (2011).

14.3 Software and Systems

The software that aids in the characterization of the hazard and estimation of network component response were introduced in Parts I and II, respectively. Some of the following tools have such capabilities, but the focus here is on the performance assessment-related features.

HAZUS 4.2

This FEMA-supported tool has been introduced in Chapter 2. The *Hazus 4.2* [17] Multi-hazard Loss Estimation Methodology provides a comprehensive framework, fragility, and consequence functions for seismic damage and reconstruction time assessment for bridges and transportation links. It also provides a model for assessment of bridge damage due to storm surge. HAZUS covers large groups of bridges with a single configuration; therefore, damage and recovery estimates cannot account for detailed information about structure type and geometry or the site-specific post-disaster conditions. Evaluation of the impact of component damage on network performance requires external tools.

OpenQuake

The risk assessment framework of the *OpenQuake* [21] tool (introduced in Chapter 13) is sufficiently flexible to enable the assessment of damage and consequences for transportation network components. Unlike HAZUS, the fragility and consequence information is not provided with the tool. The functions available in the HAZUS Technical Manual (FEMA, 2020) can be adopted with minor effort.

14.3.1 Relevant SimCenter Tools

The SimCenter develops *PELICUN* [12], a performance assessment tool that integrates multiple conventional damage and loss assessment methods and allows researchers to take advantage of synergies between them when developing new approaches. PELICUN is available as a standalone Python library and it is the performance assessment engine behind the applications developed by the SimCenter. Currently, the databases bundled with PELICUN support the assessment of buildings only; if researchers are interested in the performance of transportation networks, they need to provide the corresponding parameters of damage models (i.e., fragility functions). Given those parameters, the SimCenter tools described in Chapter 13 can handle the damage assessment of transportation networks and their components—PBE can be used to investigate individual bridges and the R2DTool is suitable for the assessment of entire networks. A future release of PELICUN will facilitate such studies by having the commonly used fragility functions for bridges bundled with the default damage and loss database.

14.4 Research Gaps and Needs

The regional assessment methodology for transportation networks in HAZUS 4.2 is known to have critical shortcomings (e.g. Mangalathu et al., 2017). State-of-the-art transportation network analyses require tools to construct robust bridge models and integrate the regional damage simulations with state-of-the-art traffic and socio-economic impact analyses. These bridge models should be shared with the broader research community so that bridge inventories at regional scales can be compiled and analyzed. Such a capability stands to revolutionize seismic resilience assessment studies and could be extended to other hazards (e.g., tsunamis and hurricanes). Efforts in the aforementioned direction are relatively sparse at the present time; see, for example, Koc et al. (2020), but they may provide a natural interface between engineers and researchers, as well as practitioners, including insurance agencies/companies, emergency response managers/planners, traffic engineers, and social scientists.

The following areas appear ripe for directing and supporting research efforts:

- Development of tools to generate large inventories of bridge models that can be improved upon as more data is available and shared with other members of the NHE community. These efforts will likely feature computer vision, machine learning, and data-harvesting techniques;
- Studies on devising system-level hazard resilience metrics that take into account the inherent dependency of the subject infrastructure (e.g., port facilities) to regional transportation network performance;
- Development of workflows and tools to facilitate regional-scale risk and loss assessment studies involving transportation networks; and
- Development of new tools to accurately estimate bridge downtimes and the resulting effects on mobility.

Chapter 15
Water, Sewer, and Gas Pipelines

Iris Tien,
along with review comments and suggestions by Craig Davis, Thomas O'Rourke, and Adam Zsarnóczay

There are many methods available for modeling and simulation of lifeline networks. These include empirical, agent-based, system dynamics-based, economics theory-based, and network-based approaches. The reader is referred to resources including Ouyang (2014) and Johansen et al. (2017) for a discussion of the general methods available and the varying measures existing for assessing community outcomes based on lifeline performance. The techniques described in the works referenced are general and can be applied to any lifeline network; they are not described in more detail here. The focus in this report is on modeling and simulation software for specific lifeline types with parameters particular to the lifeline and resource flow type. The emphasis is on open and publicly available software tools.

The objective of water, sewer, and gas pipeline network simulation is to assess the ability to provide critical water, wastewater, and natural gas services for populations under varying scenarios. Natural hazards engineering (NHE) must assess the states of these lifeline systems under hazard events and inform decision makers on approaches to improve the expected performance of these systems when subjected to these hazards. The reader is referred to N.I.S.T. and O'Rourke (2016) on the role of lifelines in NHE and recovery, and O'Rourke (2014) and DEP (2013) for information on lifeline resilience to earthquake and hurricane hazards, respectively. The creation of digital twins, where parallel computational models for water supply, wastewater, and gas and liquid fuel delivery systems are created as a cyber-system counterpart to the real system, are also relevant for the modeling and simulation of lifelines (Fan et al., 2019; O'Rourke, 2010). A digital model of the real system allows users to look into natural hazards effects and then use the digital twin to improve the real system. For water, sewer, and gas pipeline natural hazard simulations, the underlying physics lie mainly with the simulation of individual components in the system, e.g., pipes, junctions, and valves, and the subsequent system-level analysis based on the component-level information through the use of network graphs or by more detailed hydraulic flow and pressure analysis through the network.

15.1 Input and Output Data

The information needed to describe the natural hazard at a regional scale is similar to the hazard characterization explained for transportation networks in the previous section. The hazard models provide a regional distribution of intensity measures (IMs) that are used as proxies to express the severity of the hazard in the area. The type of IM depends on the hazard type and the network component under investigation. While the effect of a seismic event on structures is typically described using PGA or spectral acceleration, the analysis of pipelines requires information about the PGV and the permanent ground deformation and their geographic distributions (Romero et al., 2010).

Lifeline models require information about the geographical location and classification of the lifeline components. Such information is often hard to obtain, especially at sufficiently high resolution for detailed regional assessment. This lack of data stems from privacy and national security concerns; most databases are privately owned, and there is a lack of records in the public domain. Water, sewer, and gas pipeline simulation relies on information about component locations, size (e.g., pipe diameter), pressure, and connectivity. Other assets of interest in modeling the performance of water, sewer, and gas systems include pump station, reservoir, treatment plant, regulator station, and compressor station components.

Output data will typically be water, wastewater, or gas pressures, flows or volumes at specific locations. Of particular interest is the ability to provide these services at final distribution points in the network. These analyses should be conducted at various times after an event to capture the time-related consequences of system damage and the geographic distribution of system service losses, and how these change with system repairs.

15.2 Modeling Approaches

The modeling approach in the simulation is often determined and constrained by the amount and resolution of available information. Regardless of the modeling fidelity, the approach is almost always based on the following two steps:

- First, given an IM at the site, component damage is estimated by assigning a damage state (DS) to each component. In HAZUS, this is done using component-specific fragility curves to estimate the damage to a given component under the hazard. For facilities and building-like structures, the damage evaluation is similar to the HAZUS method described in Section 3.1. For pipeline networks (i.e., water, sewer, and gas), two types of damages are considered: leaks and breaks. Buried pipeline fragility functions are continuing to be developed, including in terms of ground strain and peak ground displacement. The sophistication of damage evaluation heavily depends on the level of analysis and the available IMs; and
- The second step, given estimated damage to lifeline components, is to assess network-level consequences. In HAZUS, direct consequences are evaluated using empirical relationships based on past experience. Direct consequences are typically limited to restoration time and replacement cost in HAZUS. Indirect consequences can have much greater social and economic impacts; however, these are often difficult to capture within a single software system.

The HAZUS earthquake model is the most sophisticated among the HAZUS models for lifeline modeling and simulation. For NHE, HAZUS hurricane and tsunami models are limited to buildings and do not cover lifelines. The HAZUS flood model provides damage and loss estimates only for a subset of potable water, wastewater, and natural gas facilities. Damage is a function of flooding as measured by water level in feet. The information below is based on the earthquake hazard modeling.

The default inventory for potable water networks in HAZUS contains estimates of pipelines aggregated at the census tract level (based on U.S. Census TIGER street file datasets). The HAZUS methodology suggests three levels of analysis for potable water networks:

- Level 1 is based on the default HAZUS inventory (i.e., census tract estimates);
- Level 2 requires additional information on transmission aqueducts, distribution pipelines, reservoirs, water treatment plants, wells, pumping stations, and storage tanks; and
- Level 3 requires additional information on junctions, hydrants, and valves, and further data about connectivity and serviceability (i.e., demand pressures and flow demands at different distribution nodes). Such information is typically available in KYPIPE, EPANET, or CYBERNET format.

Analysis of other lifelines requires similar types of information:

- Wastewater networks are described by the geographical layout and characteristics of the transmission network and its treatment components; and
- Natural gas networks are described by the geographical layout and characteristics of buried or elevated pipelines and compressor stations.

Although the diameter of pipes is not always considered as a parameter in damage functions, it may provide a good proxy for capacity of the given network element and used in network performance assessment in more sophisticated analyses. The rigidity of the pipes in a network is an important input parameter that heavily influences the damage to the pipelines by earthquakes. In HAZUS, three levels of modeling fidelity are described that correspond to the previously introduced analysis level:

- Level 1: Results are limited to number of leaks and breaks per census tract resulting in a simplified evaluation of network performance (i.e., total number of households without water);
- Level 2: The network is modeled as a graph. This approach allows for estimates of component functionality, component damage ratio, and flow reduction to each area served by the network. Overall network performance can be estimated as a function of the average repair rate (repairs/km) of the pipes in the network. Such evaluations have been performed for San Francisco (Markov et al., 1994), Oakland (G&E Engineering Systems, 1994), and Tokyo (Isoyama and Katayama, 1982); and
- Level 3: The suggested model is based on the work of Khater and Waisman, 1999. It provides more accurate estimates of the hydraulic flow in the network. This translates into improved accuracy and reliability of results when compared to Level 2 analyses.

15.3 Software Systems

HAZUS 4.2

This methodology classifies potable water, wastewater, oil, natural gas, electric power, and communication systems as lifelines. It provides a similar methodology for the modeling and simulation of these systems. Electrical networks are the only lifelines that have influence on other lifelines in the HAZUS methodology (i.e., damage to the electrical network and the consequent loss of power results in loss of function and potential damage in other lifelines). Electrical system modeling is described in more detail in Chapter 16.

The dependency between network component repair times is not considered by HAZUS. The dependencies of one lifeline damage or the consequences of such damage on other lifelines is not taken into consideration in the HAZUS methodology, with the exception of electrical networks. Assessment of network performance is out of the scope of the HAZUS methodology for wastewater systems. In general, HAZUS 4.2 allows estimation of lifeline damage and consequent reduction in network performance. Further details of the software and its limitations are explained in Chapter 2.

EPANET

EPANET [75] is a software package developed by the U.S. Environmental Protection Agency (EPA) for water pipeline distribution modeling and simulation. It has been widely adopted by municipalities and water utilities as a standard format to evaluate their systems. Its two main uses are for hydraulic modeling (including maintaining flows and pressures in a system) and contaminant transport simulation. EPANET files can be used as input files for water distribution pipeline information. EPANET modeling and simulation does not include the ability to assess the impacts of natural hazards on lifeline components or network performance. Using EPANET information, the pressure dependent demand (PDD) approach is becoming the preferred approach to hydraulic network modeling of water distribution systems heavily damaged by earthquakes and the modeling of hydraulic networks damaged and/or those that have sustained heavy demands. The reader is referred to references including Jun and Guoping (2013) and Sayyed et al. (2014) for modeling the relation between pressure and flow in EPANET. Available flow at a network node depends on the available pressure.

GIRAFFE

The Graphical Iterative Response Analysis for Flow Following Earthquakes (*GIRAFFE* [76]) was developed at Cornell University to provide a performance assessment tool for pipeline networks (Wang and O'Rourke, 2008). It uses the EPANET engine to define the water network and perform hydraulic network analysis. Performance estimates are presented in a user interface using a GIS framework. Its advantage compared to EPANET is the capability to analyze the performance of leaking systems.

WNTR

WNTR [77] (Water Network Tool for Resilience) is an open-source library of functions developed in the Python programming language by Sandia Laboratories. It uses input data in the EPANET format to define a network and perform an analysis that is similar to the Level 2 and 3 analyses in the HAZUS methodology. WNTR adds the hazard element to water pipeline simulation. Using WNTR requires basic Python programming skills, but in return it provides a platform-independent solution that can easily work in a high-performance computing (HPC) environment. In addition to the damages and estimated restoration times, it provides estimates of the hydraulic performance of the damaged network. The library is hazard-agnostic; as long as the IMs and the corresponding fragility curves are supplied, it performs the damage calculations and evaluates the estimated consequences of the damage. Compared to GIRAFFE, WNTR incorporates emitters as an improvement to modeling damaged systems.

Gas pipeline simulation software

Compared to water pipeline simulation software, natural gas pipeline modeling and simulation software is mostly commercial and proprietary, e.g., Synergi Gas from DNV-GL conducts hydraulic modeling and analysis and NextGen from Gregg Engineering creates hydraulic simulation models to run simulations and calculate pressures, flow rates, and other operational parameters. Given the emphasis on open-source software in this report, these are not discussed in more detail.

15.3.1 Relevant SimCenter Tools

The SimCenter develops *PELICUN* [12], a performance assessment tool that integrates multiple conventional damage and loss assessment methods and allows researchers to take advantage of synergies between them when developing new approaches. PELICUN is available as a standalone Python library and it is the performance assessment engine behind the applications developed by the SimCenter. Currently, the databases bundled with PELICUN support the assessment of buildings only; if researchers are interested in the performance of buried pipelines, they need to provide the corresponding parameters of damage models (i.e., fragility functions). Given those parameters, the R2DTool described in Chapter 13 can simulate the damage states of a network of buried pipes and the supporting facilities. The commonly used fragility functions for pipelines are planned to be bundled with a future release of PELICUN to facilitate the analyses of pipelines. The SimCenter is also developing a testbed that focuses on the Memphis, TN, area and will provide exposure data and templates of workflows and models for interested researchers.

15.4 Research Gaps and Needs

There is great need for improved fragility functions for buried pipelines in terms of ground strain. Advancing component-level fragility curves and improved simulation of structural response for critical facilities will lead to a better estimate of expected damage, both in terms of accuracy and resolution in a simulation. In lifeline modeling and simulation, there is the need for improved consideration of interdependencies between lifelines (Dueñas-Osorio et al., 2007; Johansen and Tien, 2018). This will enable researchers to better understand the impacts of natural hazards on communities. Finally, improved simulation of the recovery process (He, 2019; Tabucchi et al., 2010; Tomar et al., 2020) will enable researchers to better understand performance and recovery of lifeline services during and after disasters.

Chapter 16
Electrical Transmission Substations and Lines

Iris Tien,
along with review comments and suggestions by Craig Davis, Thomas O'Rourke, and Adam Zsarnóczay

The objective of the simulation of electrical substations and transmission and distribution lines is similar to that of other lifelines: namely, to assess the ability to provide critical electricity services for populations under varying scenarios. Considering natural hazards engineering (NHE), the purpose is to assess the state of these lifeline systems subjected to various hazards and inform decision makers on approaches to improve the expected performance of these systems under such hazards. For example, compared to hydraulic or pressure flow analyses for water, sewer, and gas pipeline simulation, the underlying physics of the simulation relies on power voltage flow analysis in addition to system-level analyses that can be conducted through the use of network graphs. Electrical power networks are also composed of connected regional and local systems. Local distribution systems are dependent upon the regional grid for supply, requiring multiple levels of analysis to capture the performance of the regional grid and local distribution systems.

16.1 Input and Output Data

Modeling electrical networks requires information about generation facilities, substations, and transmission and distribution circuits. In addition to the geographical location, the level of voltage is an important property in a general assessment. The availability of electrical power system data is subject to many of the constraints of lifeline data given privacy and national security concerns, and the fact that the databases are privately owned. When there is a lack of network data availability—particularly a lack of detailed information at the distribution level—only low-resolution analyses at the transmission system level are possible. Depending on the type of hazard, other details can be required, such as anchorage of components for seismic analysis or elevation information for flood hazard assessment. The required inputs and produced outputs for the power grid depend in part on the type of hazard, e.g., climatic compared to geologic, and the target fidelity for reliability and risk analysis.

16.2 Modeling Approaches

In general, given the intensity measure (IM) at the site, component-specific fragility curves can be used to estimate the damage to a given component under a hazard. For facilities and building-like structures the damage evaluation is similar to the HAZUS method described in Chapter 13. Given the damage to the network component, the direct consequences are evaluated using empirical relationships based on past experience. Direct consequences are typically limited to restoration time and replacement cost in HAZUS, where fragility of electrical substations and distribution circuits is defined with respect to the percentage of damaged subcomponents.

Modeling indirect consequences of damage in the electric power network is an ongoing area of research (Moore et al., 2005). HAZUS does not consider interaction between nodes of the power network. Interaction between other lifeline systems is considered as follows: the loss of electric power is assumed to influence the slight/minor and moderate DSs of components in other lifelines that depend on power. More severe DSs are not influenced by the lack of power. The substation that serves connected components is assumed to experience the event at the location of the served component. An even more simplified approach uses a generic damage algorithm to describe the availability of power as a function of an IM.

16.3 Software Systems

HAZUS 4.2

As mentioned in Chapter 15, *Hazus 4.2* [17] groups electric power and communication networks with the other lifelines and provides similar methodologies for their analysis. Electrical networks are the only lifeline type that has influence on other lifelines in the HAZUS methodology (i.e., damage to the electric network and the consequent loss of power results in loss of function and potential damage in other lifelines). HAZUS 4.2 software allows estimation of lifeline damage and consequent reduction in performance. Further details of the software and its limitations are explained in Chapter 2, and its application to lifeline simulation and pipelines in particular are described in Chapter 15.

OpenDSS

OpenDSS [79] is a software package developed by the Electric Power Research Institute (EPRI). It conducts electrical power system simulation for electric utility power distribution systems. It supports simulations of power flow across frequencies and is mainly used to evaluate distributed energy resource generation, its integration with utility distribution systems, and grid modernization technologies. Assessments do not include the impacts of natural hazards on the system components or network performance for NHE applications.

MatPower

MatPower [78] (Zimmerman et al., 2011) is a free toolbox available in MATLAB for conducting power flow analysis. It does not have the capability to directly model the effects of natural hazards.

16.4 Research Gaps and Needs

Similar to the description of the research gaps and needs in water, sewer, and gas pipeline simulation (Chapter 15), there is the need for improved consideration of interdependencies between lifelines as related to electrical systems. Given the critical role of electricity for many lifelines, this will enable researchers to better understand the impacts of natural hazards on communities. Advancing component-level fragility curves and improved simulation of structural response for critical facilities will lead to better estimates of expected damage, both in terms of accuracy and resolution in a simulation. Needed are improved fragility functions for specialized structures for each lifeline sector, e.g., generation plants, substations and components, and transformers for electrical systems. An analysis of equipment supporting these specialized facilities is also needed. The focus on selected structural components in electrical power network damage analysis, where fragility functions do exist, can also lead to missing failure mechanisms and inaccurate risk assessment. Finally, improved simulation of the recovery process will enable researchers to better understand performance and recovery of lifeline services during and after disasters. The high computational cost and sometimes computational intractability of network-level performance analyses for electrical systems is an ongoing research challenge.

Part IV
Recovery Modeling

This section provides an introductory discussion on the modeling of disaster recovery for infrastructure, residential buildings, businesses, and communities. The aim of this section is not to present an exhaustive list or propose an ideal approach given the complexity of the recovery process and the wide variation across hazard types and geographies. Rather, empirical studies are reviewed to identify factors that are associated with recovery, providing the basis for conceptual models of recovery. Note: although recovery simulations are often used to obtain proxies of the disaster resilience, disaster recovery is only one among many metrics of resilience (Kwasinski et al., 2016; NAS, 2019). For this reason, the scope of this section does not include a comprehensive review of the broader topic of disaster resilience.

Disaster recovery modeling consists of assessing over time the performance of a system subjected to a shock (see Figure IV.1). Prior to the shock, the system has a baseline state, Q_b. At the time of the event, t_0, disturbances to the system reduce its functionality to a new state, Q_0. Subsequently, the system is restored until a time t_R, when its new normal is established. Recovery may be partial, with the new normal below the pre-disaster state, or improvements might elevate the new normal above the pre-disaster state.

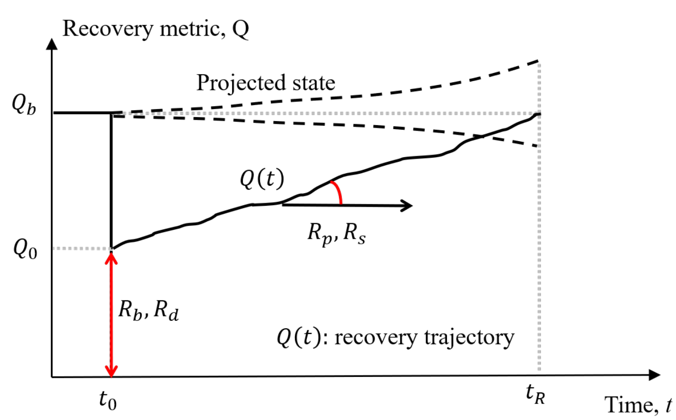


Fig.IV.1 Resilience triangle (adapted from Bruneau et al., 2003).

While comparing recovery with pre-disaster state is a common practice, another alternative is to compare it to the projected state of the system had the shock not occurred. Plotting the state of the system over time, $Q(t)$, against the time since the shock provides a graph as the one shown in Figure IV.1. The curve $Q(t)$ is called the recovery trajectory (Bruneau et al., 2003). While loss assessments focus on the magnitude of the initial drop in the functionality of the system, recovery modeling is devoted to simulating the recovery trajectory. Hence, the main output from a recovery model is the time series of $Q(t)$.

The magnitude of the initial drop at t_0 is a function of the robustness, R_b, and the redundancy, R_d, of the system. A perfectly robust system is one that can experience a shock without significant changes. A perfectly redundant system is one that, if disrupted, can immediately and cost effectively rearrange itself to provide the same level of service as before the event. The ability of the system to regain functionality can be estimated from the slope of the recovery trajectory. The slope is influenced by the capacity of the system to mobilize resources and meet priorities. These are often called the system's resourcefulness, R_s, and rapidity, R_p (Bruneau et al., 2003). The concepts in the figure can be employed to study the recovery of critical infrastructure, housing, and businesses. The following sections discuss the state of the art in simulation the recovery of these three systems.

Chapter 17
Communities

Rodrigo Costa with contributions by Ann-Margaret Esnard, along with review comments and suggestions by Henry Burton

A community can be defined as a place designated by geographical boundaries that functions under the jurisdiction of a governance structure, such as a town, city, or county (Kwasinski et al., 2016). Communities are composed of physical, social, and economic infrastructure systems within these geographical boundaries, as well as the relationships between them. Our understanding of disaster recovery for individual systems has progressed significantly over the last decades. That said, individual system analysis often lack recognition of dependencies on other systems, or do not holistically address the impacts to a community (Kwasinski et al., 2016). Science-based measurement tools to evaluate recovery at community scales, integrated supporting databases, and risk-informed decision frameworks to support policies aimed at enhancing community resilience are at a rudimentary stage of development (Ellingwood et al., 2016). In short, modeling approaches for disaster recovery at the community level are still in their infancy. Yet, concepts of community recovery are valuable in developing recovery models with more limited scopes, e.g., for infrastructure, housing, or business recovery. This section introduces some of these key concepts that provide guidelines for the development of community recovery models.

17.1 Concepts in Community Recovery Modeling

Modeling community recovery requires a comprehensive understanding of post-disaster circumstances and conditions. This includes damage and serviceability of buildings and lifelines, their interactions with social and economic systems, the availability of human and financial resources for recovery activities, and the decisions made by relevant stakeholders (Deshmukh and Hastak, 2012). The challenges in modeling a community start with the definition of what recovery looks like. Table 17.1 provides a partial list of goals and indicators of community recovery. Different models may be required to evaluate the metrics in Table 17.1. Thus, the choice of the recovery metric will determine the most appropriate approach, data needs, and complexity of the community recovery model.

One of the early conceptual frameworks for the simulation of community disaster recovery was proposed by Miles and Chang (2003) and subsequently improved in Miles and Chang (2006). This conceptual framework is shown in Figure 17.1. It consists of three levels: lifelines, neighborhood, and community. Within these are the critical infrastructure networks, residential buildings, and households, as well as businesses. The arrows in the figure indicate the interactions

Table 17.1 Example of community recovery goals and indicators (Cutter et al., 2013; Kwasinski et al., 2016).

Community performance goals	Examples of recovery indicators
Population stability	Number of households dislocated; percent population remaining in the community; percent population remaining in homes; change in housing vacancy rate
Economic stability	Household income; employment; earnings by sector; assessed value of property; change in taxes and revenue (resources); change in gross city product (GCP)
Social services stability	Hospital bed demand/supply ratio; school teacher/student ratio; availability of key retail and financial services
Physical services stability	Percent functionality of buildings and transportation systems; percent of population served by water, wastewater, electric power, gas, and telecommunication systems
Governance stability	Percent of population with access to police and fire protection and other essential public government services

between these systems. Recent advances in the understanding of disaster recovery (Miles et al., 2019) have demonstrated the complexity in these interactions. Nonetheless, this framework provides a solid foundation for the development of more sophisticated models for community disaster recovery.

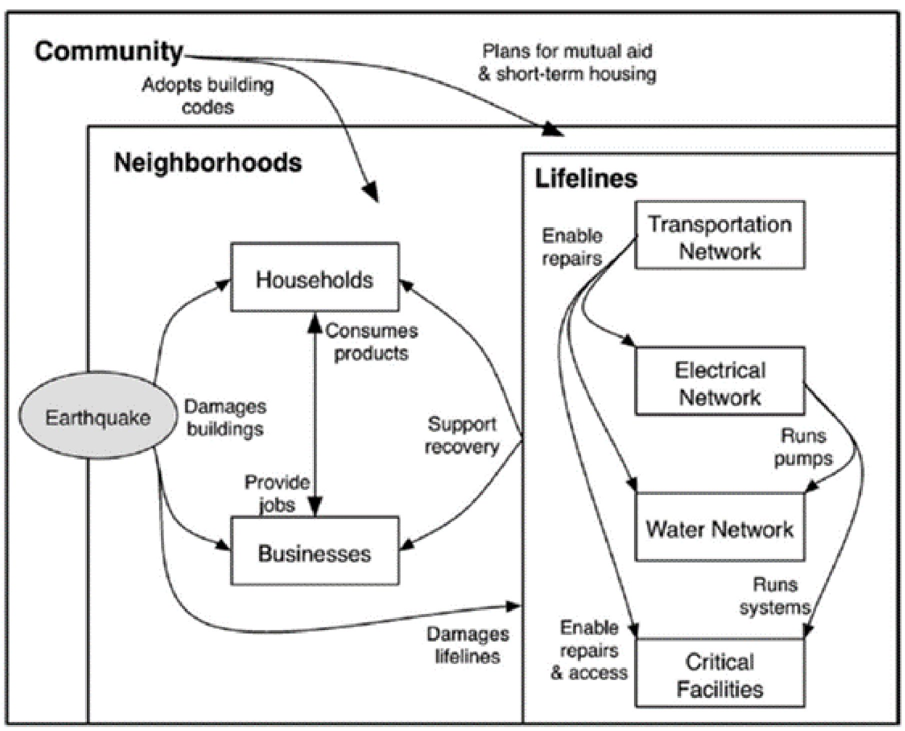


Fig. 17.1 Conceptual model for community recovery (Miles and Chang, 2003).

To overcome some of the data constraints for community recovery modeling, the Centerville Virtual Community Testbed was developed as part of the NIST-funded Center of Excellence for Risk-based Community Resilience Planning initiative (Ellingwood et al., 2016). This testbed is aimed at enabling fundamental resilience assessment algorithms to be initiated, developed, and coded in a preliminary form, and tested before the refined measurement methods and supporting data classifications and databases necessary for a more complete assessment have fully matured. The Centerville testbed and other testbeds under development are a valuable resource for anyone developing models for community recovery.

Simulation models for community recovery can greatly improve our ability to evaluate the benefits of selected mitigation measures. For example, the true benefits of retrofitting transportation infrastructure may be underestimated if the gains to the business sector are not accounted for. A more resilient business sector may also improve the recovery capacity of households. Thus, more than any model for the recovery of individual systems, fully integrated models for community recovery can greatly increase our capacity to demonstrate the benefits of building resilience in our communities.

17.2 Major Research Gaps and Needs

A concerted and coordinated research effort is needed to do more and better modeling of community recovery. As per (Miles et al., 2019), part of this effort can simply be researching appropriate means of integrating existing infrastructure, housing, and business recovery models. The development of guidelines for the systematic collection of empirical data in future events is another area that requires more research. Empirical data play an important role in benchmarking and verification of simulation models, and yet this type of data is still scarce. The development of virtual testbed communities, for which detailed and granular information about infrastructure, buildings, households, and businesses is available, can improve our ability to design community recovery models. Finally, collaborations between researchers from varied fields should be encouraged, facilitated, and rewarded. Community recovery is a multi-disciplinary subject, with physical, social, and economic dimensions. The creation of centers of excellence to foster multi-disciplinary approaches, facilitate information sharing, and develop partnerships with public and private sectors can greatly improve our understanding of this field.

17.3 Software and Systems

As discussed in the previous sections, the topic of recovery modeling has gained attention in recent years. Several modeling tools have been developed, as will be demonstrated throughout this chapter. The innovations in these tools are briefly discussed in their respective sessions; references are provided to those interested in obtaining more details. Although there are a large number of recovery modeling tools developed for specific use,they have been shown to have limited transferability to other problems and contexts and are not discussed herein. The following list only includes software and scripts that are targeted at simulating community recovery and are under continuous development with the intent of widespread use by the research community. These software and scripts include (or are in the process of including) models for infrastructure, businesses, and buildings, as well as households, and are targeted at simulating systems of systems.

IN-CORE

The Interdependent Networked Community Resilience Modeling Environment (*IN-CORE* [81]) was developed as a collaborative effort by researchers from different institutions and backgrounds, including social scientists, urban planners, and engineers. It contains modules for building and infrastructure loss assessments and economic and sociological analysis. Although version 1.0 of IN-CORE has limited recovery modeling features, its strong multi-disciplinary foundation is expected to be leveraged for recovery assessments in future versions.

DESaster

DESaster [80] is a Python library for discrete event simulation of disaster recovery. Currently, DESaster focuses on housing recovery. In the discrete-event framework of DESaster, the steps needed to repair residential buildings are the events, which include inspections, financing, and construction itself. An update for DESaster is expected in 2021 to include critical infrastructure restoration and to integrate it to housing recovery modeling.

RecovUS

RecovUS is a spatial, agent-based model that includes spatial locations of homes and community assets, and captures interactions of households with their neighbors and perceived community assets. It also simulates the effect of recovery of community, including infrastructure, neighbors, and community assets, on households' recovery decisions (Moradi, 2020).

Rts

Rts is a framework of agent-based object-oriented models developed to study housing recovery (Costa et al., 2020a) and population displacements (Costa et al., 2020b). The Rts framework includes models for water, power, and transportation infrastructure, resource suppliers, and buildings (Costa, 2019); it includes a sophisticated modeling approach for the simulation of the requests and the delivery of supplies.

Chapter 18
Infrastructure Systems

Rodrigo Costa, **Luis Ceferino**, and **Rodrigo Silva-Lopez** with contributions by Ann-Margaret Esnard,
along with review comments and suggestions by Henry Burton, and Vesna Terzic

Critical infrastructure is the term used to describe systems and assets that if incapacitated or destroyed would have a debilitating effect on security, national economic security, national public health or safety, or any combination thereof (DHS, 2020). This report focuses on critical infrastructure in the transportation, water, wastewater, power, fuel, and health systems, which are dependent on each other, with failures of one system being potentially propagated to others. Compared to disaster recovery models of housing or businesses, the modeling of disaster recovery for individual critical infrastructure systems has been more extensively investigated. More comprehensive studies of system interdependence, cascading failures, and its impact on society are still needed to foster community resilience. This review introduces some key concepts on the modeling of critical infrastructure systems, first at a broader level, followed by a discussion of specific points regarding different systems.

18.1 Input and Output Data

Modeling the recovery of critical infrastructure systems requires estimates of the time needed to repair each component (including facilities) in these systems. This topic is discussed in detail in Part III. Beyond repair time estimates, it is necessary understand the interdependencies between these components, as well as the interdependencies with other systems. Reports by local authorities are the primary source of publicly available information for critical infrastructure systems. These provide information on the location, characteristics, and connections of the components, which can be used for simplified analyses.

Detailed analysis, e.g., hydraulic models of water systems, are often reliant on information from private entities that can only be obtained through agreements with system operators. Beyond that, operators of a system are rarely aware of how other systems are reliant on the system they operate. Due to this siloed management, there is no one organization that can provide comprehensive information on the interdependencies of the system they operate. This is one of the main challenges to the development of comprehensive and integrated models for critical infrastructure recovery.

18.2 Concepts in Critical Infrastructure Modeling

The disruption of certain components comprising critical infrastructure have the potential to cause cascading effects on the whole system (Rinaldi et al., 2001). For this reason, the modeling of critical infrastructure interdependence has gained much attention in the last two decades, prompting the development of several modeling techniques. Eusgeld and Kroger (2008) reviewed almost 100 articles on modeling of interdependent infrastructure systems published between 1987 and 2007, identifying eight modeling techniques: (1) agent-based modeling; (2) system dynamics modeling; (3) hybrid system; (4) input-output-model; (5) hierarchical holographic modeling; (6) critical path method; (7) high-level architecture; and (8) Petri nets. In a more recent review of nearly 200 articles, Ouyang (2014) defined five main groups of modeling techniques: (1) empirical approaches; (2) agent-based approaches; (3) system dynamics models; (4) economic theory-based approaches; and (5) network-based approaches. Ouyang (2014) compared these techniques to evaluate their applicability to evaluating and improving resilience. Agent-based and network flow-based models were able to support the most resilience improvement strategies. The readers are referred to the review papers by Eusgeld and Kroger (2008) and Ouyang (2014) for descriptions of these techniques, including their strengths and limitations.

Beyond interdependence within a system, critical systems may also be dependent on each other, creating a system of systems, as discussed in the seminal paper by Rinaldi et al. (2001). The recovery of interdependent systems requires a decision about the modeling approach. Two alternatives are illustrated in Figure 18.1. On the left-hand side, a multi-layer approach is shown. In this approach each system can be simulated independently (Guidotti et al., 2017). The results of the analyses of the upper systems are inputs to the lower systems. The main advantage of this approach is that each system can be simulated using a different technique and level of detail. Cimellaro et al. (2016, p.243) provides a detailed description of the multi-layer approach. The right-hand side shows a single-layer approach. In this approach, all systems are simulated simultaneously, and one simulation technique has to be used throughout. These limitations are offset by the capacity of this approach to simulate interdependence between facilities rather than systems. For example, a single-layer approach can simulate in the same time step the interdependence between a power substation and a water pump station, as well between a water pump station and a power generation facility. This is not possible with a multi-layer approach.

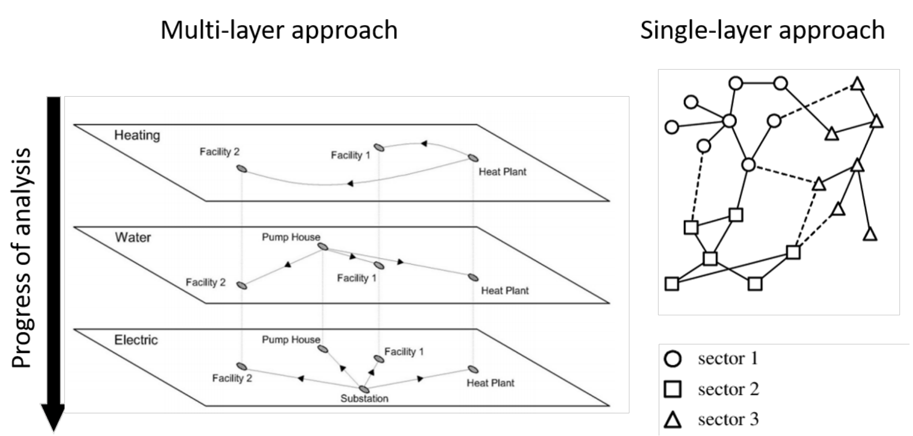


Fig. 18.1 Approaches to interdependency modeling [adapted from Cimellaro et al. (2016)].

18.2.1 Land Transportation Systems

Transportation network disruption due to natural hazards has been shown to generate significant impacts on a community's ability to recover. Traffic disruption following the collapse of bridges and roads can affect businesses long after the triggering event (Boarnet, 1998). In addition, the downtime of transportation systems affects the long-term recovery of regional economies (Chang, 2000). Thus, the recovery of these systems is an important aspect to incorporate when modeling urban resilience.

The recovery of transportation systems imposes several challenges derived from the inherent complexities of these networks: the interdependencies between bridges are highly nonlinear, and modeling how people will travel has proven to be difficult, especially after natural disasters (Chang, 2010a). As the first step to model recovery, several studies have attempted to estimate repair time for bridges and roads through the development and implementation of restoration curves (FEMA, 2015; Padgett and DesRoches, 2007). While these curves are fundamental to assess the recovery of transportation systems, it is necessary to develop models that account for the network interactions of roads, bridges, and traffic demand. It is in that regard that researchers have developed different strategies to help decision-makers to manage transportation assets for enhanced recovery.

One strategy has been to develop optimized scheduling of bridge repairs. This approach aims to propose the order in which bridges should be repaired or restored so that travel flow in the region recovers to its previous level in the shortest time (Vugrin et al., 2014). Besides focusing on the flow of the network, some studies have explored how resources, funds, and crews should be allocated (Karlaftis et al., 2007). A second strategy explored has been to propose retrofitting strategies that mitigate damage from the event and thus decrease the initial network disruption (Zhang and Wang, 2016). These two strategies are complementary and can often be implemented synergistically.

18.2.2 Power Systems

The timely recovery of electric power systems is particularly critical because most other lifeline systems need electricity for their operation and management. Recovery for power systems is often measured by the amount of flow or services delivered, the availability of power for critical facilities, the number of customers served, or the support of economic activities. Although power systems are composed of several components, e.g. transformers and switches, it may be impractical to include all such components in a model. Typical critical facilities of electric power systems include generation power plants and transmission substations that are connected by transmission and distribution lines. The transmission lines connect generation power plants to transmission substations that carry high voltage electricity over long distances. Additionally, distribution lines, carrying lower voltage electricity, deliver electricity to end users.

Developing models of post-disaster recovery of electrical power systems fall into two categories: statistical or simulation-based models. Although statistical approaches are easier to implement and require less computational power, these approaches require a significant amount of training data and cannot be used for "what-if" analyses, which are important for recovery planning. A review of a statistical model is provided by Liu et al. (2007). The authors collected data on the duration of power shortages at different locations after Hurricane Ivan in 2004. A

10-fold cross-validation method was employed, and the out-of-sample error was calculated and compared to a naive model defined simply as the mean power shortage duration. Five methods were investigated: (1) accelerated failure time (AFT); (2) Cox proportional hazard models (Cox PH); (3) regression trees (CART); 4) Bayesian additive regression trees (BART); and (5) multivariate additive regression splines (MARS). The BART, MARS, and AFT approaches improved prediction capacity when compared to the naive model, whereas the Cox PH and CART models did not demonstrate any improvement over the naive model.

Among the simulation-based approaches, those based on arcs and nodes, as well as discrete-event simulation, and agent-based approaches are the most common (Eusgeld and Kroger, 2008; Ouyang, 2014; Sun et al., 2019). In these approaches, the components of the system are modeled explicitly and their post-disaster state is evaluated using fragility curves. The availability of resources and the sequence of restoration are also modeled (Ouyang and Duenas-Osorio, 2014). The main advantage of these approaches is their ability to consider the effects of different strategies to support resilience, e.g., different restoration sequences. Their disadvantage is that they require detailed information about the system, which may not be publicly available.

18.2.3 Water and Wastewater Systems

Disruptions to water and wastewater systems can exacerbate the impact of a disaster by compounding sanitary and ecological issues. Moreover, households and businesses in physically safe buildings may be forced to leave or suspend operations due to interruptions in water and wastewater services. These reasons make water and wastewater systems pivotal for recovery.

Infrastructure involved in water delivery and wastewater collection include pumping stations, treatment and purification stations, reservoirs, storage tanks or towers, and water pipelines. Another consideration relevant to water and wastewater systems is the post-disaster capacity of the system. Water stored in distribution tanks may provide residual capacity to serve customers during recovery; however, comprehensive studies of storage tanks subjected to earthquake loads have shown that there is correlation between the tank fill level and physical vulnerability (Cooper and Cooper, 1997; Eidinger and Davis, 2012; O'Rourke and So, 2000). For wastewater systems, if their post-disaster capacity is significantly compromised, the system may overflow some time after the event. In both cases, it is important for recovery models to account for the demand for these systems during recovery.

Water and wastewater systems have been studied using several modeling approaches. Miles et al. (2019) separated these models into seven groups: resource-constrained modeling, machine learning, network modeling, system dynamics, agent-based, discrete-event, and stochastic simulation. A review of these techniques and their advantages and limitations are discussed in detail in Miles et al. (2019); they are not replicated here for brevity. The choice between these approaches is influenced by the recovery metric being used. For example, machine-learning algorithms excel in estimating the duration of probable disruptions but offer limited guidance for operational management especially in the case of insufficient data. Agent-based and discrete event simulations do not share this limitation; however, they may require significant effort to simulate the flow relevant characteristics of various components. Network-based approaches can represent flow well, but if overly-abstracted can result in erroneous conclusions, leading to ineffective allocation of resources (Hines et al., 2010).

18.2.4 Fuel Systems

Fuel shortages in the aftermath of disasters are not uncommon (Holguin-Veras et al., 2014; Smythe, 2013). These disruptions can cause logistical as well as public relations concerns, compound emergency response difficulties, and affect public services. The reality however is that no one entity has control over the fuel system. Fuel caches are stored at gas stations and local authorities may have difficulty controlling the distribution of fuel. Additionally, panic-buying, or hoarding, is a common practice after extreme events (Helbing et al., 2006; Shen, 2017), and the demand for fuel may significantly increase following a disaster. These characteristics make the simulation of the recovery of fuel systems reliant on a deep understanding of the system and community at hand.

Two approaches exist in the literature to simulate hoarding behavior. The economic theory assumes that consumers are rational individuals that seek to maximize their utility. Thus, models based on utility theory are good candidates to simulate hoarding from the economic theory perspective. Game theory (Hallsworth and Tolley, 2000), and the "Tragedy of the Commons" (Hardin, 2009) fall in this category. The assumption of perfect rationality is appealing because it simplifies the models. Other scholars challenge this assumption and view consumers and individuals with bounded rationality, imperfect information, and limited cognitive ability and time to make decisions. A comprehensive discussion on the bounded-rationality theory is provided by Wheeler (2020).

18.2.5 Hospital Systems

Hospitals are critical in the aftermath of a disaster because they must respond to the emergency by treating patients and preventing additional deaths. Disasters can place particularly high strains on hospitals because they can cause injuries as a result of damage to infrastructure (Ceferino et al., 2018a,b; Johnston et al., 2014; Jun et al., 2010). Additionally, natural disasters can dramatically reduce a hospital's ability to function. Damage to a hospital's structural and non-structural components can rapidly disrupt the functionality of treatment procedures highly necessary for earthquake patients (Bambaren, 2011; Mitrani-Reiser et al., 2012). The recovery of hospital systems is particularly dependent on other infrastructure systems. Hospitals dependent on utilities such as power and water to operate (Achour et al., 2014; Hiete et al., 2011; Jacques et al., 2014; McDaniels et al., 2008); on fuel for ambulances and power generation if electrical power is disrupted (Hiete et al., 2011); and on the transportation network for accessibility. Organizational challenges, e.g., limited staff, are another issue for the recovery of hospital systems (Cimellaro and Pique, 2016).

The literature suggests using the quality of the healthcare provided as a metric of recovery (Hamby and Fraser, 2004; Vieth and Rhodes, 2006). The length of waiting time that a patient spends in the queue before receiving care is often used as a proxy of the quality of the medical care. Methods to model hospital response after disasters have been developed mainly at the single-hospital scale. Structural modeling and functionality models have been key to evaluating the hospital's ability to provide treatment after disasters (Cimellaro et al., 2011; Jacques et al., 2014; Yavari et al., 2010). Other methods based on discrete event simulation and minimum-cost flow models have been developed to represent emergency response and allocate resources during the earthquake aftermath but also at the single-hospital scale (Aghapour et al., 2019; Gul and

Guneri, 2015; Vugrin et al., 2015; Yi, 2005). More recently, a model on emergency response of hospitals at the system-scale rather than at the single-hospital scale was proposed (Ceferino et al., 2020). The higher complexity and data requirements of this approach are offset by its ability to simulate coordination between hospitals to effectively allocate medical resources and patients. This coordination is key to guarantee patients are treated in a timely manner after disasters.

18.3 Major Research Gaps and Needs

While the modeling of individual critical infrastructure system recovery has progressed significantly, the modeling of the recovery of interdependent systems requires further research. To foster community resilience, it is fundamental to understand how the recovery of each system relies on other systems and how this affects the recovery of businesses and households. This effort will require solid collaborations between researchers and the public and private sectors due to privacy concerns regarding the data needed for the development of these models. Recent studies have also demonstrated that hindcasting can be effectively used to validate the recovery of individual infrastructure systems (Tomar et al., 2020). Model validation via hindcasting, as well as the collection of data to support hindcasting are topics that require further research.

Chapter 19
Housing

Rodrigo Costa with contributions by Ann-Margaret Esnard,
along with review comments and suggestions by Henry Burton and Vesna Terzic

The recovery of residential buildings is essential in restoring a sense of normalcy post-event. Recent events have demonstrated that housing recovery estimates based solely on building damage underestimate reality (Comerio, 2006). Repairs to residential buildings took between two and ten years after earthquakes in 1989 in Loma Prieta (Comerio, 2006), 1994 in Northridge (Olshansky, 2006), 1995 in Kobe (Comerio, 2014; Olshansky, 2006), 2009 in L'Aquila (Di Ludovico et al., 2017a,b), 2010 in Chile (Comerio, 2013), and 2011 in East Japan (Ranghieri and Ishiwatari, 2014). The repairs needed after the 2010 and 2011 Canterbury earthquakes are expected to extend beyond 2020 (Wood et al., 2016). During recovery, economic growth and quality of life are impacted, and socioeconomic inequities can be exacerbated (Bolin, 1985; Peacock et al., 2014; Wang et al., 2015).

It is generally accepted that predictive models of housing recovery can provide valuable insights and serve as a platform for evaluating the benefits of different mitigation actions. There is growing agreement that housing recovery needs to be modeled in the context of the community, being influenced by infrastructural and socioeconomic factors, and constrained by the availability of resources (Bilau et al., 2018; Davidson, 2015; Ellingwood et al., 2018; Lee et al., 2019; Masoomi and van de Lindt, 2018; Sutley et al., 2017). This section introduces key concepts that become important when modeling the recovery of a portfolio of residential buildings: limited resources, decisions of owners, and interdependency with other systems. Previous sections have discussed the estimation of repair times for single- and multi-family buildings. This section assumes the reader is familiar with the concepts of repair-time estimation.

19.1 Input and Output Data

The simulation of housing recovery starts with estimating the repair time for buildings of interest. Repair-time estimation is discussed in detail in Part III. In short, it requires information about building locations, type, and occupancy, as well as hazard levels at the buildings sites. Repair time is a measure of the time needed for damage to be fixed. Repair time should be differentiated from recovery time, which encompasses both the repair time and the time needed to procure the resources required for repairs to begin. The time needed to procure resources depends on building characteristics, as well as the resources of the building owners themselves. A building owner may be less capable of procuring resources due to financial constraints. Thus, two buildings requiring equal repair time may have significantly different recovery times. Because socioeconomic factors may affect the recovery capacity of the building owners, associating socioeconomic data to individual buildings becomes a requirement for housing recovery simulations. Since these data are not directly available from the Census, an alternative has been the use of synthetically generated data. In this case, aerial data aggregated at the Census tract/block level is used to simulate the socioeconomic demographics of the owners of each building in the portfolio (Rosenheim et al., 2019).

Another aspect of housing recovery modeling is the availability of resources. Disasters may lead to a surge in the demand for materials or skilled workers, and a reduction in resources, such as construction materials due to supply chain disruptions. The resource constraints will determine how many buildings can be repaired simultaneously, introducing another source for extensions in the recovery time. The number of workers in the construction sector can be estimated from Census data, city reports, permit data, or housing databooks (Costa et al., 2020a; Kang et al., 2018).

Obtaining detailed data on all aspects highlighted above may prove to be a challenge. The level of detail sought in the simulation outputs should determine the level of detail in the input data. The use of "what-if" simulations to investigate the importance of certain considerations can help identify which inputs need to be refined. For example, one can compare a scenario where resource scarcity is not a problem to a scenario where only a fraction of the buildings can be repaired at the same time. This comparison provides insights on the importance of collecting detailed data on the availability of resources.

19.2 Concepts in Housing Recovery Modeling

As previously discussed, housing recovery is as much a socioeconomic process as an engineering process, as evidenced by a wide range of approaches that integrate social, economic, and engineering considerations observed in the recent literature (Bilau et al., 2018; Burton et al., 2018; Costa et al., 2020a; *DESaster* 2018; Hamideh et al., 2018; Moradi, 2020; Nejat et al., 2020). These integrated approaches are motivated by the premise that the homeowners are rational in that they must have both the means and willingness to embark on repairs and recovery. The means are often represented by financial capital. The willingness refers to the decision to repair immediately after the shock, wait and see, or sell the building. Socioeconomic status, perception of value of reconstruction, the decision of neighbors, and the state of the community have been shown to influence the ability to fund and willingness to repair for homeowners (Bilau et al., 2015; Boiser et al., 2011; Bothara et al., 2016; Burton et al., 2018; Chang et al., 2011; Comerio, 2006; Hwang et al., 2015; Moradi, 2020; Nejat and Damnjanovic, 2012).

Statistical and simulation-based models have been developed for post-disaster housing recovery. The former type of model is based on observations of past events and the use of machine-learning procedures. Nejat and Damnjanovic (2012) presents a model for housing recovery that uses the Least Absolute Shrinkage and Selection Operator (LASSO). A hierarchical Bayesian geo-statistical model has recently been proposed by Nejat et al. (2020). Although statistical models are simpler to implement and have lower computational costs when compared to simulation-based models, the scarcity of data on post-disaster housing recovery is a limiting factor for using this type of approach.

Simulation-based approaches rely on models for the hazard, its consequence, and the post-disaster recovery itself. Hazard and consequence modeling are discussed in the previous parts in this report. Regarding the recovery modeling, Figure 19.1 shows a conceptual algorithm for housing recovery simulation. The algorithm assumes that the recovery of a portfolio of N_B buildings is of interest. Four decisions are evaluated sequentially. Decision (1) guarantees that the state of each building is evaluated on each time step. Decision (2) checks for the occurrence of a shock on the current time step. If the shock has occurred, damage, loss, and the time needed to repair building i, $T_{r,i}$, are assessed. Part III in this report describes the methodology to assess the immediate impact. If there is no shock, the assessment of impacts is skipped. Decision (3) checks if building i is still damaged, and if it returns "No," the algorithm moves to building $i + 1$. Decision (4) is the core of the algorithm, where the decision of the building owners, the availability of resources, and neighborhood conditions among many other factors are evaluated to determine if the building can be repaired. If willingness and capability to repair are identified, the repairs can advance. The conceptual algorithm in Figure 19.1 should be evaluated repeatedly to simulate the progress along the timeline of recovery.

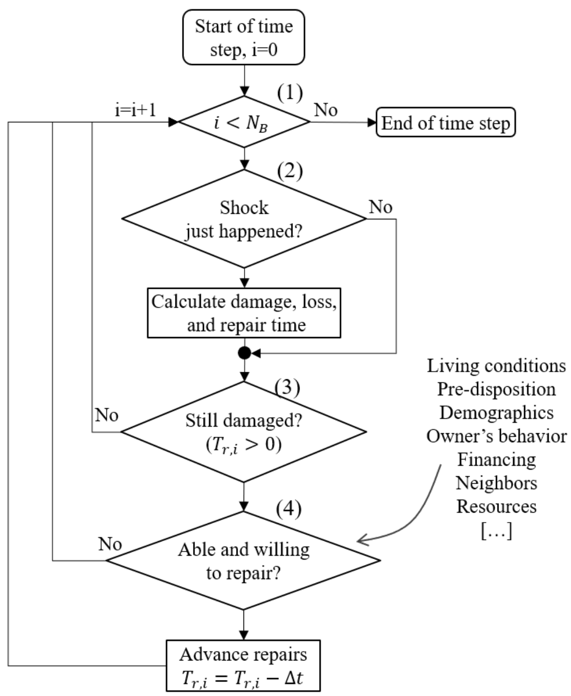


Fig. 19.1 Conceptual algorithm for housing recovery.

The framework in Figure 19.1 is conceptual. More sophisticated frameworks that incorporate the concepts outlined in the figure are presented in Sutley et al. (2017), Burton et al. (2018), and Costa et al. (2020a). In particular, Decision (4) in Figure 19.1 is complex, and many individual models may be necessary to assess it. Table 19.1 compiles some of the factors identified as drivers of recovery in past events. These factors should be acknowledged in Decision (4). The literature reviews in Costa (2019) and Moradi (2020) are the main sources for Table 19.1. Note: the majority of the studies in Table 19.1 investigated recovery of single-family buildings from earthquakes.

Table 19.1 Drivers of recovery.

Race	Bullard and Wright, 2009; Fussell et al., 2010; Kamel and Loukaitou-Sideris, 2004; Nejat et al., 2019; Peacock et al., 2014; Wu, 2004
Income	Bilau et al., 2015; Bolin and Bolton, 1983; Hamideh et al., 2018; Nejat et al., 2018, 2019; Peacock et al., 2014; Wang et al., 2015; Wu, 2004; Zhang and Peacock, 2009
Immigration status	Kamel and Loukaitou-Sideris, 2004; Loukaitou-Sideris and Kamel, 2004
Education	Burton, 2015; Nejat et al., 2018, 2019
Family structure	Nejat, 2018; Nejat et al., 2018; Nejat and Ghosh, 2016
Age	Henderson et al., 2010; Nejat et al., 2018; Ngo, 2001; Sanders et al., 2004
Gender	Nejat et al., 2018
Employment	Bolin and Bolton, 1983; Wang et al., 2015
Household size	Nejat et al., 2019; Sadri et al., 2018
Home ownership	Hamideh et al., 2018; Kamel and Loukaitou-Sideris, 2004; Loukaitou-Sideris and Kamel, 2004; Mayer et al., 2020; Peacock et al., 2014; Wu, 2004; Zhang and Peacock, 2009
Disaster experience	Binder et al., 2015; Kick et al., 2011; Moradi, 2020; Nejat, 2018; Sadri et al., 2018
Disaster damage	Fussell et al., 2010; Hamideh et al., 2018; Mayer et al., 2020; McNeil et al., 2015; Myers et al., 2008; Peacock et al., 2014; Sadri et al., 2018
Social capital	Airriess et al., 2008; Aldrich, 2010, 2011, 2012; Burton, 2015; Li et al., 2010; Sadri et al., 2018
Place attachment	Binder et al., 2015; Chamlee-Wright and Storr, 2009; Cutter et al., 2010; Kick et al., 2011; McNeil et al., 2015; Reid and Beilin, 2015
Neighbor's recovery	Dacy and Kunreuther, 1969; Nejat and Damnjanovic, 2012; Rust and Killinger, 2006
Financing	Comerio, 2014; Kamel and Loukaitou-Sideris, 2004; Loukaitou-Sideris and Kamel, 2004; Nejat and Ghosh, 2016; Wood et al., 2016; Wu, 2004
Materials	Almufti and Willford, 2013; Bilau et al., 2015; Comerio, 2006
Skilled workforce	Almufti and Willford, 2013; Bilau et al., 2015; Boiser et al., 2011; Bothara et al., 2016; Chang et al., 2011; Comerio, 2006; Hwang et al., 2015
Infrastructure	Burton, 2015; Comerio, 2014; Miles and Chang, 2011; Nejat et al., 2019
Community assets	Burton, 2015; Comerio, 2014; Miles and Chang, 2011; Nejat et al., 2019

19.3 Major Research Gaps and Needs

One of the main challenges for the development housing recovery models is verification and validation. Empirical data on housing recovery collected longitudinally and systematically are still scarce, as catastrophic events are rare and data have been consistently collected only recently for the purpose of informing simulations models. The development of testbeds, as well as devoting funds to longitudinal studies of post-disaster housing recoveries are important steps to close this gap.

Although current housing recovery simulations have limited predictive power, they are valuable tools for comparing proposed disaster recovery strategies. Housing recovery simulations can be employed to inform the development of new policies, by identifying regions or socioeconomic groups less capable of recovering. This topic has not yet been explored extensively from a research perspective.

Risk is not static in time. As cities grow, new technologies are developed, population behaviors evolve, and the assets exposed as well as the vulnerabilities change. Integrating risk dynamics models with housing recovery simulations can significantly improve the assessment of the benefits of housing recovery policies. This is another topic that can benefit from further research.

Chapter 20
Businesses

Rodrigo Costa

Businesses play a major role in the recovery of a community because they provide a large portion of the local jobs. Without employment, households may experience difficulty in financing the restoration of their homes and will be forced to relocate (Bolin and Bolton, 1983; Wang et al., 2015). With fewer clients, even businesses that survive a disaster may be forced to close, creating a synergy between slow business recovery and failed housing recovery. Despite its importance for community recovery, the literature on post-disaster business recovery is scarce. On the one hand, the rarity of extreme natural events make the systematic and longitudinal collection of business recovery data challenging. On the other hand, larger economic cycles exert a strong influence on the well-being of individual firms, making it difficult to disaggregate macroeconomic and disaster-related effects.

Some of the most comprehensive studies of business recovery in the U.S. were conducted by the Disaster Research Center (Webb et al., 2000). These studies found that direct physical damage is only one of the many factors influencing business loss and recovery. Often, physical damage plays a secondary role to financial and market stability.

20.1 Input and Output Data

The majority of the existing business recovery models have been developed using survey data, collected shortly after or even years after a disaster. These surveys collected data on the number of full time employees, a surrogate measure of size, age, industry sector, and pre-disaster financial conditions of the surveyed businesses. Data about the business neighborhood and how it was impacted have also been shown to be relevant (Chang, 2010b). The level of engagement in disaster preparedness activities of the businesses is another dimension of interest. Measures of disaster impact, such as physical damage or disruptions to utilities are also important data. Finally, scholars have also argued that the ability of owners to make quick decisions about relocation, financial injection, and switching to new business models is crucial for recovery (Morrish and Morrish, 2011; Stevenson et al., 2014). These data can also be obtained from surveys. The outputs of business recovery models are often a list of factors that lead businesses to recover more quickly or in a more sustainable manner.

20.2 Concepts in Business Recovery Modeling

Businesses are diverse in nature. Industry sector, size, age, being a franchise, location, primary market, and financial stability are a few of the factors that may influence how a business responds to a shock and recovers from it. For this reason, understanding what factors contributed to the successful recovery of business in past events is important to guide data collection and development of new models.

Within the U.S., business recovery was studied in the aftermath of a few major events. Short-term business recovery after the 1994 Northridge, California, earthquake was affected by direct physical impact on business operations, ecological aspects, and neighborhood location of the business (Dahlhamer and Tierney, 1998). Conversely, in the long-term, the business sector, its primary market, disaster impacts, and the broader economic climate affected business recovery. The post-disaster business climate was also determinant for the recovery of businesses affected by the 1989 Loma Prieta, California, earthquake and Hurricane Andrew in 1992 (Webb et al., 2002). Business size and disaster preparedness were also significant predictors for recovery after these two events. In 2001, a meta study involving seven disasters in seven communities across the U.S. identified the business and market stability, asset losses, and entrepreneurial savvy as good predictors of recovery (Alesch et al., 2001). Also in 2001, after the Nisqually, Washington, earthquake, size, ownership over property, access to resources, market diversification, market stability, and neighborhood conditions influenced the recovery of businesses in two districts of Seattle (Chang and Falit-Baiamonte, 2002).

Outside of the U.S., the most extensively studied event in terms of business recovery is the 2010 and 2011 Canterbury earthquake sequence. These events led to the cordoning of the Christchurch Central Business District for nearly two and a half-years (Brown, 2019). One outcome was that many local businesses had to relocate to distant regions, thereby losing much-needed staff and customers (Morrish and Jones, 2020). Businesses that struggled to gain new customers and find new employees in their new location suffered the most, denoting a correlation between business relocation and recovery. Businesses whose suppliers were disrupted were significantly more likely to experience decreased productivity (Brown, 2019). The ability of owners to make quick decisions about relocation, financial injection, switching to new business models, or stating inter-organizational cooperation for sharing of knowledge, resources, risks, and profits was crucial for recovery (Morrish and Morrish, 2011; Stevenson et al., 2014). Beyond that, commercial insurance, industry sector, property ownership, and customer issues were shown to affect recovery, whereas business size and age did not (Brown et al., 2017, 2015; Kachali et al., 2015).

The majority of empirical studies focusing on business recovery have utilized statistical modeling techniques to identify the various predictors of successful recovery, but without focusing on the development of predictive models (Aghababaei et al., 2020); among those, logistic regression was widely used (Dahlhamer and Tierney, 1998; Marshall et al., 2015; Watson et al., 2020). Logistic regression models share many similarities with linear regression models. The important difference is that the independent variable, Y, is binary, e.g., having states "Yes" and "No", or "1" and "0". Logistic regression is named after the function used at the core of the method, the logistic function. This is an S-shaped curve that can take any real-valued number and map it into a value between 0 and 1, but never exactly at those limits. The logistic function is used to estimate the probability that $Y = 1$

$$P(Y=1) = \frac{\exp(\beta_0 + \sum_{i=1}^{p} \beta_i \cdot x_i)}{1 + \exp(\beta_0 + \sum_{i=1}^{p} \beta_i \cdot x_i)} \tag{20.1}$$

which can be rearranged as

$$\ln\left(\frac{P(Y=1)}{1 - P(Y=1)}\right) = \beta_0 + \sum_{i=1}^{p} \beta_i \cdot x_i \tag{20.2}$$

where p is the number of predictors, and the coefficients β_i can be estimated using maximum-likelihood estimation. Although logistic regression is a linear method, the transformation using the logistic function makes it so that we can no longer understand the predictions as a linear combination of the inputs. Everything else being equal, the coefficients β_i represent the increase in the odds-ratio of $Y = 1$ to $Y = 0$ when x_i is increased by one unit. Section 4.4 in Friedman et al. (2001) provides in-depth explanations of logistic regression models.

More recently, Aghababaei et al. (2020) described a model for post-disaster business recovery that employs Bayesian methods. The main advantage of this approach, compared to approaches based on regression analysis, is that it can be constantly improved as new data becomes available; however, aggregating data from different communities and different disasters is not a trivial task.

20.3 Major Research Gaps

The recovery of businesses remains an under-studied topic, even when compared to the recovery of infrastructure and housing. Business recovery after catastrophic disasters has only been investigated for a handful of events, e.g., Hurricanes Ike and Katrina, and the Northridge and Canterbury earthquakes. It is unclear if the findings from these events are transferable to other locations and hazards. It is also unclear if business recovery after concentrated but destructive events shares the same patterns.

Previous studies have been inconsistent in their findings. For example, the existence of a correlation between disaster preparedness and recovery performance is debatable. While a positive correlation is intuitively expected, studies of business recovery after major disasters show no relationship at all between preparedness measures and recovery outcomes; see Webb et al. (2000). There remains the questions of whether or not these studies were designed in a way whereby the effect of disaster preparedness on business recovery could be captured (Xiao and Peacock, 2014). This is a topic that remains open and in need of further investigation.

The role of entrepreneurial decision on the post-disaster survival of businesses is another topic that deserves more attention. The majority of the studies conducted to date have focused on physical damage and disaster preparedness metrics. Nonetheless, it is argued that quick and informed decisions by the owners have had a large impact on business recovery (Morrish and Jones, 2020).

Part V
Cross-Cutting Methodologies

This section of the report examines two related cross-cutting topics—uncertainty quantification and artificial intelligence—which have applications across all phases of natural hazards engineering (NHE). Both areas are developing rapidly, propelled by the capabilities of modern high-performance computing (HPC), information technologies (IT), and data harvesting technologies, and supported by algorithmic developments.

Uncertainty quantification (UQ) covers a broad range of topics that include: (1) characterization of uncertainties in natural hazards, their damaging effects on the built environment, and the resulting consequences on communities; (2) propagation of uncertainties through simulations of natural hazards through to their consequences; (3) statistical calibration of simulation models, including Bayesian inference methods to update models with observed data; and (4) design under uncertainty, including design of physical assets through to strategies and practices to mitigate risk and promote recovery from natural disasters.

Artificial intelligence (AI) and machine learning (ML) have a wide range of potential applications to NHE, the capabilities of which are just beginning to be realized, including:

1. Developing features of buildings and other assets that form the basis for simulating the effects of natural hazards on communities;
2. Developing surrogate data-driven models at various scales, ranging from material models in finite-element simulations, to models of natural hazard intensity parameters, to simplified models of buildings and other assets in regional simulations; and
3. Detecting and assimilating observational data from post-disaster reconnaissance.

As described in Chapter 22, AI/ML tools encompass a range of techniques, including knowledge-based expert systems, statistical-based neural networks, kernel-based methods, and deep-learning approaches. While the AI/ML show great potential and promise to revolutionize NHE, success in this regard hinges on identifying appropriate uses of these technologies and taking care to validate and develop confidence in the methods.

Chapter 21
Uncertainty Quantification

Alexandros Taflanidis, **Joel P. Conte**, **George Deodatis**, and **Sanjay Govindjee**,
along with review comments and suggestions by Aakash B. Satish, Michael D. Shields, Lance Manuel, and Sang-ri Yi

Uncertainty quantification (UQ) is a rapidly evolving scientific field, with advances in computer science and statistical computing promoting constant developments in the way uncertainty is incorporated in predictive analysis of engineering systems (Smith, 2013). In particular, over the last few decades, the popularity of high-performance computing (HPC) and machine-learning tools have dramatically impacted the way computational simulation is utilized within the UQ field, lifting many barriers that were traditionally associated with simulation-based UQ techniques, and allowing the incorporation of detailed characterization and propagation of uncertainties in computationally intensive numerical models to solve highly complex problems. The current consensus within the UQ community is that these advances will remove or have already removed the need for simplified approaches with respect to both the uncertainty characterization (assumptions/models used to describe uncertainty and system performance) or uncertainty propagation (estimation of statistics of interest).

When discussing computational advances and state-of-the-art tools in UQ, greater emphasis is typically placed on algorithmic approaches than the corresponding software facilitating the implementation of these approaches. The reason for this is that development of scientific tools for UQ has focused traditionally on a specific UQ sub-field [for example, surrogate modeling to support UQ analysis (Gorissen et al., 2010; Lophaven et al., 2002)], with a large number of researchers (e.g., Bect et al., 2017; Clement et al., 2018) offering open-source algorithms to address a specific class of problems even within each of these sub-fields. Although many of these algorithms have been developed in MATLAB, in recent years significant emphasis has been placed on open-source libraries developed using Python (or less frequently C++ or R) and typically distributed though GitHub.

Since UQ is a very broad field, discussions herein focus on applications within the natural hazards engineering (NHE) domain, with some references to relevant general UQ advances also offered. Emphasis is on computational aspects, the most pertinent UQ feature for a review of the state of the art in UQ simulation methods. Additionally, discussions focus on algorithmic developments, with some references also on relevant software. With respect to description of uncertainty, emphasis is placed on probabilistic characterization. Alternative approaches exist (Beer et al., 2013), such as use of fuzzy sets and interval analysis, however, the current standard of practice in NHE is to rely on probabilistic UQ analysis. This can be attributed to the tradition in civil engineering design codes to describe performance with respect to statistical measures (probability of exceeding performance limit states), or because hazard severity, the most significant source of variability when discussing risk in the context of NHE, is almost always described using probabilistic measures (McGuire, 2004; Resio et al., 2007).

Note: all references provided here are examples and general in scope; several of them can be regarded as seminal work since the UQ field—even with respect to NHE applications—is very broad and constantly expanding.

21.1 Uncertainty Characterization

In NHE, characterization of the uncertainties impacting predictions is integrally related to risk quantification. Performance-based engineering (PBE) (Barbato et al., 2013; Ciampoli et al., 2011; Fischer et al., 2019; Goulet et al., 2007; Riggs et al., 2008; Whittaker et al., 2003) represents undoubtedly the foundational development for this task. Performance-based engineering decouples the risk quantification to its different components, mainly hazard and exposure analysis, structural analysis (vulnerability), and loss analysis (consequences), with uncertainties included (and impacting predictions) in all these components. Variability of the hazard itself, in terms of both occurrence and intensity, is widely acknowledged to correspond to the most significant source of uncertainty in this setting. Frequently, hazard variability is represented through a resultant intensity measure (IM) (Baker and Cornell, 2005; Kohrangi et al., 2016), though comprehensive approaches that focus on connecting the excitation to parameters of the geophysical process creating it also exist. For example, in earthquake engineering, the description of time-histories through stochastic ground motion models dependent on seismological parameters (Bijelić et al., 2018; Vlachos et al., 2018); in coastal risk estimation surge modeling numerical tools are dependent on atmospheric storm characteristics (Resio et al., 2007). Beyond the hazard variability, uncertainties related to parameters of the structural model or generalized system model (for applications not examining directly structural risk) and to the characteristics for describing performance are also recognized as important for inclusion in risk estimation (Porter et al., 2002). The term “system” will be used herein to describe the application of interest; e.g., this may pertain to a building model, to an infrastructure network, or to a soil–structure interaction system configuration.

Uncertainty within this NHE risk characterization setting is ultimately described through a discrete number of parameters (treated as random variables) pertaining to either the hazard or the system/performance model—including parameters—to describe interdependencies and deterioration characteristics (Akiyama et al., 2020; Jia and Gardoni, 2018). Even when the uncertainty description for the underlying problem actually entails a stochastic sequence/process or a random field, a discretized approximation of these functions is commonly utilized, as necessitated by the numerical tools used to compute the system response (Gidaris et al., 2014). This translates into use of a parameterized realization for the excitation or model characteristics, an approach that seamlessly fits within the overall PBE framework. Exceptions exist primarily for stochastic dynamics problems, for which propagation of the stochastic excitation uncertainty can be performed using random vibration theory, such as exact or approximate solution of stochastic differential equations or estimation of stationary statistics in the frequency domain (Li and Chen, 2009). Though such approaches offer substantial benefits, their implementation is primarily constrained to linear systems or nonlinear systems with moderate degree of complexity (dos Santos et al., 2016; Wang and Der Kiureghian, 2016), such as systems with very small number of degrees-of-freedom or nonlinearities having a simple, analytical form. As such, their utility within NHE is limited to specialized applications. Even in such cases, the remaining uncertainties, beyond the stochastic excitation itself, must be described using a parametric description. The overall parameterized uncertainty description promoted within PBE is therefore well aligned with such approaches, as their adoption simply requires substitution of the deterministic simulation system model with a stochastic simulation system model, the latter representing the solution of the stochastic dynamics problem.

When using Monte Carlo simulation (MCS) techniques to propagate uncertainty (see discussion in the next paragraph), a critical part of the methodology is the numerical generation of sample functions of the stochastic processes, fields, and waves involved in the problem, modeling the uncertainties in the excitations (e.g., wind velocities, seismic ground motion, and ocean waves) and in the structural system (e.g., material, mechanical, and geometric properties). These processes, fields, and waves can be stationary or non-stationary, homogeneous or non-homogeneous, scalar or vector, one dimensional or multi-dimensional, Gaussian or non-Gaussian, or any combination of the above. It is crucial for a simulation algorithm to be computationally efficient as a very large number of sample functions might be needed. A wide range of methodologies is currently available to parametrically describe uncertainty and perform these simulations including the spectral representation method (Benowitz and Deodatis, 2015; Li and Kareem, 1991; Shields et al., 2011; Shinozuka and Deodatis, 1991), Karhunen-Loeve expansion and polynomial chaos decomposition (Ghanem and Spanos, 1991), auto-regressive moving-average models (Deodatis and Shinozuka, 1988; Spanos, 1983), local average subdivision method (Fenton and Vanmarcke, 1990), wavelets (Zeldin and Spanos, 1996), Hilbert transform techniques (Wang et al., 2014), and turning bands methods (Mantoglou and Wilson, 1982).

The setting outlined in the previous two paragraphs leads, ultimately, to risk characterized as a multidimensional integral over the parametric uncertainty description (input), with uncertainty propagation (output) translating to estimation of the relevant statistics (estimation of integrals representing moments or failure probabilities with respect to different limit states). Through proper definition of the statistics of interest, different attitudes towards risk can be further described, including risk aversion which is especially relevant for NHE applications (Cha and Ellingwood, 2012). The aforementioned integral is frequently expressed with respect to the conditional distributions of the different resultant risk components (Barbato et al., 2013; Goulet et al., 2007), e.g., hazard / response given hazard / consequences given response. This represents merely a simplification for risk quantification purposes as it allows for the decoupling of the different components. Even when this simplification is invoked, risk fundamentally originates from the uncertainty in the model parameters of the problem formulation (including hazard/system/performance description), quantified by assigning a probability distribution to them, representing the UQ input. Note: in many NHE applications, some aspects of the performance (and of the associated risk) are described by utilizing resultant statistical models instead of explicitly addressing the underlying sources of uncertainty. For example, in PBE, fragility functions are frequently leveraged to describe the combined effect of the uncertainties influencing the parameters of capacity and demand models, while in loss estimation, resultant distributions are leveraged to encompass the multiple sources of uncertainty influencing consequence quantification. In such cases, the integral quantifying risk is expressed with respect to the remaining parametric uncertainty sources.

21.2 Uncertainty Propagation

For uncertainty propagation, the traditional approach in NHE has been the use of point estimation methods, either methods that focus on the most probable values of the model parameters like the first-order second moment (FOSM) method (Baker and Cornell, 2008) and its variants (Vamvatsikos, 2013), or methods that focus on the peaks of the integrand of the probabilistic integral (design points) like the first- and second-order reliability methods (FORM/SORM) (Koduru and Haukaas, 2010). Point estimation methods are inherently approximate, with no available means to control their accuracy. Recent advances in computer science and statistics, including the development of innovative MCS techniques, such as Subset Simulation (Au and Beck, 2003b), Efficient Global Reliability Analysis (EGRA) (Bichon et al., 2013), and Adaptive Kriging with Monte Carlo Simulation (AK-MCS) (Echard et al., 2011), have encouraged researchers to rely more heavily on Monte Carlo simulation (MCS) tools for uncertainty propagation in NHE (Deb et al., 2019b; Esposito et al., 2015; Smith and Caracoglia, 2011; Taflanidis and Jia, 2011; Vamvatsikos, 2014).

Although point estimation methods do still maintain utility and popularity, NHE trends follow the broader UQ community trends in promoting computer and MCS approaches, as these techniques facilitate high-accuracy uncertainty propagation (unbiased estimation) with limited fundamental constraints on the complexity of the probability and numerical models used. Of course, computational complexity is still a concern for MCS, especially for applications with high-dimensional uncertainties and challenging quantities of interest (such as rare event simulation), creating in many instances practical constraints for the efficient implementation.

The current state of the art in NHE for addressing these constraints is to leverage both advanced MCS techniques (Au and Beck, 2003b; Bansal and Cheung, 2018; Li et al., 2017) but, more importantly, machine-learning and advanced computational statistics tools (Abbiati et al., 2017; Ding and Kareem, 2018; Echard et al., 2011; Su et al., 2018; Wang et al., 2018). Relevant recent advances for MCS focus on variance reduction techniques, e.g., Latin hypercube sampling (Vamvatsikos, 2014), stratified sampling (Jayaram and Baker, 2010), importance sampling (Papaioannou et al., 2018), Markov chain Monte Carlo methods (Au and Beck, 2003b) and sequential approaches for rare event simulation (Jia et al., 2017), with substantial emphasis on problems with high-dimensional uncertainties (Au and Beck, 2003b; Wang and Song, 2016). For machine learning, the focus is primarily on use of a variety of surrogate modeling (meta-modeling) techniques (Bernier and Padgett, 2019; Gentile and Galasso, 2020; Le and Caracoglia, 2020; Stern et al., 2017; Zhang and Taflanidis, 2018; Zhang et al., 2020).

Many machine-learning implementations in NHE fall under the category of direct adoption of techniques developed by the broader UQ community, though a number of studies do address challenges unique to the integration of surrogate modeling in NHE problems, e.g., the need to address high-dimensionality of input when stochastic description is utilized for non-stationary excitations (Gidaris et al., 2015).

Note: the NHE modeling community has been continuously increasing the complexity of the models they adopt. Such high-fidelity numerical models, which are able to capture the behavior of structural, geotechnical and soil–foundation–structural systems all the way to collapse or the brink of collapse, are inherently nonlinear hysteretic (path-dependent) and frequently degrading/softening. Therefore, such models present serious challenges in term of robustness of convergence of the iterative schemes used to integrate their equations of motion.

The significance of these challenges will further increase in the MCS-based UQ context and requires much research effort to overcome. One of the implicit outcomes of this complexity increase is a further increase of the input/output dimensionality in NHE UQ problems. This leads to applications with high-dimensional uncertainties that, traditionally, pose challenges for UQ algorithms (Au and Beck, 2003a; Schuëller et al., 2004). Different approaches have been explored to address this challenge within NHE applications, ranging from specialized MCS algorithms (Au and Beck, 2001; Wang and Song, 2016) to the formal integration of dimensional reduction techniques (Jia and Taflanidis, 2013), to the use of global sensitivity analysis indices to the selection of subsets of inputs to emphasize in different MCS schemes (Jia et al., 2014). It is evident, though, that greater research effort will be required on this topic.

Discussing more broadly the advances in the UQ field, current emphasis is on machine-learning techniques for accelerating UQ computations (Ghanem et al., 2017; Murphy, 2012; Tripathy and Bilionis, 2018). The relevant developments are frequently integrated with advanced MCS techniques, e.g., for topics like rare event simulation (Balesdent et al., 2013; Bourinet, 2016; Li et al., 2011). Regarding machine learning, although some emphasis is being given on the approaches for tuning and validation (Mehmani et al., 2018), the primary focus is on the proper design of the computer simulation experiments (DoE) (Kleijnen, 2008; Kyprioti et al., 2020; Picheny et al., 2010) that are used to inform the development of the relevant computational statistics tools.

Adaptive DoE is widely acknowledged to offer substantial advantages in balancing computational efficiency and accuracy for UQ analysis when machine-learning techniques are used, and significant research effort is currently focused on advancing DoE techniques; this remains an open challenge for the community. Note: characteristics of the adaptive DoE depend on the utility of the surrogate model (Liu et al., 2018), whether it is intended to serve as a global replacement of the original numerical model (i.e., develop the surrogate model first and then leverage it to perform different UQ tasks) or it is used for very specific UQ tasks (e.g., to estimate the reliability index for a specific limit state).

The concept of model fidelity remains unexplored within the NHE community, but it plays a central role in modern UQ techniques, with a range of algorithms developed to properly integrate hierarchical fidelity models to promote efficient and accurate uncertainty propagation (Geraci et al., 2017; Peherstorfer et al., 2018). Combination of machine-learning (primarily surrogate modeling) techniques with different fidelity models is also a topic that has been receiving increasing attention for facilitating the use of expensive numerical models in UQ (de Baar et al., 2015; Zhou et al., 2016b). In the NHE setting, discussions on explicitly exploiting model fidelity for risk estimation are very limited; therefore, the community still heavily emphasizes use of high-fidelity models while still examining how different levels of simulation fidelity and the use of reduced order models can be properly combined to promote efficient and accurate risk estimation. Undoubtedly, multi-fidelity Monte Carlo and hierarchical surrogate modeling techniques constitute important opportunity areas for advancing UQ analysis in NHE.

Another important aspect of uncertainty propagation is the concept of sensitivity analysis. In NHE, this has been primarily implemented as local sensitivity analysis, i.e., estimation of gradient information (Gu et al., 2009; Haukaas and Der Kiureghian, 2007), since this fits well with the point estimation methods used frequently for calculation of statistics (facilitating the identification of design points). Within the UQ setting, global sensitivity analysis is more relevant (Rahman, 2016; Saltelli, 2002; Sobol, 1990), as it allows identification of the relative importance of the different sources of uncertainty, offering insights with respect to both accelerating UQ computations (facilitating, in particular, the use of high-dimensional applications as discussed earlier), as well as providing additional understanding of the critical factors impacting the overall risk. Though global sensitivity analysis can be particularly useful for hazard applications (Vetter and Taflanidis, 2012), it is currently receiving limited practical interest within NHE. Implementations do exist even for all purpose codes; see Bourinet et al. (2009) for example. More formal integration of global sensitivity analysis tools within the NHE community represents another topical area where advancements should and can be made. The computational cost for global sensitivity analysis—say, calculation of first and higher order sensitivity indexes—is much higher than the cost of simple uncertainty propagation; relevant techniques range from use of quasi-Monte Carlo (Saltelli, 2002) to surrogate modeling (Sudret, 2008) to sample-based methods relying on approximation of conditional distributions (Hu and Mahadevan, 2019; Li and Mahadevan, 2016).

21.3 Model Calibration and Bayesian Inference

Model updating/calibration plays an important role in NHE, with data coming from both experiments (at component or system level) experiments and observations (at system level) during actual excitation conditions or post-excitation. Within the UQ setting, the current standard to perform this updating is Bayesian inference (Beck, 2010; Kontoroupi and Smyth, 2017). Using observation data, Bayesian inference can be leveraged to provide different type of outputs/results (Beck and Taflanidis, 2013) through the following three tasks: (1) identifying the most probable model parameters or even update the entire probability density function for these parameters (obtain posterior distributions); (2) performing posterior predictive analysis and updating the risk using the new information; and (3) when different numerical models are examined, identifying the probability of each of them (as inferred by the data) to either select the most appropriate or calculate the weights when all of them will be used in a model averaging setting (model class selection).

Typical implementation refers to model parameter updating, which is traditionally viewed as model calibration. Model class selection is less frequently used, especially within NHE community applications. Still, Bayesian model class selection offers a comprehensive tool for evaluating appropriateness of different models (Muto and Beck, 2008). For NHE, such applications can be integrated with health monitoring tools (Oh and Beck, 2018). Ideally, model parameter updating should be performed accounting for pertinent sources of real-world uncertainties (e.g., noisy input–output measurements, uncertainty in model parameters, model form uncertainty, and environmental variability). Formulating the likelihood equation to account for such uncertainties is a crucial part of the Bayesian model updating/calibration process. The so-called Kennedy O'Hagan framework has emerged as a robust approach to account for all these uncertainties, especially the model form error (Kennedy and O'Hagan, 2001).

From a computational perspective, Bayesian updating may correspond to a significant computational burden, especially when complex finite-element models are utilized. Such finite-element models contain numerous unknown parameters that drastically increase the computational cost of the Bayesian updating process. This necessitates the use of identifiability and sensitivity analyses prior to model updating to select the most significant parameters to use in the updating process. This step substantially improves the calibration process run-time of complex finite-element models with numerous parameters, resulting in better parameter estimation results (Ramancha et al., 2021b). In addition, non-identifiable parameters result in non-unique parameter estimates (Ramancha et al., 2020). Fisher information-based local identifiability analysis and variance-based global sensitivity analysis are commonly used methods for parameter screening to identify the most significant and identifiable parameters (Ramancha et al., 2021b).

Beyond this critical dimensionality reduction, a variety of algorithmic approaches are commonly used to address the computational complexity in Bayesian updating applications. Common approaches include the use of advanced MCS techniques to reduce the total number of simulations needed (Quiroz et al., 2018), the integration of meta-modeling to approximate the complex system model (Angelikopoulos et al., 2015; Giovanis et al., 2017; Wang and Shafieezadeh, 2019; Zhang and Taflanidis, 2019), or the use of direct differentiation tools to accelerate computations (Astroza et al., 2017). The second candidate implementation, the use of surrogate modeling techniques, has undoubtedly significant potential in accommodating the use of complex models within Bayesian calibration schemes.

Bayesian updating may rely on point estimates, which is equivalent to identifying and using only the most probable (based on the observation data) model parameter values (expressed as a nonlinear optimization problem), or leveraging the entire posterior distribution (expressed as a problem of sampling from this distribution). For the latter, Markov Chain Monte Carlo (MCMC) techniques need to be used for any of the three tasks entailed in Bayesian inference (Catanach and Beck, 2018). In particular, transitional MCMC (TMCMC) is a versatile method for sampling the posterior distribution (Betz et al., 2016; Ching and Chen, 2007). Due to its computationally parallel nature, it is ideal for Bayesian inference of computationally expensive FE models (Ramancha et al., 2021a,b). For problems involving inference for dynamic models (pertinent to the majority of applications in NHE), updating can be done in batch mode, using all observation data at once, or recursive mode, sequentially updating model characteristics during the time history for the observations (Astroza et al., 2017; Ramancha et al., 2021b).

The batch approach is a direct implementation of the broader Bayesian inference framework. The recursive implementation typically leads to filtering approaches, including Kalman filters (KF) and its variants (Extended KF or Unscented KF), that rely on linear or Gaussian assumptions (Astroza et al., 2017; Erazo and Nagarajaiah, 2018; Kontoroupi and Smyth, 2017), and particle filters (PF) that reproduce the work of KF in nonlinear and/or non-Gaussian environment by a sequential MCS approach (Chatzi and Smyth, 2009; Olivier and Smyth, 2017; Wei et al., 2013). This recursive approach is used primarily for real-time or online applications, focusing mainly on the most probable parameter values.

21.4 Design under Uncertainty

In NHE, design under uncertainty has been traditionally expressed as a reliability-based design optimization (RBDO) (Chun et al., 2019; Spence and Gioffrè, 2012) or as a robust design optimization (RDO) (Greco et al., 2015) problem. Some recent approaches deviate from this pattern and follow directly PBE advances, formulating the design problem with respect to life-cycle cost and performance objectives (Shin and Singh, 2014), and even adopting multiple probabilistic criteria to represent different risk-attitudes (Deb et al., 2019a; Gidaris et al., 2017; Haukaas and Mahsuli, 2012; Li and Conte, 2018). Practical applications focus on design of supplemental dissipative devices (Altieri et al., 2018; Gidaris et al., 2017; Shin and Singh, 2014) member-sizing (Huang et al., 2015; Suksuwan and Spence, 2018), or even topology-based optimization of structural systems (Bobby et al., 2017; Zhu et al., 2017b).

With respect to the solution of the corresponding optimization problem, the NHE community follows broader UQ trends. Design under uncertainty optimization problems undoubtedly present significant computational challenges since they combine two tasks, each with considerable computational burden: uncertainty propagation and optimization. Discussed next is how uncertainty propagation is handled within this coupled problem.

Common approaches, especially within context of RBDO and RDO, typically rely on approximate point-estimation methods like FORM/SORM (Papadimitriou et al., 2018) with some sort of decoupling of the optimization/uncertainty-propagation loops to accelerate convergence (Beyer and Sendhoff, 2007). Over the past decade, advances in the use of simulation techniques within UQ have created new opportunities to incorporate MCS techniques in solving design under uncertainty problems (Flint et al., 2016; Spall, 2003), lifting some of the traditionally associated computational barriers. Greater emphasis is continuously placed on solving design under uncertainty problems using advanced Monte Carlo techniques (Medina and Taflanidis, 2014), which are frequently coupled with an intelligent integration of surrogate modeling tools (Bichon et al., 2013; Dubourg et al., 2011; Zhang and Taflanidis, 2018). This trend is expected to continue since computer science and machine-learning advances have dramatically altered the computational complexity for leveraging MCS for design optimization under uncertainty, offering an attractive alternative to traditional approaches that relied on the approximate (but highly efficient) point estimation methods.

21.5 Relevant Software

Beyond specific UQ algorithms developed by individual researchers and shared in repositories like GitHub or MATLAB's File Exchange, two other important UQ software categories exist:

- Libraries integrated with existing modeling tools appropriate for NHE analysis, like the general purpose finite-element model reliability tools offered through FERUM (Bourinet et al., 2009). These libraries frequently address a specific type of UQ analysis, e.g., direct MCS or reliability estimation.
- Software that approach UQ analysis with a broad brush that could be appropriate for use in NHE applications (but as of yet has not necessarily been developed specifically for that purpose). Such software typically covers the entire range of UQ analysis, with continuous integration of the relevant state-of-the art advances. They are composed of scientific modules that perform different UQ tasks, connected through the main software engine and, in addition, are commonly equipped with an appropriate GUI.

The last category of UQ software packages is of greater interest, especially since it covers the entire domain of a rapidly expanding field and facilitates the integration of the relevant developments, which typically leverage different classes of tools, e.g., rare-event simulation using surrogate models with adaptive refinement. UQ software programs typically address the following tasks:

- **Probabilistic modeling** This pertains to standard uncertainty characterization, extending from simple parametric description to stochastic characterization (including dimensionality reduction), and represents the input to the UQ software.

These tasks encompass direct MCS with Latin hypercube sampling, use of point estimation methods (FORM/SORM), variance reduction, and rare event simulation. UQ outputs considered correspond typically to statistical moments, probabilities of exceedance for different limit states or fitted distributions. The numerous software programs adopt different tools for the aforementioned tasks and most lack a complete adaptive implementation; some degree of competency on behalf of the end-user for selecting appropriate algorithms and parameters is assumed. Recently, many types of software have begun to integrate multi-fidelity MCS approaches;

- **Surrogate modeling** Common classes of meta-models used include Gaussian processes, polynomial chaos, support vector machines, and radial basis functions. The developed surrogate models can be then leveraged within the software to accelerate computations for other UQ tasks. Adaptive DoE options are typically available and used frequently; standard DoE approaches are not, however, necessarily tailored to the specific UQ task of interest to the end-user. Most software programs sacrifice robustness (an approach that is reliable and is independent of the end-user competency) for efficiency (the ability to develop high-accuracy meta-models with the least number of simulation experiments);
- **Global sensitivity analysis** This is typically performed through calculation of Sobol indices (UQ output) using some approximate (quasi-Monte Carlo) technique or surrogate modeling (polynomial chaos expansion);
- **Data analysis and model calibration** with some emphasis on Bayesian inference techniques. Although Bayesian updating is very common, model class selection is not. Addressing modeling complexity remains a bigger challenge for Bayesian inference applications since integrating meta-modeling techniques is not trivial. The challenge here is to establish a fully automated integration that can address different degrees of competency for the end-user and a wide range of application problems with certain degree of robustness (impact of metamodel error). For problems with dynamical models, the typical approach is to use the batch updating method since that leads to a common broader Bayesian inference framework; and
- **Design-under-uncertainty** Though this is not a common option, some software programs do offer the ability to perform some form of optimization under uncertainty; most of these programs are applicable to RBDO and RDO problems. Integrating state-of-the-art MCS techniques in this setting remains a challenge. Implementations are typically computationally expensive or rely on approximate approaches for the uncertainty propagation.

Out of the many UQ software programs that currently exist, the programs listed below are worth direct mention as they represent the state of the art:

DAKOTA

Developed by the Sandia National Laboratory and written in C++, *Dakota* [83] is widely considered as the standard for UQ software and delivers both state-of-the-art research and robust, usable tools for optimization and UQ (Adams et al., 2009). It has a range of algorithms for all aforementioned UQ tasks and has a wide community that supports its continuous development.

OpenTURNS

It is an open-source (C++/Python library) initiative for the treatment of uncertainties and risk in simulations (Andrianov et al., 2007). It addresses all aforementioned UQ tasks apart from design under uncertainty.

UQLab

Developed at ETH Zürich, *UQLab* [89] is a MATLAB-based general purpose UQ framework (Marelli and Sudret, 2014). Like OpenTURNS it addresses all the aforementioned UQ tasks apart from design under uncertainty.

OpenCOSSAN

OpenCOSSAN [86] is the MATLAB based open-source version of the commercial software *COSSAN-X* [82] (Patelli et al., 2017), which was initially developed to integrate UQ and reliability techniques within FEM analysis, with modules that extend across all aforementioned UQ tasks.

UQpy

UQpy [90] is a continuously expanding open source (Python-based) library of tools for UQ analysis (Olivier et al., 2020). It addresses all UQ tasks apart from design-under-uncertainty (at least in its current form).

MUQ

MIT Uncertainty Quantification Library [85] is an open source (C++/Python library) collection of tools for UQ analysis, with emphasis on probabilistic modeling, Bayesian inference, and surrogate modeling. Although developments in MUQ have been slightly more accelerated recently, overall it has not kept pace with the other open-source initiatives mentioned above.

Beyond these specific software and open-source tool collections, there is an increasing number of Python-based open-source libraries that are offered by researchers for UQ analysis, including *UQ-Pyl* [88], *FilterPy* [84], and *SMT* [87]. Most of them are focused on specialized UQ tasks (or groups of tasks) and do not intend to establish a generalized UQ analysis workflow. The degree of ongoing improvement and bug fixes also varies substantially between these efforts.

21.5.1 Relevant SimCenter Tools

The SimCenter supports uncertainty quantification in natural hazards engineering by developing interfaces that can connect the state-of-the-art UQ engines mentioned above with the simulation tools used by the NHE research community. The connected UQ engines currently provide uncertainty propagation capabilities to the research tools (e.g., EE-UQ, WE-UQ, R2DTool) and they will enable the development of surrogate models within those tools in a future release. Meanwhile, the full functionality of connected UQ engines is embedded in *quoFEM* [7], a UQ-specific research tool that features a graphical user interface to facilitate the use of the underlying UQ software.

quoFEM

The Quantified Uncertainty with Optimization for the Finite-Element Method (*quoFEM* [7]) tool supports model calibration, optimization, uncertainty propagation, reliability analysis, surrogate modeling, and sensitivity analyses of numerical materials, components, and systems. The graphical user interface currently supports finite-element software (OpenSees and FEAP) and can also interface with custom analysis packages, including, but not limited to those based on the discrete element and finite difference method and other commercial software that cannot be bundled with the open-source SimCenter applications (e.g., LS-DYNA, ABAQUS). The GUI can also be configured by users to employ custom UQ engines that are not currently provided with the tool. These features provide instant uncertainty analysis and optimization capabilities for numerical models. Furthermore, quoFEM provides an opportunity for researchers working with experimental facilities to use advanced UQ methods and tools to design experiments and calibrate numerical models. Some of the planned future capabilities of quoFEM include support for multi-fidelity models, sequential Bayesian updating, surrogate enhanced optimization and calibration, and optimization under uncertainty.

Chapter 22
Artificial Intelligence and Machine Learning

Kincho H. Law, **Chaofeng Wang**, **Barbaros Cetiner**, **Sascha Hornauer**, **Qian Yu**, **Frank McKenna**, **Stella Yu**, **Satish Rao**, and **Ertugrul Taciroglu**

At present, Artificial Intelligence and Machine Learning (AI/ML) research is one of the fastest-growing fields in academia and industry. Between 1998 and 2018, the volume of peer-reviewed AI papers has grown by more than 300%, accounting for 3% of peer-reviewed journal publications and 9% of published conference papers (Perrault et al., 2019). The global market for machine-learning technologies, including hardware, software and services, is expected to grow astronomically from about $3 Billion in 2017 and the current $7 Billion in 2020 to over $30 Billion in 2024 (Future, 2019). Artificial intelligence and machine-learning technologies have already penetrated in many aspects of our everyday life, including health care, business and commerce, transportation, agriculture, manufacturing, natural and built environment, education, etc. These technologies will continue to have tremendous impacts to our society as a whole (NSTC, 2016a,b, 2019). As advances in computing technologies such as computer graphics, finite-element methods and CAD/CAE have had in the past, AI/ML will potentially revolutionize how engineering modeling, design, and simulations are conducted. With rapid advances in hardware and software technologies, and continuing developments in all aspects of computational science and engineering, natural hazards engineering (NHE) and simulations will be dramatically impacted by AI/ML.

Generally speaking, the field of artificial intelligence (AI) aims to create computational systems (or machines) that behave and solve problems in ways that emulate human intelligence. Often based on stipulated rules and pieces of knowledge, AI systems have the ability to learn, reason, adapt to changes, and self-correct with facts and data. Machine learning (ML) is a sub-field of AI that enables machines to learn from past data or experiences, self-adapt in a changing environment, and self-correct with new information. By optimizing the (feature) parameters of an ML model using training data or past experiences, the model may have the ability to make generalizations and predictions for certain events in the future and/or gain new knowledge within the model domain. Deep learning (DL), typically consisting of many (deep) layers of computational units, is a technique for realizing machine learning by automatically discovering possible model features from the data. Data mining shares many of the same techniques in machine learning; however, data mining aims to discover interesting patterns, extract rules, or construct models from large volumes of data. While data mining models possess high predictive ability similar to ML models, they often lack the "intelligence" to learn and adapt automatically to changes. As opposed to optimization, where a single well-defined objective function of the problem is to be maximized or minimized, a machine-learning model is devised from the training data by finding the optimal values for the (feature) parameters using scoring metrics that give the best predictive accuracy. While a mathematically optimized model is not easily adapted to a new set of parameters, constraints, or data, an ML model may be generalized to apply beyond the training data; the model can be adapted and transferred—with appropriate accuracy measurements and validation—to build models for problems of similar types.

The purpose of this report is to provide a brief review of the latest AI/ML technologies and how they can potentially be applied to NHE. As AI/ML is a rapidly growing field with new methods and new applications being discovered constantly, comprehensive coverage of all the developments is beyond the scope of this report. The report is purposely written in general terms with a short introduction to the different methodologies in AI and machine learning. Similarly, NHE is a very broad field dealing with impacts due to earthquake, tsunami, wind/hurricane, flood, liquefaction, fire, and other hazards. Covering all possible applications of AI/ML in all hazard areas is a task beyond this report and the ability of the writers. A few selected examples of prior works in different natural hazard domains are briefly described herein to illustrate the potential applications of AI/ML. Additionally, some of the ongoing efforts on the use of DL methods at the SimCenter towards the development of workflows for natural hazard modeling and analysis are discussed. Lastly, potential opportunities for AI/ML technologies in NHE are discussed to engender further research and developments in this field. Finally, it should be emphasized that the references and the works cited in this report represent only a small number of illustrative examples in the field as the possibilities of AI/ML are almost boundless.

22.1 Overview of AI/ML methods

Knowledge-based expert systems

Since the 1950s, when the term AI was coined, considerable progress has been made. Early research and developments in the 1980s (often known as the first wave of AI) were dominated by the rise of rule-based expert system and knowledge-based expert system (KBES) technologies (Hayes-Roth et al., 1983). With expert knowledge handcrafted as “if-then” or logic rules, expert systems with enabled reasoning and inference mechanisms have been used to address many interesting ill-posed problems, albeit often in some narrowly defined domains (Simon, 1973). One class of ill-posed problems is the conceptual structural design of buildings, which often requires prior experiential knowledge and considers downstream design and construction constraints (Jain et al., 1991a,b; Kumar and Raphael, 1997; Sriram et al., 1985). Indeed, KBES technologies have created significant excitement in all disciplines of civil engineering, including structural, geotechnical, earthquake, transportation, and environmental engineering (Cohn and Harris, 1992; Dym and Levitt, 1991; Kostem and Maher, 1986; Palmer, 1987; Sriram, 1997). How knowledge is represented is crucial to the usefulness of KBES as the representation would dictate how the system interacts with rules and data. While research on KBES has slowed down for the past couple of decades, advances in semantic information modeling and ontology continue to prevail (Noy et al., 2009; Stevens et al., 2000). For instance, in civil engineering, research on semantic modeling and the process of capturing the semantic information about buildings and infrastructures has given rise to Building Information Modeling, which has been embraced by the building and construction industry worldwide for the delivery of project information throughout a facility’s life cycle (Sacks et al., 2018). Ontology, with defined terms and relationships among the terms in a domain, can play a critical role in bringing together disparate sources of information and effectively supporting NHE modeling and simulation, e.g., in estimating earthquake damage to structures and infrastructures (Yu and Baker, 2016).

Statistical-based AI

Artificial intelligence research and developments in the 1980s and 1990s have popularized a number of reasoning and inference mechanisms (such as decision trees, Bayesian networks, etc.) and statistics-based classification, clustering and regression techniques (such as logistic regression, k-means, random forest, etc.) that find ample applications in data mining and knowledge discovery as well as in engineering. For instance, Bayesian networks are commonly used in structural reliability analysis (Straub and Der Kiureghian, 2010). Boosted decision trees have been applied to detect pipe failures and to assess weak points of geographically distributed water systems (Kumar et al., 2018; Winkler et al., 2018). Neural networks (also commonly known as artificial neural networks or ANNs) have emerged as a powerful computational and knowledge representation paradigm to build self-organized models that are able to discover patterns or draw associative relationships between input and output data (Bishop, 1995). Fitting (mathematical) models to experimental data and extracting knowledge from the data to explain physical observations are nothing new in science and engineering. However, the ability for a computational "machine" to automatically "learn" models by analyzing the data and extract relationships and patterns can have important implications for modeling complex systems. Neural networks have found many applications in all disciplines of civil engineering (Garrett and Smith, 1996; Kartam et al., 1997). For instance, instead of expressing material behaviors and constitutive relations in mathematical forms, neural network models are trained to represent constitutive models and thermal properties of complex materials, such as composites and laminated materials, and nonlinear behaviors of structural components directly using experimental data and observations (Aquino and Brigham, 2006; Ghaboussi and Garrett, 1991; Ghaboussi et al., 1998).

Kernel-based methods

Another notable development in data-driven ML is a class of statistical-based Kernel methods (such as support vector machine (SVM), principal component analysis (PCA), Gaussian process regression (GPR) models), which draw on measuring similarity between data samples (Hofmann et al., 2008; Rasmussen and Williams, 2006). Like neural networks, kernel methods, such as support vector regression (SVR), have been employed to develop material and component behavior models (see, e.g. Luo and Paal, 2018). Kernel methods are also commonly used as surrogate models in multi-scale modeling, inverse problems, and optimization (Eriksson, 2018; Park and Law, 2016; Santin and Haasdonk, 2019; Wirtz et al., 2012). Often known as Kriging in geoscience and mapping, kernel methods have been widely used for geospatial analysis and employed as a geostatistical estimator for interpolating geospatial information with quantifiable uncertainties (Jia et al., 2016; Olea, 2012). As material modeling, multi-scale modeling and analysis, inverse and optimization problems, reliability analysis and uncertainty quantifications, and regional geostatistical analysis are all fundamental components of NHE, AI-based inference, and statistical and data-driven ML methods that are likely to find ample applications in natural hazards modeling and simulation.

Deep (machine) learning

With the present abundance of data of different types (text, time series, numerical/audio/video data, images, etc.) available from a large variety of sources (web and social media), as well as devices (sensors, cameras), data-driven statistical learning (often known as the second wave of AI) has become popular since the 2000s; this area of research has largely been dominated by what is known as "deep learning" (DL) (LeCun et al., 2015). Deep-learning methods are typically based on multi-layered neural networks that can automatically discover features from the data and use the learned features to perform predictions and make decisions for a specific task. Many different DL architectures exist—such as deep (multi-layered) neural networks, recurrent neural networks, convolutional neural networks, generative adversarial networks, and many others—with each having different designs and learning strategies. The learning or training process can be typically classified by supervised (with labeled training data), unsupervised (without labeled training data), semi-supervised (with a small number of labeled but large amounts of unlabeled data), or iterative reinforcements (by optimizing the model according to some pre-defined criteria and policy).

Deep-learning methods have been successfully applied to many fields, such as computer vision, image processing, speech and audio recognition, natural language processing, and language translation, producing results that often exceed human expert performance. The successes of DL, particularly in pattern recognition and computer vision, have drawn significant attention in the civil and environmental engineering community. Within structural engineering, DL methods have been widely applied in the field of structural health monitoring (Salehia and Burguernoa, 2018). By treating the damage detection problem as object detection, and classification and segmentation of images, computer vision (CV)-based DL methods have been applied successfully to detect and identify many types of structural and material damage (Cha et al., 2017; Ferguson et al., 2018; Gao and Mosalam, 2018a; Lenjani et al., 2020; Yeum et al., 2019). For instance, during the 2018 Structural ImageNet and PEER Hub ImageNet Challenge (Gao and Mosalam, 2018b), DL methods were shown capable of performing relatively well on several detection tasks, including classification and identification of scenes, damage states/levels/types, material types, collapse states, and component types. With the publicly available street and satellite images, CV-based DL methods hold significant potential for being an integral component in (regional) natural hazards modeling and simulations.

Among these approaches, knowledge-based expert systems are intuitive and interpretive, but building them requires a lot of domain knowledge. In contrast, statistics-based AI and kernel-based methods are more data-driven, often requiring handcrafted features. The former approach assumes that the features are given, while the latter finds ways to implicitly lift the given feature to a more expressive space. The significance of DL approaches is that they eliminate the need for feature engineering and allows a classification or regression model to be trained entirely from the data in an end-to-end learning fashion. With the availability of large-scale datasets and increasingly powerful computing hardware such as GPUs, DL models that have a very large number of parameters can be explored and—particularly for problems that are highly "nonlinear" in nature—can deliver high performance unmatched by previous approaches.

22.2 AI/ML in Natural Hazards Engineering

Artificial intelligence and machine learning have been applied across many fields of NHE for quite some time and have gained increasing popularity in recent years. Such applications range from data acquisition, hazard modeling, engineering simulation, reconnaissance studies, to developing predictive surrogate models using observed and simulated data. The following are some examples of machine learning applications in the areas of natural hazards.

- In earthquake engineering, ML has been used for seismic wave discrimination and early earthquake warning (Li et al., 2018b), ground-motion simulation (Alimoradi and Beck, 2015), pre-earthquake vulnerability screening (Yu et al., 2019), post-earthquake damage detection from imagery data (Bai et al., 2017; Cooner et al., 2016), and seismic damage and risk analysis of structures (Gidaris et al., 2015). Deep-learning approaches have also been shown capable of estimating earthquake magnitude from recorded raw seismic signals (Mousavi and Beroza, 2020). Recently, a comprehensive review of the current and potential applications of AI/ML to a broad range of research in earthquake engineering has been provided by Xie et al. (2020);
- Landslides, induced by earthquakes or heavy rainfall, are another natural hazard phenomenon that has attracted much attention (Dou et al., 2014). Machine-learning methods such as SVM, ANN, Kriging, Random Forest, etc., have been employed to predict the susceptibility of a landslide based on topographic, geological, and hydrological data (Goetz et al., 2015; Pham et al., 2016; Yao et al., 2008). More recently, deep convolutional neural networks have shown the potential for recognizing landslides using aerial and satellite imagery (Ghorbanzadeh et al., 2019);
- Flood is one of the most destructive natural hazards, which can cause massive damage to the built infrastructural systems and significant socioeconomic loss. Machine-learning methods have been shown to provide better insight for flood prediction and better predictive accuracy that outperform conventional modeling approaches (Abbot and Marohasy, 2014; Mosavi et al., 2018). Methods such as ANN, SVM, SVR, long short-term memory (LSTM), neuro-fuzzy, decision tree, etc., have been found effective for short- or long-term flood susceptibility and damage assessment (Darabi et al., 2019; Gizaw and Gan, 2016; Kim et al., 2016; Le et al., 2019; Resch et al., 2018). More recently, deep convolutional neural networks have been employed for regional flood susceptibility analysis using remote sensing images (Gebrehiwot et al., 2019; Li et al., 2019b; Wang et al., 2020b); and
- Hurricanes are another disastrous hazard that can cause significant damage to buildings and infrastructure systems. It has been shown that ML methods such as ensemble learning and bagging decision trees are capable of predicting wind-induced damages of individual buildings with better accuracy compared to HAZUS models (Subramanian et al., 2013). Methods such as random forest and logistic regression have also been employed to predict damage to residential structures due to hurricanes and high winds (Salazar, 2015). Deep learning has been applied to classify damages using post-hurricane aerial imagery (Kersbergen, 2018; Li et al., 2018a; Thomas et al., 2011).

The examples cited are merely illustrative examples of a wide range of possible applications of AI/ML to NHE, from hazards susceptibility analyses to post-disaster reconnaissance studies. Complementary to conventional numerical modeling and simulations, AI/ML can be employed to support a number of NHE tasks, such as characterization of the built, natural, and socioeconomic environments, enhancing understanding of hazard models, constructing data-driven response estimation models, assessing structural performance, and simulating recovery processes. Among the many challenges in applying data-driven AI/ML methods to NHE is the critical need in gathering, generating, and managing the data, as well as making the data readily usable for NHE modeling and simulations (Padgett et al., 2020)

22.3 SimCenter's Ongoing AI/ML Efforts

As noted, significant research efforts have been reported in applying ML methods to NHE. With the advances in computer hardware and the abundance of data, in the form of text, time-series signals, point clouds, and images that are being generated and made publicly available (Rathje et al., 2017), innovative applications of advanced ML technologies in NHE will undoubtedly continue to grow. Nevertheless, extracting meaningful information from such data and rendering the data useful for natural hazard modeling and simulations is labor-intensive, computationally demanding, and requires significant infrastructural investments. Another challenge is that data from public sources is often incomplete with missing information. Learning from available data, ML can potentially and effectively extract the relevant features and reconstruct the missing information, which are needed for engineering analyses and hazard modeling. As shown in Figure 22.1, one of the ongoing efforts at the SimCenter is to develop frameworks for natural hazards modeling and simulation, and to demonstrate the workflows from data acquisition to hazard/risk analyses and simulation. Machine learning can play a key role in the overall workflows for NHE modeling and analysis, particularly for regional-based simulations.

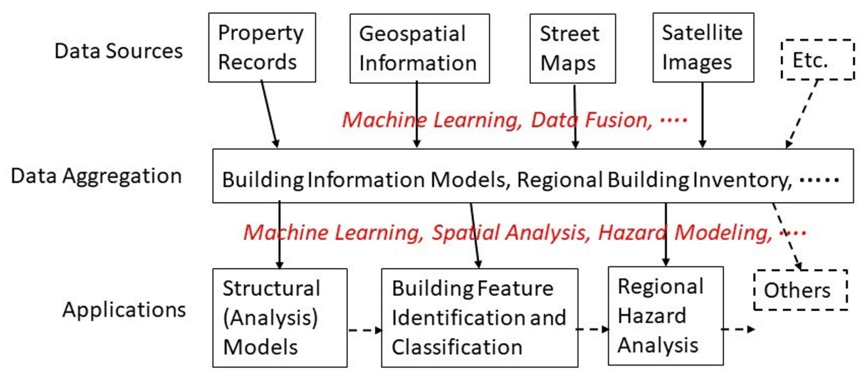


Fig. 22.1 Computational framework for natural hazards modeling and analysis: from data acquisition to simulations.

22.3.1 From Building Information Model (BIM) to Structural Analysis Model (SAM)

Widely adopted by the architecture, engineering, and construction professionals, building information modeling is defined as a process that involves the generation and management of a "shared digital representation of physical and functional characteristics of any built object [...] which forms a reliable basis for decisions," (ISO, 2016). The digital Building Information Models (BIMs) can be an ideal source of information for natural hazard analyses. For example, based on the data and information captured in a BIM, structural analysis models (SAM) can potentially be created for dynamic finite-element analysis of buildings under seismic or wind load conditions (Lu et al., 2020).

Converting BIM to SAM is not a trivial process, however, and requires advanced knowledge of computer-aided design, structural engineering, finite-element analysis, and practical experience. Manual conversion is an expensive and labor-intensive task, especially for large-scale regional simulations. To this end, SimCenter has initiated an effort to develop a framework to demonstrate the applicability of ML for bridging the gap between a BIM and a SAM.

The BIM-to-SAM framework is schematically shown in Figure 22.2. Information in BIM is first distilled into a vector representing the features of the BIM. These features are then used as the input to a neural network, which yields another vector that represents features of the corresponding SAM. Based on the generated features, a SAM can be constructed programmatically. The BIM and SAM can then be stored in a standard neutral file format, such as JSON, which is a data-interchange format that uses human-readable text to store and transmit data objects consisting of attribute-value pairs and array data types. It should be emphasized that the framework is designed primarily to illustrate the overall workflow and the tasks involved in generating SAM from BIM using the ML approach. Continuing research and development efforts are needed to generalize the methodology, from the current effort on modeling of structural walls and frames to other structural components and systems. Demonstrations of the framework can be found in SimCenter's GitHub repositories (*NHERI-SimCenter/BIM2SAM.AI* [98]; *SWIM* [53]).

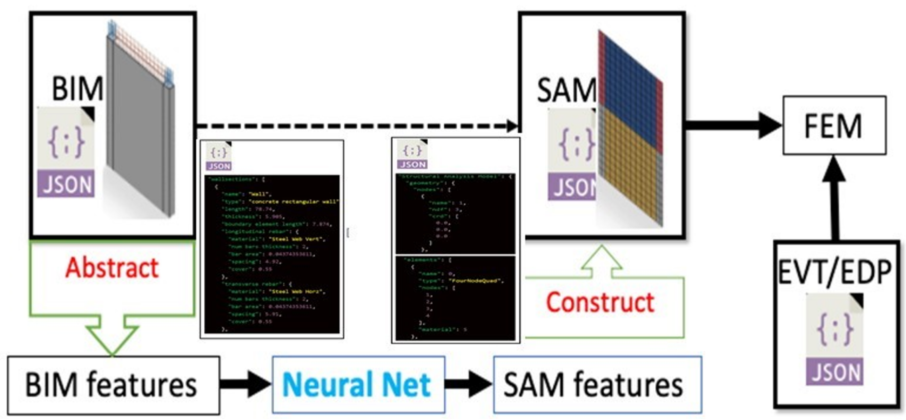


Fig. 22.2 BIM to SAM framework.

22.3.2 Building Features Extraction and Characterization—Soft-Story Identification

Rapid and accurate identification of building features and structural integrity is crucial in evaluating the seismic vulnerability of buildings city-wide. Structural irregularities due to abrupt variations of story stiffness, such as a soft-story building, increase the likelihood of damage to a building during a moderate or severe earthquake. Identifying and retrofitting soft-story buildings in a city represents a vital effort in earthquake preparedness and mitigation; however, soft-story building identification at a city-scale is a labor-intensive and time-consuming process. Visual screening is often the first step in the identification process. For instance, FEMA 154 (ATC, 2015) provides a screening methodology to evaluate the seismic safety of buildings mainly based on the visual cues of the building exteriors and to determine whether a building requires more detailed evaluation. The purpose of this effort is to design a workflow that can be applied to rapidly identify potential soft-story buildings on a city scale.

The availability of street-view images and recent advances in computer vision and ML techniques make the automated screening of soft-story buildings a viable proposition. Structural attributes—e.g., frame types, geometric irregularities, and foundation conditions—can often be identified from certain observable visual cues. Many of such visual cues—such as a garage with relatively narrow wall widths on both sides of the garage opening, a large opening at the ground floor level, a story with less wall area or fewer columns than other stories, etc.—are used by trained professionals to rapidly screen for potential soft-story buildings. To date, the visual screening process remains labor-intensive as it requires collecting a large amount of image data of the buildings, and subjective interpretations can be error-prone. An automated process that is able to extract building features and identify a specific type of structural vulnerability by interpreting the relevant features would be beneficial to the rapid screening of a large number of buildings in a city or a region.

As a demonstrative workflow on visual screening of building features, the SimCenter has developed an automated process using a ML approach to rapidly identify buildings that potentially have soft-story characteristics (Yu et al., 2019, 2020). Using the data available for the study, five cities in California, namely, Santa Monica, Oakland, San Francisco, San Jose, and Berkeley, were selected. As shown in Figure 22.3, the first step of the workflow process is to collect street view images of the buildings (e.g., using Google Street View Static API) based on the addresses in each city obtained from the official city website. A training set is then developed with annotations to train the soft-story classification model using convolutional neural networks, such as the Inception (Szegedy et al., 2017, 2016) and ResNet (He et al., 2016) architectures. The trained classification model can then be used to identify potential soft-story buildings in the city of interest. Two specific novelties of the workflow are worth mentioning. First, as a large number of images need to be labeled as having a soft story or not, a semi-automated annotation process has been developed to minimize the manual labeling effort. Second, as shown in Figure 22.3, a class activation map (Zhou et al., 2016a) is employed to highlight the regions (that are likely to correspond to a soft-story) and to help interpret the predictive results.

22.3.3 Regional-Scale Natural Hazard Risk Management

Many environmental and geographical models, such as those used to understand regional hazards and those used in climate studies, often rely on spatially distributed data as input that are known to be scarce and imperfect. Generally, there is a lack of knowledge about the distribution pattern of the variables over the spatial area in the region. In other words, spatial uncertainties exist because of noise, incompleteness, and the uncertainties in the data. For regional risk analyses, spatial uncertainties in the input data, such as the hazard intensities or asset attributes, can propagate into model predictions across the whole region. To quantify such uncertainties, SimCenter has developed a Spatial Uncertainty Research Framework, SURF (Wang, 2019). The framework has been implemented as a Python package for performing spatial uncertainty analysis using random fields and neural networks. Given a spatially scattered dataset, SURF learns the variation patterns in the dataset and infers missing attributes and values where there observations are absent.

For regional hazard evaluation, an important first step is to collect the relevant information of existing buildings to establish an inventory of buildings in the region. Attributes of a building, such as the number of stories, the year of construction, structure type, occupancy type, and

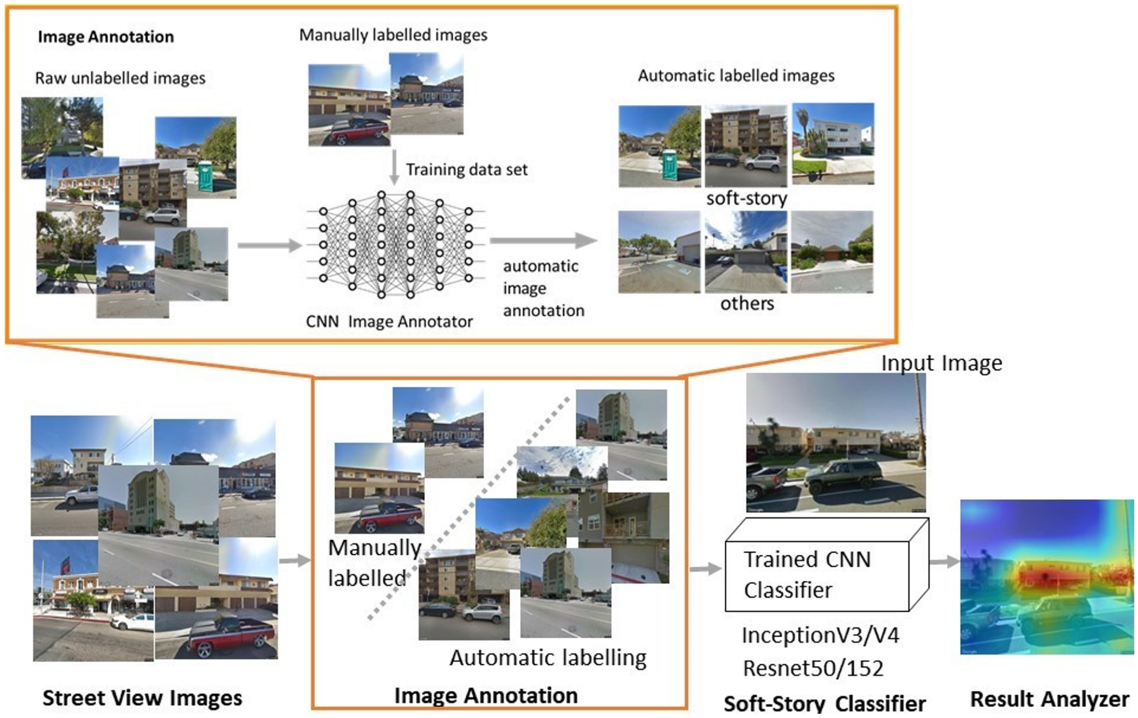


Fig. 22.3 A workflow framework for soft-story identification.

others, are important parameters to assess the effects of natural hazards on the building structure. Many of these textual building attributes are available as public information, e.g., tax assessor records. That said, the building record is often incomplete with missing data. Furthermore, key attributes (e.g., roof types) needed for specific hazard assessment studies are often not recorded. With the availability of street view and satellite images and other open data sources, recent advances in computing technologies, including computer vision, geospatial analytics, and ML, can help bridge the information gaps for regional hazard modeling and risk analysis. To this end, the SimCenter has initiated a building information modeling project, BRAILS (Building Recognition using AI at Large Scale) (Yu et al., 2019). BRAILS employs ML/DL methods to help create building inventories at the city or regional scale.

As illustrated earlier, DL methods can be applied to screen seismically vulnerable buildings by capturing the visual cues of a building with geometric irregularities (Yu et al., 2020). Similarly, many building attributes, such as structural and material types, can be "learned" and identified using the observable cues from building images via ML. For instance, CNN is shown to be effective in classifying roof shapes (flat, gabled, or hipped) using satellite images (Yu et al., 2020). In addition to extracting attribute information using individual building images, ML can also infer missing building information using geospatial patterns in the region of interest. To develop a geospatial learning module, the aforementioned Python package (SURF) is encoded as a part of the BRAILS framework, which has been designed for regional hazard analysis (Wang, 2019).

Figure 22.4 shows the BRAILS workflow for the building inventory development process for regional hazard risk analysis (Wang et al., 2020b). The workflow infers building information from multiple sources (e.g., tax assessment, street view images, satellite images, etc.) to form a large building inventory. For example, in one of the testbeds, the coastal cities of Atlantic County in New Jersey are selected to assess the effects of high wind and hurricanes on the region's buildings. The data sources included the tax assessor records, Microsoft's Building Footprints dataset, and street view and satellite images obtained using Google Maps API. Textual data from tax assessor records and the information inferred from images using convolutional neural networks are aggregated or "fused" to establish the building information needed by the damage models and fragility functions defined in FEMA's HAZUS MH2.1 (FEMA, 2011a). The source code, the data, the pre-trained CNN models, and the building inventory database are available at SimCenter's repository (Yu et al., 2019). The key significance of this effort is to create an AI/ML-based workflow from data acquisition, building information model development, and hazard modeling to spatial hazard risk analysis.

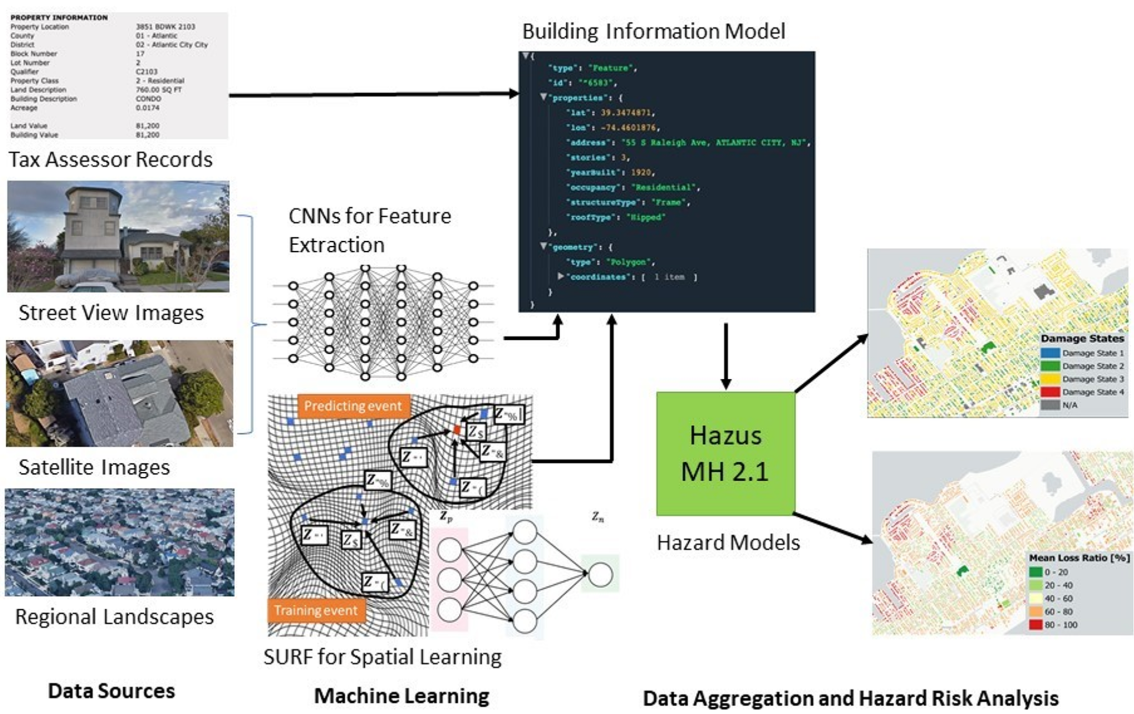


Fig. 22.4 A workflow framework for regional hazard modeling and analysis.

22.4 Research Challenges and Opportunities

Applications of AI/ML to NHE are numerous in that almost all facets of NHE can potentially benefit from AI/ML. For instance, instead of traditional physics-based representations, material constitutive models can be represented using ML models (such as SVR, ANN, GPR, or DL), which can self-adapt and "learn" with new data. At the large scale, ML can be (and has been) used to understand human behaviors (such as evacuation), social structure (such as the population residing in an area), and environmental and hazard conditions (such as wind intensity and seismicity) that could have implications on regional NHE decision-making processes.

While the field of AI/ML in NHE is too broad to enumerate, this report presents three general issues that could enhance the adoption and facilitate the development of AI/ML in NHE. First, an

AI/ML model should be able to provide documentation of the outcomes to help build the users' trust and confidence in the model. Second, while an ML model, once trained or built adaptively with new information that can be incorporated as a "surrogate" and used efficiently in a larger simulation or optimization setting, the limitations and the uncertainties that can potentially propagate to the system need to be addressed. Lastly, as significant amounts of relevant and labeled data are necessary to build even the baseline AI/ML models in support of NHE, the data issues from acquisition to management require new approaches and a collaborative community effort to enable progress and advancements in this field.

22.4.1 Explainable and Physics-Informed AI/ML

Early AI research such as knowledge-based expert systems have inherent inference mechanisms that can be used to explain how a system leads to a conclusion based on the rules and knowledge executed. For instance, incorporated with handcrafted rules and first principles, SACON (Bennett et al., 1978)—an expert consultant system for structural analysis that was built upon the EMYCIN framework (Van Melle et al., 1984)—could not only recommend an appropriate analysis class for solving a given engineering problem but also provide associated explanations for the specific recommendation. While DL methods (such as multi-layered neural networks) have been shown to be superior and capable of solving many complex and difficult problems where it is infeasible to write down the explicit rules, they are often criticized as black-box models that lack transparency. It is not always clear how an ML model reaches a decision. Developing ML models that can provide contextual explanation, interpretation, and induction of the model is challenging; thus, it is exceedingly important to validate the models and justify their use with hindcasting-type studies (DARPA, 2016; Rudin and Radin, 2019; Samek et al., 2019).

Artificial intelligence and machine-learning models that are unable to adequately answer questions on how a problem is solved and why a conclusion is made may suffer trust and confidence issues in practice. The users may hesitate to deploy these models and utilize their results. Naturally, ML-based models that lack the ability to explain their output and interpret their own performance will likely encounter skepticism and slow adoption in NHE.

Much active research effort is now underway that aims to enhance our understanding of why AI/ML techniques work well in practice, what classes of problems AI/ML are capable of solving, and which AI/ML algorithms are particularly effective in solving certain types of problems. The advancements in attention-based methodologies, which mimic human cognition and intuition, have enabled tools to recognize the important features of a trained model and highlight the results generated by the model (Kafle and Kanan, 2017; Nakka and Salzmann, 2018; Xu et al., 2015; Zhou et al., 2016a). For example, the highlighted results could help a user to gain insights about the ML-trained model, trace the features involved in the correct (or incorrect) identification of the results, and assess the relevance of the information that propagates through the model.

Graph-based methodologies that are able to incorporate domain concepts and features into ML models have also attracted much attention (Baru, 2017; Hamilton et al., 2017; Koller and Friedman, 2009; Wu et al., 2020). For instance, graph neural networks are now widely used in bridging ML methodologies with modeling of engineering problems (Park and Park, 2019; Seo and Liu, 2019). The feature information embedded in graph-based models can help construct interpretable models, enhance the reasoning process, and ensure the quality of the generated results.

The ability to interpret the results and to explain the trained model using domain terminologies is important to encourage the adoption of ML methods. Traditionally, engineering models are developed using fundamental principles of physics or other fields of science and statistically validated with experimental data and empirical evidence. For obvious practical reasons, engineering models are often simplified to lessen the complexity of physical phenomena and to allow the selection of model parameters that are measurable. On the other hand, ML models constructed using data can often perform well even for complex problems; but as discussed above, their inferences are hard to explain, and the models are difficult to generalize. One common approach is to evaluate a ML model based on qualitative interpretation and quantitative correlation between the behavior of the trained ML model and the physical system. For example, Kratzert et al. (2019) show the interpretation of LSTM (long short-term memory) for a rainfall-runoff model by examining the outputs of the LSTM network based on the domain knowledge about the annual variation of the hydrological pattern and the correlation between the memory cells of the LSTM network with the physical state of the hydrological system. Linking the relationships between the ML model and the physical problem is important to realize the significance of the outputs and gain confidence over the results.

Recently, much research effort has been dedicated to taking advantage of first-principle domain knowledge and ML methodologies by combining the data and the domain features when training an ML model (Willard et al., 2020). The research typically focuses on two basic questions: (1) to what extent should first-principle knowledge be embedded in an ML model?; and (2) how should the features of the physical system and the first principles be incorporated in the training process? For instance, using examples in turbulence modeling and crystal plasticity, Ling et al. (2016a) discussed how symmetric and invariance properties inherent in physical systems could be incorporated and learned by ML algorithms such as random forests and deep neural networks. Another approach is to train the ML models in accordance with physical laws, e.g., which are described by differential equations (Raissi et al., 2019). One advantage of a physics-based ML model is that it may be possible to assess the uncertainties of the model parameters using data collected from sensor measurements on the physical systems (Zhang et al., 2019a). One other approach is to augment an ML method with physics-based features such that these features penalize inconsistencies with the laws of physics (e.g., conservation of momentum), e.g., using an appropriately devised loss function during the training process (Jia et al., 2020). This physics-guided approach has been demonstrated for simulating the temperature profile of a lake using sparse observation data while achieving high-prediction accuracy. Methods that incorporate first-principle knowledge into the training of ML models could provide the basis needed for verification and validation and ensure that the models are consistent with physical systems.

Explainability and interpretability of ML models are important for their adoption in NHE. Further studies are needed to set the foundations in this field. In a broader context, research in explainable ML models advocates fruitful synergy and provides ample opportunities for collaborations between AI/ML researchers and domain experts in NHE.

22.4.2 Surrogate Modeling

Particularly in the last decade, the number of surrogate modeling studies involving data-driven methods has seen a steady increase in NHE. Despite differences in the ML methods utilized, these efforts share a common goal. They are aimed at creating computationally efficient alternatives to procedures that are otherwise too resource-intensive for the considered application (which, typically, requires large-scale simulations as in regional-level risk assessment). These studies range from surrogate model development efforts for peak or time-dependent storm surge predictions based on high-fidelity hydrodynamic model outputs (Jia et al., 2016) to deck unseating fragility of bridges subjected to hurricane-induced wave loading developed using the results of nonlinear fluid-structure interaction simulations (Ataei and Padgett, 2015). However, the concentration of these studies across the sub-domains of NHE is not uniform. Most surrogate modeling studies focus on flood forecasting. In some areas, such as in earthquake engineering, the research is just beginning, whereas surrogate models to be applied in geotechnical engineering are practically non-existent.

Virtually all of the existing data-driven surrogate modeling studies in NHE rely on simulated data. Hence, in the process of creating computationally-efficient representations of processes, the use of surrogate models may introduce epistemic (model) uncertainties and bias, depending on the ability of the training data to cover the entire domain of the modeled process and the capability of the ML method used to capture the underlying mechanisms from this data without overfitting. Model uncertainties are significant for many NHE problems (Gokkaya et al., 2016), yet limited attention is being paid to the uncertainty associated with data-driven surrogate models and the effects of the uncertainties to the overall system. This may be due to the long-standing research gap in this area.

In recent years, key advancements were made in uncertainty quantification for neural network-based learning methods. As a direct outcome of these developments, various accepted practices continue to become public. The confidence interval determination methods summarized by Kabir et al. (2018) provides a snapshot of the procedures for determining uncertainties associated with neural network models. Many successful implementations of the ideas presented in this work exist in finance, medicine, and control systems applications. Bayesian Neural Networks (Blundell et al., 2015) are another alternative that enables the assessment of uncertainties in neural network models. McDermott and Wikle (2019) demonstrated that the practical implementation of Bayesian Neural Networks to different network architectures, such as recurrent neural networks, is possible.

So far, translation of the recent progress in uncertainty quantification for neural network-based methods and ML models in general to surrogate modeling of NHE processes remains a largely unexplored territory. Given that the computational foundations of such studies are currently being established, ample opportunities remain open for further research.

22.4.3 Data Generation and Management

Data plays an indispensable role in NHE and ML. There are at least three categories of information commonly employed in NHE: assets of the built infrastructures, models of the natural hazards, and geospatial information about the built, natural, and socioeconomic environments. For instance, in addition to the physical, architectural (such as footprints, exterior walls, roof shapes, openings, etc.) and structural (such as materials and framing systems) information, other attributes of buildings such as year built and property values may contribute to the evaluation of structural integrity and affect the decision making on retrofitting and repair strategies. Environmental information such as wind speed and direction, weather conditions, seismicity, etc., may be required for the hazard simulation models. In addition, geospatial data/metadata about the terrain, vegetation, and landscapes, proximity to water bodies, nearby highways and lifeline networks are essential to regional hazard evaluation. Even socioeconomic data—such as residential, commercial, and industrial zonings, tax assessments, and real estate values— play a part in regional impact, risk analyses, and emergency planning.

Different datasets and different types of data are needed for different hazard models and for the different objectives and purposes of an NHE evaluation. A typical data collection process involves identifying available data from public and private sources, getting access to the data, and integrating the data in a meaningful way that is suitable for the tasks at hand. Gathering high-quality and well-organized useful data is often the most time consuming and challenging task in NHE research. Indeed, the data issue has often been considered one of the main impediments in NHE studies.

Natural hazard engineering, particularly at a regional scale, requires a wide variety and large volume of data. Many ongoing data initiatives exist, such as those towards developing digital twins for smart cities (Day, 2019; Lehner and Dorffner, 2020; NIC, 2017; Schrotter and Hürzeler, 2020). While such efforts, which often involve computer vision, sensing, and ML technologies, could potentially help create useful digital data and providing geometric descriptions of the built environment in a city or a region in the future, many significant research challenges remain in gathering and creating the data needed for NHE studies as well as in managing and facilitating access to the data. Presently, NHE researchers rely heavily on publicly accessible datasets, such as building inspection files and tax assessor records. To date, many of such data are collected and gathered manually and entered manually into databases (with tools such as Excel, Access, etc.), often with subjective judgments and interpretations. Despite the best intentions and efforts from all parties involved, erroneous entries and missing information are common. Information specific to NHE, such as material types, roof type and geometry, and building configuration, are often not recorded. ML can be a valuable tool to generate and fill in some of the data needed to support NHE applications.

For certain problems and data types, an ML model can be developed and applied to enhance data quality, augment existing datasets, and create new datasets useful for NHE applications. For example, ML methods, combined with engineering simulations, can potentially be applied to cross-check field measurement data. Methods such as PCA, SVR, and recurrent neural network (RNN) have been shown capable of identifying erroneous measurements and reconstructing vibration signals (Jeong et al., 2019; Kerschen et al., 2005). Kriging has been combined with statistical-based methods to estimate wind speeds and extrapolate information at locations that are not physically measured (Xu et al., 2014). Historical (analog) seismic records can be converted to useful digital seismic signals using DL (Wang et al., 2019b). Machine learning has the potential to ensure data quality and provide estimates (or predictions) on some of the missing attribute data that are critical to NHE simulations. While developing ML models often requires a large amount of labeled data, active and assistive learning strategies can help alleviate some of the time consuming and laborious annotation efforts and build useful ML models (Joshi et al., 2009; Wong et al., 2019; Yu et al., 2020).

One of the main challenges in regional hazard analysis is to establish an inventory of assets and their properties over a geospatial area of interest. With advances in computational geometry, computer vision, and ML, street view, satellite, and aerial images are tremendous data sources that can be used to acquire 2D and 3D building geometry metadata and to extract other valuable information about the buildings and their surrounding environment. For instance, semantic segmentation and polygonalization of aerial images have produced over 125 million building footprint geometries in the U.S. (https://github.com/microsoft/USBuildingFootprints). Similar techniques can be used to help identify other building attributes, such as garages, windows, number of floors, structural materials, and other meaningful metadata. Depending on the level of detail (LoD) required for a specific NHE application, different computational algorithms and AI/ML methodologies have been proposed to construct 3D building models. For instance, 3D block models (consisting of building envelope and roof geometry) can be extruded from footprint data and ML edge extraction techniques (Maninis et al., 2017; Yu et al., 2017). Such 3D block models could be useful for low-fidelity NHE simulations or prescriptive code-based analyses. Many active ongoing research efforts, utilizing a combination of computational geometry algorithms, ML methods, and rule-based inferences that incorporate design and planning principles are underway that aim to construct detailed building information models (Chen et al., 2018; Martinović et al., 2015). The generated models with detailed descriptions of buildings—including materials, windows and openings, roof shapes, and chimneys—can be used for conducting high-fidelity computational simulations such as nonlinear structural analyses and CFD studies. In short, AI and ML can find ample applications to help build data inventory necessary for NHE modeling and analyses, as well as for training and testing ML models.

Numerous current efforts have focused on collecting and generating data for individual simulation applications and for ML model development. The challenges in achieving tangible advances in NHE go well beyond the abilities of individual researchers or even organizations and require well-coordinated community efforts. The significant impact of publicly available large datasets—such as ImageNet (Deng et al., 2009) and COCO (Lin et al., 2014)—is critical in advancing the fields of computer vision and ML. Within the NHE domain, open-source tools, such as OpenSees (McKenna, 2011) and OpenFoam (Chen et al., 2014), have greatly facilitated research and developments in earthquake and wind engineering. The current community-driven initiative in making NHE data accessible on the DesignSafe CyberInfrastructure platform will help expedite progress in this field (Rathje et al., 2017). To promote, encourage, and facilitate the adoption of AI and ML research in NHE, a community-based platform that is specific to the NHE domain would be useful, analogous to the "model zoo" established in the ML community (see https://github.com/collections/ai-model-zoos) that allows publishing and sharing of ML models and datasets.

Even when researchers and organizations are willing to share and make their data and models available publicly, the data objects (i.e., the data and the models) need to be "Findable, Accessible, Interoperable and Reusable" (FAIR) (Wilkinson et al., 2016). Metadata constructed using standardized representation, authorization, and authentication protocols can play a key role in improving on the FAIR quality of data. Machine-learning and NHE applications have to "understand the data" in order to use it for training and engineering simulations. Metadata and domain ontologies will enable data shareability, interoperability, and usability, and advances in ML and NHE. For instance, BioPortal, enabled with an ontology authoring and accessing tool Protégé, has provided researchers and interested users access to a library of biomedical ontologies and terminologies, that, in turn, has facilitated a broad spectrum of medical research activities (Whetzel et al., 2011). Semantic web technologies—such as RDF, OWL, SPARQL, and other tools (see https://www.w3.org/standards/semanticweb/fordetails)—can help define, publish, link, and query data objects. Recently, knowledge graphs, a representation for capturing data objects and their relations describing a domain or a field of study, have been proposed to manage and to facilitate retrieval of unstructured data objects, such as video, images, audio, and text, that do not fit neatly into the tabular structure of relational databases (Bonatti et al., 2018; Paulheim, 2016; Reinanda et al., 2020). The traversable graph representation allows search and access to different data objects and enables the fusion of information from different sources. Knowledge graphs have also been shown great promise to integrate with ML (Lin et al., 2018).

Developing and managing data, models, and knowledge bases is an expensive endeavor. To alleviate some of the burdens on individual communities or organizations, Open Knowledge Network is one recent movement that attempts to build an open national-scale domain-agnostic infrastructure accessible to a broad community (Baru, 2017). The open infrastructure has the potential to drive innovation across science and engineering and allows data sharing within and outside a specific domain such as NHE.

In summary, data is at the core of ML methods and many aspects of NHE. To enable advances in AI/ML and NHE, the availability of large volumes of high-quality and relevant data is essential. Using existing data and knowledge, ML methods can, at times, build models that can help generate new (possibly labeled) data needed to train ML models and to support NHE applications. A common open platform that can attract a broad-base community involvement will be useful to promote collaborations and encourage the sharing of data and models. The adoption of semantic technologies will potentially further enhance data accessibility and model interoperability, and further facilitate the research and development as well as deployment of AI/ML in NHE.

22.5 Summary and Discussion

Artificial intelligence and machine learning is poised to bring significant changes to scientific research and engineering practice. Although the potential applications of AI/ML in NHE is enormous, the field is still in its infancy. This report aims to provide a glimpse of the possibilities of applying AI/ML technologies in NHE, to encourage collaborations between NHE and AI/ML researchers, and to engender further research and developments in this promising field. However, many open questions and barriers remain that may deter the pace of progress and the adoption of the technologies in practice.

First, just like with any new technological advancement, unrealistic expectations by the NHE researchers and practitioners about the applicability of AI/ML technologies should be avoided. While research and exploration of AI/ML and its applications in NHE are encouraged, their misuse and flawed developments can quickly draw disproportionate criticisms within the NHE community and hinder advancements in the field. While statistics-based measures—such as root-mean-square-error, precision, recall, F1 scores, mean IoU, and other metrics—are commonly used to assess ML model accuracy, proper verification and validation of their results based on engineering knowledge, and professional judgment remain valuable. It should be cautioned that an accurate DL model does not necessarily imply a good model in practice (Mignan, 2019). Furthermore, a model trained using a dataset (say, obtained in a residential neighborhood) may not necessarily be generalized to data that differs from the training set (say, from a commercial area), even within the same domain of interest. In other words, AI/ML does not diminish the importance of the fundamental knowledge and professional know-how in NHE.

Additional research is needed to develop a broad spectrum of evaluation techniques that include standards, benchmarks, and testbeds. Most importantly, community engagement is essential to guide and evaluate progress.

Advancements in this field require a strong and well-trained community of researchers from both AI/ML and NHE. The demands for developing such a community entail educating a new generation of NHE researchers and practitioners who become well-versed in AI/ML. Researchers in NHE should acquire a knowledge of AI and ML methods and understand the applicability of the technologies and their limitations. Synergistic and genuine collaborations between NHE and AI/ML researchers are necessary in order to foster new and innovative solutions as advances in AI/ML will continue to grow rapidly in years to come.

22.6 Relevant AI/ML Software

With the growing interests and importance of AI/ML in academic research and commercial developments, universities and companies have built a number of frameworks and tools that are now used by researchers and practitioners to build and execute AI/ML models. Both Matlab and Mathematica, the computational tools commonly used in education settings, have ML and DL toolboxes. Cloud service vendors, such as Amazon AWS, Google Cloud, Microsoft Azure, IBM, Oracle, and others, all have ML platforms that support end-to-end model training and executing (scoring) functions.

In addition to commercial platforms, examples of open ML frameworks and tools publicly available include:

Scikit-learn

Originally developed as a Google Summer of Code project, *Scikit-Learn* [95] is a free software ML library that features a collection of statistical-based ML algorithms for classification, regression, and clustering, such as support vector machines, random forests, k-means, decision trees, and numerous others. The library is designed to interoperate with NumPy and SciPy, Python's numerical and scientific libraries.

CAFFE

Originally developed at UC Berkeley, *CAFFE* [91] (Convolutional Architecture for Fast Feature Embedding) is an open-source DL framework, written in C++ with a Python interface, featuring CNN, RCNN, LSTM, and other deep neural networks and specializing in computer vision and image classification and segmentation. It is no longer being actively developed as CAFFE2 was merged into PyTorch in 2018.

TensorFlow

Originally developed by the Google Brain team, *TensorFlow* [96] is a free and open-source software library for high-performance numerical computation and dataflow and differentiable programming. Its flexible architecture allows for easy deployment of computation across various platforms (CPUs, GPUs, and TPUs). TensorFlow is commonly used to develop ML applications such as deep neural networks.

PyTorch

Primarily developed by Facebook's AI Research Lab, *PyTorch* [94] is an open-source machine learning library (based on the Lua-Torch library) with Python and C++ interface, featuring accelerated tensor computing on GPU and deep neural networks built on automatic differentiation system. PyTorch also supports CAFFE2, a version of CAFFE. PyTorch has been used for applications such as computer vision and natural language processing.

CNTK

Developed by Microsoft Research, Microsoft Cognitive Toolkit (*CNTK* [92]) is an open-source toolkit for distributed DL with parallelization across multiple GPUs and servers. The CNTK describes neural networks as a series of computational steps via a directed graph and allows users to easily realize and combine popular model types such as feed-forward DNNs, convolutional neural networks (CNNs), and recurrent neural networks (RNNs/LSTMs).

Theano

Developed at the University of Montreal, *Theano* [97] is a Python library and optimizing compiler for manipulating and evaluating mathematical expressions efficiently on either CPU or GPU architectures, and supports ML application developments.

Keras

Developed as part of the research project ONEIROS (Open-ended Neuro-Electronic Intelligent Robot Operating System) at Google, *Keras* [93] is an open-source neural network library written in Python. It offers a higher-level, intuitive set of abstractions that make it easy to develop DL models regardless of the computational backend used. It is capable of running on top of TensorFlow, Microsoft Cognitive Toolkit, R, Theano, and other platforms. Keras is supported in Tensorflow's core library.

Note that all of these tools are publicly available. Additionally, a large number of ML and DL models developed using the open-source frameworks can be found at `https://github.com/collections/ai-model-zoos`.

Part VI
Appendix

Appendix A
List of Software Tools

The tables in this appendix were prepared to provide an overview of a few important features of the tools mentioned in each chapter. The presented information is meant to help researchers compare the available tools and see which one fits their needs.

The type of license and supported platforms are based on the available descriptions and data on each software's website. An empty license means that the developers have not provided that information; it does not necessarily mean that the software is freeware. Even though applications with an open source code could often be compiled on all three platforms considered here, the information in the tables corresponds to their availability for typical usage. That is, if there are pre-built binaries available and typical users would download those binaries, then the information in the tables refers to the platforms supported by those binaries.

Ticks in the DesignSafe column identify applications that are either available in the Workspace on the DesignSafe website or they can take advantage of DesignSafe resources by establishing a secure remote connection to the service.

The identification of certain commercial systems and research tools in the tables does not imply recommendation or endorsement by the SimCenter or the academic institutions of contributing authors. Nor does such identification imply that those products are necessarily the best available for the task.

The abbreviations used in the tables are listed in tables A.1 and A.2.

Table A.1 Abbreviations of license names used in appendices.

	Full license name
MPL 2.0	Mozilla Public License 2.0 (MPL 2.0)
LGPLv2	GNU Lesser General Public License v2 (LGPLv2)
GPL	GNU General Public License (GPL)
NA	NA
CeCILL-2.1	CEA CNRS Inria Logiciel Libre License, versio...
Other/Proprietary	Other/Proprietary License
GPLv2+	GNU General Public License v2 or later (GPLv2+)
BSD	BSD License
OSI Approved	OSI Approved
LGPL	GNU Library or Lesser General Public License ...
GPLv3	GNU General Public License v3 (GPLv3)
MIT	MIT License
AGPLv3	GNU Affero General Public License v3 (AGPLv3)
Apache Software	Apache Software License
Other	Other
Free for non-commercial use	Free for non-commercial use
CC-BY-NC-ND	Attribution-NonCommercial-NoDerivs (CC-BY-NC-ND)
LGPLv3	GNU Lesser General Public License v3 (LGPLv3)
Public Domain	Public Domain
Free For Educational Use	Free For Educational Use

Table A.2 Abbreviations of operating system names used in appendices.

	Operating System
Win	Windows
Mac	MacOS
Lin	Linux

Table A.3 Introduction

Name	License	Platforms	Prog. Lang.	DesignSafe
ADCIRC	NA	Mac/ Win/ Lin	Fortran	✓
BRAILS	BSD	Mac/ Win/ Lin	Python	-
EE-UQ	BSD	Mac/ Win/ Lin	C++	✓
GEOCLAW	BSD	Mac/ Win/ Lin	-	✓
HydroUQ	BSD	Mac/ Win/ Lin	C++	-
OpenFOAM	GPLv3	Mac/ Win/ Lin	C/ C++	-
OpenSees [1]	BSD	Mac/ Win/ Lin	C++	✓
PBE [2]	BSD	Mac/ Win	-	✓
PELICUN	BSD	Mac/ Win/ Lin	Python	-
R2DTool	BSD	Mac/ Win	C++	✓
SURF	BSD	Mac/ Win/ Lin	Python	-
WE-UQ	BSD	Mac/ Win	C++	✓
quoFEM	BSD	Mac/ Win/ Lin	C++	✓

[1] Finite-Element based
[2] Analyze individual buildings

Table A.4 Hazards: Earthquake - Ground Shaking

Name	License	Platforms	Prog. Lang.	DesignSafe
AWP-ODC	BSD	Lin	C	-
CyberShake	BSD	Lin	-	-
EE-UQ	BSD	Mac/ Win/ Lin	C++	✓
EvW [7]	BSD	Mac/ Win	C++	-
HAZ	GPLv3	Win	Fortran	-
Hazus 4.2 [1,2]	-	-	-	-
MDOF [7]	BSD	Mac/ Win	C++	-
NSHMP-Haz	Public Domain	Mac/ Win/ Lin	Java	-
OpenQuake [3]	AGPLv3	Mac/ Win/ Lin	Python	-
OpenSHA	Apache Software	Mac/ Win/ Lin	Java	-
OpenSees [6]	BSD	Mac/ Win/ Lin	C++	✓
PBE [5]	BSD	Mac/ Win	-	✓
PGT [7]	BSD	Mac/ Win	C++	-
R-CRISIS	Apache Software	Win	-	-
R2DTool	BSD	Mac/ Win	C++	✓
S3HARK [7]	BSD	Mac/ Win	C++	-
SW4 [4]	LGPLv2	Lin	C++/ Fortran	-
TFT [7]	BSD	Mac/ Win	C++	-
The Broadband Platform	Apache Software	Lin	Fortran/ Python	-
smelt	BSD	Mac/ Win/ Lin	C++	-

[1] HAZUS MH only
[2] Regional level
[3] Regional analysis
[4] Finite-Difference based
[5] Analyze individual buildings
[6] Finite-Element based
[7] Educational Tool

Table A.5 Hazards: Earthquake - Surface Fault Rupture

Name	License	Platforms	Prog. Lang.	DesignSafe
ABAQUS [1]	Other/Proprietary	Win/ Lin	-	✓
FLAC [4]	Other/Proprietary	Win	-	-
LAMMPS	GPL	Mac/ Win/ Lin	C++	-
LIGGGHTS-PUBLIC [3]	GPLv2+	Lin	C++	-
LMGC90	CeCILL-2.1	Mac/ Win/ Lin	-	-
LS-DYNA [1]	Other/Proprietary	Win/ Lin	-	✓
OpenSees [1]	BSD	Mac/ Win/ Lin	C++	✓
PFC [3,5]	Other/Proprietary	Win	-	-
PLAXIS [1]	Other/Proprietary	Win	-	-
YADE [2]	-	Lin	C++	-
quoFEM	BSD	Mac/ Win/ Lin	C++	✓

[1] Finite-Element based
[2] Discrete Element Method
[3] Pseudostatic & dynamic analysis
[4] Finite-Difference based
[5] Distinct-Element Modeling Framework

Table A.6 Hazards: Earthquake - Soil Liquefaction

Name	License	Platforms	Prog. Lang.	DesignSafe
Cliq [1]	Other/Proprietary	Win	-	-
FLAC [3]	Other/Proprietary	Win	-	-
LiqIT [1]	Other/Proprietary	Win	-	-
Liquefy-Pro [1]	Other/Proprietary	Win	-	-
NovoLIQ [1]	Other/Proprietary	Win	-	-
OpenSees [2]	BSD	Mac/ Win/ Lin	C++	✓
PLAXIS [2]	Other/Proprietary	Win	-	-

[1] Simplified methods
[2] Finite-Element based
[3] Finite-Difference based

Table A.7 Hazards: Earthquake - Slope Stability and Landslides

Name	License	Platforms	Prog. Lang.	DesignSafe
ABAQUS [2]	Other/Proprietary	Win/ Lin	-	✓
FLAC [3]	Other/Proprietary	Win	-	-
LS-DYNA [2]	Other/Proprietary	Win/ Lin	-	✓
OpenSees [2]	BSD	Mac/ Win/ Lin	C++	✓
PLAXIS [2]	Other/Proprietary	Win	-	-
SLAMMER [1]	Public Domain	Mac/ Win/ Lin	Java	-
quoFEM	BSD	Mac/ Win/ Lin	C++	✓

[1] Newmark sliding block
[2] Finite-Element based
[3] Finite-Difference based

Table A.8 Hazards: Tropical Cyclone - Wind

Name	License	Platforms	Prog. Lang.	DesignSafe
EvW [1]	BSD	Mac/ Win	C++	-
MDOF [1]	BSD	Mac/ Win	C++	-
smelt	BSD	Mac/ Win/ Lin	C++	-

[1] Educational Tool

Table A.9 Hazards: Tropical Cyclone - Storm Surge

Name	License	Platforms	Prog. Lang.	DesignSafe
ADCIRC	NA	Mac/ Win/ Lin	Fortran	✓
CFD Notebooks [2]	BSD	Mac/ Win/ Lin	C++	✓
Clawpack	BSD	Mac/ Win/ Lin	-	-
Delft3D	-	Win/ Lin	-	-
FVCOM	Other	-	-	-
GEOCLAW	BSD	Mac/ Win/ Lin	-	✓
HydroUQ	BSD	Mac/ Win/ Lin	C++	-
OpenFOAM	GPLv3	Mac/ Win/ Lin	C/ C++	-
SLOSH [1]	-	-	-	-

[1] Surge hazard results available from NOAA
[2] Educational Tool

Table A.10 Hazards: Tsunami - Inundation

Name	License	Platforms	Prog. Lang.	DesignSafe
ADCIRC	NA	Mac/ Win/ Lin	Fortran	✓
CFD Notebooks [1]	BSD	Mac/ Win/ Lin	C++	✓
GEOCLAW	BSD	Mac/ Win/ Lin	-	✓
HydroUQ	BSD	Mac/ Win/ Lin	C++	-
OpenFOAM	GPLv3	Mac/ Win/ Lin	C/ C++	-
Tsunami-HySEA	CC-BY-NC-ND	-	CUDA	-

[1] Educational Tool

Table A.11 Response: Structural Systems

Name	License	Platforms	Prog. Lang.	DesignSafe
BFM [2]	BSD	Mac/ Win	C++	-
EE-UQ	BSD	Mac/ Win/ Lin	C++	✓
EvW [2]	BSD	Mac/ Win	C++	-
FEAP [1]	Other/Proprietary	Mac/ Win/ Lin	Fortran	-
FEAPpv [1]	Free for non-commercial use	Mac/ Win/ Lin	Fortran	-
LS-DYNA [1]	Other/Proprietary	Win/ Lin	-	✓
MDOF [2]	BSD	Mac/ Win	C++	-
OpenFOAM	GPLv3	Mac/ Win/ Lin	C/ C++	-
OpenSees [1]	BSD	Mac/ Win/ Lin	C++	✓
R2DTool	BSD	Mac/ Win	C++	✓
SWIM [2]	BSD	Mac/ Win	C++	-
WE-UQ	BSD	Mac/ Win	C++	✓
quoFEM	BSD	Mac/ Win/ Lin	C++	✓
smelt	BSD	Mac/ Win/ Lin	C++	-

[1] Finite-Element based
[2] Educational Tool

Table A.12 Response: Geotechnical Systems

Name	License	Platforms	Prog. Lang.	DesignSafe
ABAQUS [1]	Other/Proprietary	Win/ Lin	-	✓
Anura3D [4]	Other/Proprietary	Win	-	-
CB-Geo-MPM	MIT	-	C++	-
Claymore	MIT	Win/ Lin	-	-
DeepSoil [2,3]	Other/Proprietary	Win	-	✓
EE-UQ	BSD	Mac/ Win/ Lin	C++	✓
FEAP [1]	Other/Proprietary	Mac/ Win/ Lin	Fortran	-
FLAC [2]	Other/Proprietary	Win	-	-
LIGGGHTS-PUBLIC [5]	GPLv2+	Lin	C++	-
LS-DYNA [1]	Other/Proprietary	Win/ Lin	-	✓
OpenSees [1]	BSD	Mac/ Win/ Lin	C++	✓
PBE [7]	BSD	Mac/ Win	-	✓
PFC [5,6]	Other/Proprietary	Win	-	-
PGT [8]	BSD	Mac/ Win	C++	-
PLAXIS [1]	Other/Proprietary	Win	-	-
ProShake [2,3]	Other/Proprietary	Win	-	-
Real-ESSI	OSI Approved	Mac/ Win/ Lin	C++	-
S3HARK [8]	BSD	Mac/ Win	C++	-
Strata	GPLv3	Mac/ Win/ Lin	C++	-
TFT [8]	BSD	Mac/ Win	C++	-
Uintah [4]	MIT	Lin	-	-
quoFEM	BSD	Mac/ Win/ Lin	C++	✓

[1] Finite-Element based
[2] Finite-Difference based
[3] Transfer function
[4] Material point method
[5] Pseudostatic & dynamic analysis
[6] Distinct-Element Modeling Framework
[7] Analyze individual buildings
[8] Educational Tool

Table A.13 Response: Computational Fluid Dynamics - Wind

Name	License	Platforms	Prog. Lang.	DesignSafe
ANSYS Fluent	Other/Proprietary	Win/ Lin	-	-
CFD Notebooks [1]	BSD	Mac/ Win/ Lin	C++	✓
OpenFOAM	GPLv3	Mac/ Win/ Lin	C/ C++	-
Turbulent Inflow Tool	BSD	Mac/ Win	C/ C++	-
WE-UQ	BSD	Mac/ Win	C++	✓

[1] Educational Tool

Table A.14 Response: Computational Fluid Dynamics - Water

Name	License	Platforms	Prog. Lang.	DesignSafe
ADCIRC	NA	Mac/ Win/ Lin	Fortran	✓
ANSYS Fluent	Other/Proprietary	Win/ Lin	-	-
CFD Notebooks [1]	BSD	Mac/ Win/ Lin	C++	✓
COMSOL	Other/Proprietary	Mac/ Win/ Lin	-	-
GEOCLAW	BSD	Mac/ Win/ Lin	-	✓
H.E.L.Y.X.	Other/Proprietary	Win/ Lin	-	-
HydroUQ	BSD	Mac/ Win/ Lin	C++	-
IHFOAM	-	-	-	-
OpenFOAM	GPLv3	Mac/ Win/ Lin	C/ C++	-
S.T.A.R.-C.C.M.+	Other/Proprietary	-	-	-
SU2	LGPLv2	Mac/ Win/ Lin	C++/ Fortran/ Python	-
olaFlow	-	-	C/ C++/ Python	-

[1] Educational Tool

Table A.15 Performance: Buildings

Name	License	Platforms	Prog. Lang.	DesignSafe
CAPRA [3,4]	-	Win	-	-
Hazus 4.2 [5,3]	-	-	-	-
MAEViz	-	-	-	-
OpenQuake [6]	AGPLv3	Mac/ Win/ Lin	Python	-
OpenSLAT	GPLv3	-	C++	-
PACT [1,2]	-	Win	-	-
PBE [2]	BSD	Mac/ Win	-	✓
PELICUN	BSD	Mac/ Win/ Lin	Python	-
R2DTool	BSD	Mac/ Win	C++	✓
SP3 [1,2]	Other/Proprietary	Mac/ Win/ Lin	-	-

[1] FEMA P58 only
[2] Analyze individual buildings
[3] Regional level
[4] HAZUS based
[5] HAZUS MH only
[6] Regional analysis

Table A.16 Performance: Transportation Networks

Name	License	Platforms	Prog. Lang.	DesignSafe
Hazus 4.2 [1,2]	-	-	-	-
OpenQuake [3]	AGPLv3	Mac/ Win/ Lin	Python	-
PELICUN	BSD	Mac/ Win/ Lin	Python	-

[1] HAZUS MH only
[2] Regional level
[3] Regional analysis

Table A.17 Performance: Water, Sewer, and Gas Pipelines

Name	License	Platforms	Prog. Lang.	DesignSafe
EPANET [1]	Public Domain	-	-	-
GIRAFFE [1]	-	Win	-	-
PELICUN	BSD	Mac/ Win/ Lin	Python	-
WNTR [1]	BSD	Mac/ Win/ Lin	Python	-

[1] Potable water network

Table A.18 Performance: Electrical Transmission Substations and Lines

Name	License	Platforms	Prog. Lang.	DesignSafe
Hazus 4.2 [1,2]	-	-	-	-
MatPower	BSD	-	Matlab	-
OpenDSS [3]	BSD	Win/ Lin	C++/ Delphi/Kylix	-

[1] HAZUS MH only
[2] Regional level
[3] Electrical networks

Table A.19 Recovery: Communities

Name	License	Platforms	Prog. Lang.	DesignSafe
DESaster	GPLv3	Mac/ Win/ Lin	Python	-
IN-CORE	MPL 2.0	-	-	-

Table A.20 Recovery: Housing

Name	License	Platforms	Prog. Lang.	DesignSafe
DESaster	GPLv3	Mac/ Win/ Lin	Python	-

Table A.21 Cross-Cutting: Uncertainty Quantification

Name	License	Platforms	Prog. Lang.	DesignSafe
COSSAN-X	-	-	-	-
Dakota	LGPL	Mac/ Win/ Lin	-	✓
FilterPy	MIT	-	Python	-
MIT Uncertainty Quantification Library	-	-	-	-
OpenCOSSAN	LGPLv3	Mac/ Win/ Lin	Matlab	-
SMT	BSD	Mac/ Win/ Lin	Python	-
UQ-Pyl	GPL	Mac/ Win/ Lin	Python	-
UQLab	Free For Educational Use	Mac/ Win/ Lin	Matlab	-
UQpy	MIT	Mac/ Win/ Lin	Python	-
quoFEM	BSD	Mac/ Win/ Lin	C++	✓

Table A.22 Cross-Cutting: Artificial Intelligence and Machine Learning

Name	License	Platforms	Prog. Lang.	DesignSafe
CAFFE	BSD	Mac/ Win/ Lin	C++/ Python	-
CNTK	MIT	-	C++	-
Keras	Apache Software	Mac/ Win/ Lin	Python	-
NHERI-SimCenter/BIM2SAM.AI	-	-	-	-
PyTorch	BSD	Mac/ Win/ Lin	Python	-
SWIM [1]	BSD	Mac/ Win	C++	-
Scikit-Learn	BSD	Mac/ Win/ Lin	Python	-
TensorFlow	Apache Software	Mac/ Win/ Lin	C++/ Python	-
Theano	BSD	-	Python	-

[1] Educational Tool

Part VII
References

Literature

Introduction

Adams, Brian M, WJ Bohnhoff, KR Dalbey, JP Eddy, MS Eldred, DM Gay, K Haskell, Patricia D Hough, and Laura P Swiler (2009). *DAKOTA, a Multilevel Parallel Object-Oriented Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis: Version 5.0 User's Manual*. Tech. Rep. SAND2010-2183. Sandia National Laboratories. *Dakota*. Sandia. URL: https://dakota.sandia.gov/.

Deierlein, Gregory G., Frank McKenna, Adam Zsarnóczay, Tracy Kijewski-Correa, Ahsan Kareem, Wael Elhaddad, Laura Lowes, Matthew J. Schoettler, and Sanjay Govindjee (2020). "A Cloud-Enabled Application Framework for Simulating Regional-Scale Impacts of Natural Hazards on the Built Environment". In: *Frontiers in Built Environment* 6. ISSN: 2297-3362. DOI: 10/ghms27.

Edge, B., J. Ramirez, L. Peek, A. Bobet, W. Holmes, I. Robertson, and T. Smith (2020). *Natural Hazards Engineering Research Infrastructure, 5-Year Science Plan, Multi-Hazard Research To Make a More Resilient World, Second Edition*. DesignSafe-CI. URL: doi.org/10.17603/ds2-4s85-mc54..

Kareem, Ahsan and Dae Kun Kwon (2017). "A Cyber-Based Data-Enabled Virtual Organization for Wind Load Effects on Civil Infrastructures: VORTEX-Winds". In: *Frontiers in Built Environment* 3. ISSN: 2297-3362. DOI: 10/ghntc3.

McKenna, F. (2020). *SimCenter Software Architecture*. NHERI SimCenter Report 2020-X.

Porter, K.A. (2003). "An Overview of PEER's Performance-Based Earthquake Engineering Methodology". In: *Proceedings of Ninth International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP9)*. San Francisco, p. 8.

Rathje, E. et al. (2017). "DesignSafe: A New Cyberinfrastructure for Natural Hazards Engineering". In: *ASCE Natural Hazards Review*. DOI: 10/ghghnv.

TPU (2020). *Aerodynamic Database*. Tokyo Polytechnic University. URL: http://wind.arch.t-kougei.ac.jp/system/eng/contents/code/tpu.

Zsarnóczay, A. and G.G. Deierlein (2020). "PELICUN - A Computational Framework for Estimating Damage, Loss and Community Resilience". In: 17th World Conference on Earthquake Engineering, p. 12.

Hazards: Earthquake - Ground Shaking

Abrahamson, Norman A., Nicolas M. Kuehn, Melanie Walling, and Niels Landwehr (Aug. 1, 2019). "Probabilistic Seismic Hazard Analysis in California Using Nonergodic Ground-Motion ModelsProbabilistic Seismic Hazard Analysis in California Using Nonergodic Ground-Motion Models". In: *Bulletin of the Seismological Society of America* 109.4, pp. 1235–1249. ISSN: 0037-1106. DOI: 10/ghmzzr.

Ancheta, T.D. et al. (2014). "NGA-West2 Database". In: *Earthquake Spectra* 30.3, pp. 989–1005. DOI: 10/f6jfjj.

Atkinson, Gail M. and Katsuichiro Goda (Feb. 1, 2010). "Inelastic Seismic Demand of Real versus Simulated Ground-Motion Records for Cascadia Subduction EarthquakesInelastic Seismic Demand of Real versus Simulated Ground-Motion Records for Subduction Earthquakes". In: *Bulletin of the Seismological Society of America* 100.1, pp. 102–115. ISSN: 0037-1106. DOI: 10/c8x4x9.

Baker, J.W., B.A. Bradley, and P.J. Stafford (2021). *Seismic Hazard and Risk Analysis*. Cambridge, England: Cambridge University Press.

Baker, J.W., T. Lin, S.K. Shahi, and N. Jayaram (2011). *New Ground Motion Selection Procedures and Selected Motions for the PEER Transportation Research Program*. PEER Technical Report 2011/03. Berkeley, CA: Pacific Earthquake Engineering Research Center, University of California.

Baker, Jack W. and Cynthia Lee (Apr. 21, 2018). "An Improved Algorithm for Selecting Ground Motions to Match a Conditional Spectrum". In: *Journal of Earthquake Engineering* 22.4, pp. 708–723. ISSN: 1363-2469. DOI: 10/ghmtg5.

Bazzurro, Paolo and C. Allin Cornell (Apr. 1, 1999). "Disaggregation of Seismic Hazard". In: *Bulletin of the Seismological Society of America* 89.2, pp. 501–520. ISSN: 0037-1106. URL: https://pubs.geoscienceworld.org/ssa/bssa/article/89/2/501/342641/Disaggregation-of-seismic-hazard (visited on 10/24/2020).

Bijelić, Nenad, Ting Lin, and Greg G Deierlein (2018). "Validation of the SCEC Broadband Platform Simulations for Tall Building Risk Assessments Considering Spectral Shape and Duration of the Ground Motion". In: *Earthquake Engineering & Structural Dynamics* 47.11, pp. 2233–2251. DOI: 10/gd3c32.

Bommer, J.J. and F. Scherbaum (2008). "The Use and Misuse of Logic Trees in Probabilistic Seismic Hazard Analysis". In: *Earthquake Spectra* 24, pp. 997–1009. DOI: 10/btvmw8.

Bradley, Brendon A., Didier Pettinga, Jack W. Baker, and Jeff Fraser (Aug. 1, 2017). "Guidance on the Utilization of Earthquake-Induced Ground Motion Simulations in Engineering Practice". In: *Earthquake Spectra* 33.3, pp. 809–835. ISSN: 8755-2930. DOI: 10/gbzgpz.

Cornell, C. Allin (Oct. 1, 1968). "Engineering Seismic Risk Analysis". In: *Bulletin of the Seismological Society of America* 58.5, pp. 1583–1606. ISSN: 0037-1106. URL: https://pubs.geoscienceworld.org/ssa/bssa/article-abstract/58/5/1583/116673/Engineering-seismic-risk-analysis (visited on 10/24/2020).

Crouse, C.B., Thomas H. Jordan, K.R. Milner, Christine A. Goulet, Scott Callaghan, and Robert W. Graves (2018). "Site-Specific MCER Response Spectra for Los Angeles Region

Based on 3-D Numerical Simulations and the NGA West2 Equations". In: *11th National Conference in Earthquake Engineering*. Los Angeles.

Cui, Y. et al. (2010). "Scalable Earthquake Simulation on Petascale Supercomputers". In: *Proceedings of the 2010 ACM/IEEE International Conference for High Performance Computing, Networking, Storage and Analysis*. New Orleans, LA. DOI: 10/bbvk5x. *AWP-ODC*. URL: http://hpgeoc.github.io/awp-odc-os/.

D'Amico, M., R. Puglia, E. Russo, C. Maini, F. Pacor, and L. Luzi (June 1, 2017). "SYNTHESIS: A Web Repository of Synthetic Waveforms". In: *Bulletin of Earthquake Engineering* 15.6, pp. 2483–2496. ISSN: 1573-1456. DOI: 10/f97zn8.

Danciu, L., K. Şeşetyan, and M. Demircioglu (2017). "The 2014 Earthquake Model of the Middle East: Seismogenic Sources". In: *Bull Earthquake Eng* 16, p. 3465.

Dávalos, Héctor and Eduardo Miranda (2019). "Filtered Incremental Velocity: A Novel Approach in Intensity Measures for Seismic Collapse Estimation". In: *Earthquake Engineering & Structural Dynamics* 48.12, pp. 1384–1405. ISSN: 1096-9845. DOI: 10/ghmtg2.

Deierlein, Gregory G., Frank McKenna, Adam Zsarnóczay, Tracy Kijewski-Correa, Ahsan Kareem, Wael Elhaddad, Laura Lowes, Matthew J. Schoettler, and Sanjay Govindjee (2020). "A Cloud-Enabled Application Framework for Simulating Regional-Scale Impacts of Natural Hazards on the Built Environment". In: *Frontiers in Built Environment* 6. ISSN: 2297-3362. DOI: 10/ghms27.

Douglas, J. (2021). *Ground Motion Prediction Equations 1964-2020*. Engineering, Glasgow, UK: Dept. of Civil End Environmental Eng., University of Strathclyde.

Federal Emergency Management Agency (2011a). *Hazus–MH 2.1: Earthquake Technical Manual*. Washington, D.C.: FEMA, p. 718.

Federal Emergency Management Agency (2011b). *Hazus–MH 2.1: Flood Model Technical Manual*. FEMA.

Federal Emergency Management Agency (2011c). *Hazus–MH 2.1: Hurricane Model Technical Manual*. Washington, D.C: FEMA, p. 1456.

Federal Emergency Management Agency (Nov. 2017). *Hazus Tsunami Model Technical Guidance*. Washington D.C.

Field, E.H., T.H. Jordan, and C.A. Cornell (2003). "OpenSHA: A Developing Community-Modeling Environment for Seismic Hazard Analysis". In: *Seismological Research Letters* 74.4, pp. 406–419. DOI: 10/ccn2qb. *OpenSHA*. URL: https://opensha.org/.

Field, E.H. et al. (2014). "Uniform California Earthquake Rupture Forecast, Version 3 (UCERF3)—The Time-Independent Model". In: *Bulletin of the Seismological Society of America* 104.3, pp. 1122–1180. DOI: 10/ghgjk8.

Frankel, Arthur, Erin Wirth, Nasser Marafi, John Vidale, and William Stephenson (Oct. 1, 2018). "Broadband Synthetic Seismograms for Magnitude 9 Earthquakes on the Cascadia Megathrust Based on 3D Simulations and Stochastic Synthetics, Part 1: Methodology and Overall ResultsMethodology and Overall Results". In: *Bulletin of the Seismological Society of America* 108 (5A), pp. 2347–2369. ISSN: 0037-1106. DOI: 10/gfcddr.

Galasso, Carmine, Peng Zhong, Farzin Zareian, Iunio Iervolino, and Robert W. Graves (2013). "Validation of Ground-Motion Simulations for Historical Events Using MDoF Systems". In:

Earthquake Engineering & Structural Dynamics 42.9, pp. 1395–1412. ISSN: 1096-9845. DOI: 10/f4z475.

Garcia, J., M. Pagani, L. Rodriguez, and G. Weatherill (2018). *Creation of a New PSHA Input Model for South America and Calculation of Results*. GEM SARA Wiki. URL: https://sara.openquake.org/hazard_rt7.

Gerstenberger, M. C. et al. (2020). "Probabilistic Seismic Hazard Analysis at Regional and National Scales: State of the Art and Future Challenges". In: *Reviews of Geophysics* 58.2, e2019RG000653. ISSN: 1944-9208. DOI: 10/ghmzzq.

Giardini, D., J. Woessner, and L. Danciu (2014). "Mapping Europe's Seismic Hazard". In: *Eos (Rome, Italy)* 95.29, pp. 261–262. DOI: 10/ghgjk9.

Goulet, Christine A, Yousef Bozorgnia, Nicolas Kuehn, Linda Al Atik, Robert R. Youngs, Robert W. Graves, and Gail M. Atkinson (Mar. 2017). *NGA-East Ground-Motion Models for the U.S. Geological Survey National Seismic Hazard Maps*. 2017/03, p. 207.

Jayaram, Nirmal and Jack W. Baker (2009). "Correlation Model for Spatially Distributed Ground-Motion Intensities". In: *Earthquake Engineering & Structural Dynamics* 38.15, pp. 1687–1708. ISSN: 1096-9845. DOI: 10/dcfq9d.

Kato, Bence and Gang Wang (2021). "Regional Seismic Responses of Shallow Basins Incorporating Site-City Interaction Analyses on High-Rise Building Clusters". In: *Earthquake Engineering & Structural Dynamics* 50.1, pp. 214–236. ISSN: 1096-9845. DOI: 10/ghtkvn.

Kusakabe, Ryota, Kohei Fujita, Tsuyoshi Ichimura, Takuma Yamaguchi, Muneo Hori, and Lalith Wijerathne (2021). "Development of Regional Simulation of Seismic Ground-Motion and Induced Liquefaction Enhanced by GPU Computing". In: *Earthquake Engineering & Structural Dynamics* 50.1, pp. 197–213. ISSN: 1096-9845. DOI: 10/ghtkvj.

Lin, Ting, Stephen C. Harmsen, Jack W. Baker, and Nicolas Luco (Apr. 1, 2013). "Conditional Spectrum Computation Incorporating Multiple Causal Earthquakes and Ground-Motion Prediction ModelsSpectrum Computation Incorporating Multiple Causal Earthquakes and Ground-Motion Prediction Models". In: *Bulletin of the Seismological Society of America* 103 (2A), pp. 1103–1116. ISSN: 0037-1106. DOI: 10/f4stxw.

Luco, Nicolas and C. Allin Cornell (Dec. 27, 2019). "Structure-Specific Scalar Intensity Measures for Near-Source and Ordinary Earthquake Ground Motions:" in: *Earthquake Spectra*. DOI: 10/dfhrrh.

Maechling, P.J., F. Silva, S. Callaghan, and T.H. Jordan (2015). "SCEC Broadband Platform: System Architecture and Software Implementation". In: *Seismological Research Letters* 86.1. DOI: 10/ghgjmf. *The Broadband Platform*. Version 19.4. May 30, 2019. URL: https://strike.scec.org/scecpedia/Broadband_Platform.

Markhvida, Maryia, Luis Ceferino, and Jack W. Baker (2018). "Modeling Spatially Correlated Spectral Accelerations at Multiple Periods Using Principal Component Analysis and Geostatistics". In: *Earthquake Engineering & Structural Dynamics* 47.5, pp. 1107–1123. ISSN: 1096-9845. DOI: 10/gc94s3.

Mueller, C.S, O.S. Boyd, M.D. Petersen, M.P. Moschetti, S. Rezaeian, and A.M. Shumway (2015). "Seismic Hazard in the Eastern United States". In: *Earthquake Spectra* 31, pp. 85–107. DOI: 10/f75q2z.

Ordaz, M., F. Martinelli, V. D'Amico, and C. Meletti (2013). "CRISIS2008: A Flexible Tool to Perform Probabilistic Seismic Hazard Assessment". In: *Seismological Research Letters* 84, pp. 495–504. DOI: 10/ghgjmh.

Padgett, Jamie E., Reginald DesRoches, and Emily Nilsson (July 16, 2010). "Regional Seismic Risk Assessment of Bridge Network in Charleston, South Carolina". In: *Journal of Earthquake Engineering* 14.6, pp. 918–933. ISSN: 1363-2469. DOI: 10/dwqhtx.

Pagani, M. et al. (2014). "OpenQuake Engine: An Open Hazard (and Risk) Software for the Global Earthquake Model". In: *Seismological Research Letters* 85.3, pp. 692–702. DOI: 10/ghghnx. *OpenQuake*. URL: https://www.globalquakemodel.org/openquake.

Paolucci, R., I. Mazzieri, G. Piunno, C. Smerzini, M. Vanini, and A. G. Özcebe (2021). "Earthquake Ground Motion Modeling of Induced Seismicity in the Groningen Gas Field". In: *Earthquake Engineering & Structural Dynamics* 50.1, pp. 135–154. ISSN: 1096-9845. DOI: 10/ghtkvp.

Petersson, N. Anders and Bjorn Sjogreen (Nov. 20, 2017). *Geodynamics/SW4*. DOI: 10.5281/zenodo.1063644. *SW4*. *SW4*. Version 2.01. Zenodo. DOI: 10.5281/zenodo.1063644.

Rezaeian, Sanaz and Armen Der Kiureghian (2012). "Simulation of Orthogonal Horizontal Ground Motion Components for Specified Earthquake and Site Characteristics". In: *Earthquake Engineering & Structural Dynamics* 41.2, pp. 335–353. ISSN: 1096-9845. DOI: 10/cjmvcf.

Rodgers, Arthur J., N. Anders Petersson, Arben Pitarka, David B. McCallen, Bjorn Sjogreen, and Norman Abrahamson (May 1, 2019a). "Broadband (0–5 Hz) Fully Deterministic 3D Ground-Motion Simulations of a Magnitude 7.0 Hayward Fault Earthquake: Comparison with Empirical Ground-Motion Models and 3D Path and Site Effects from Source Normalized Intensities". In: *Seismological Research Letters* 90.3, pp. 1268–1284. ISSN: 0895-0695. DOI: 10/ghmtg4.

Rodgers, Arthur J., Arben Pitarka, and David B. McCallen (Aug. 1, 2019b). "The Effect of Fault Geometry and Minimum Shear Wavespeed on 3D Ground-Motion Simulations for an Mw 6.5 Hayward Fault Scenario Earthquake, San Francisco Bay Area, Northern CaliforniaThe Effect of Fault Geometry and Minimum Shear Wavespeed on 3D Ground-Motion Simulations". In: *Bulletin of the Seismological Society of America* 109.4, pp. 1265–1281. ISSN: 0037-1106. DOI: 10/ghmtgz.

Seifried, A. E. and J. W. Baker (Nov. 1, 2016). "Spectral Variability and Its Relationship to Structural Response Estimated from Scaled and Spectrum-Matched Ground Motions:" in: *Earthquake Spectra*. DOI: 10/f9dhkp.

Seylabi, Elnaz, Doriam Restrepo, Ricardo Taborda, and Domniki Asimaki (2021). "Deterministic Ground Motion Simulations with Shallow Crust Nonlinearity at Garner Valley in Southern California". In: *Earthquake Engineering & Structural Dynamics* 50.1, pp. 43–59. ISSN: 1096-9845. DOI: 10/ghtkvk.

Shome, Nilesh, C. Allin Cornell, Paolo Bazzurro, and J. Eduardo Carballo (Aug. 1, 1998). "Earthquakes, Records, and Nonlinear Responses". In: *Earthquake Spectra* 14.3, pp. 469–500. ISSN: 8755-2930. DOI: 10/cdpnsq.

Small, Patrick, David Gill, Philip J. Maechling, Ricardo Taborda, Scott Callaghan, Thomas H. Jordan, Kim B. Olsen, Geoffrey P. Ely, and Christine Goulet (Nov. 1, 2017). "The SCEC

Unified Community Velocity Model Software Framework". In: *Seismological Research Letters* 88.6, pp. 1539–1552. ISSN: 0895-0695. DOI: 10/gcm83k.

Taborda, R., J López, H Karaoglu, J Urbanic, and J Bielak (2010). *Speeding up Finite Element Wave Propagation for Large-Scale Earthquake Simulations*. Technical report no. CMU-PDL-10-109, Carnegie Mellon University, Parallel Data Lab.

Tu, T, H. Yu, L Ramírez-Guzmán, J Bielak, O Ghattas, K Ma, and D. O.'Hallaron (2006). "From Mesh Generation to Scientific Visualization: An End-to-End Approach to Parallel Supercomputing". In: *Proc. of the 2006 ACM/IEEE Int. Conf. for High Performance Computing, Networking, Storage and Analysis*. Tampa, Florida: IEEE Computer Society. DOI: 10/ff38cv. *Hercules*. URL: https://github.com/CMU-Quake/hercules.

USGS (2020). *USGS Vs30 Models and Data*. URL: https://www.usgs.gov/natural-hazards/earthquake-hazards/science/vs30-models-and-data (visited on 11/23/2020).

Zhang, Wenyang, Doriam Restrepo, Jorge G. F. Crempien, Bulent Erkmen, Ricardo Taborda, Asli Kurtulus, and Ertugrul Taciroglu (2021). "A Computational Workflow for Rupture-to-Structural-Response Simulation and Its Application to Istanbul". In: *Earthquake Engineering & Structural Dynamics* 50.1, pp. 177–196. ISSN: 1096-9845. DOI: 10/ghtkvm.

Hazards: Earthquake - Surface Fault Rupture

Anastasopoulos, I. and G. Gazetas (2007). "Foundation–Structure Systems over a Rupturing Normal Fault: Part II. Analysis of the Kocaeli Case Histories". In: *Bulletin of Earthquake Engineering* 5.3, pp. 277–301. ISSN: 1573-1456. DOI: 10/czjhcg.

Anastasopoulos, I. et al. (Nov. 1, 2008). "Numerical Analyses of Fault–Foundation Interaction". In: *Bulletin of Earthquake Engineering* 6.4, pp. 645–675. ISSN: 1573-1456. DOI: 10/bn7fbj.

Berrill, J. (1983). "Two-Dimensional Analysis of the Effect of Fault Rupture on Buildings with Shallow Foundations". In: *International Journal of Soil Dynamics and Earthquake Engineering* 2.3, pp. 156–160. ISSN: 0261-7277. DOI: 10/fmp9c4.

Bransby, M. F., M. C. R. Davies, A. El Nahas, and S. Nagaoka (Nov. 1, 2008a). "Centrifuge Modelling of Reverse Fault–Foundation Interaction". In: *Bulletin of Earthquake Engineering* 6.4, pp. 607–628. ISSN: 1573-1456. DOI: 10/dmvhnd.

Bransby, M., M. Davies, and A.E. Nahas (2008b). "Centrifuge Modelling of Normal Fault–Foundation Interaction". In: *Bulletin of Earthquake Engineering* 6.4, pp. 585–605. ISSN: 1573-1456. DOI: 10/bmswqr.

Bray, Jonathan D (2001). "Developing Mitigation Measures for the Hazards Associated with Earthquake Surface Fault Rupture". In: *Workshop on Seismic Fault-Induced Failures—Possible Remedies for Damage to Urban Facilities.* University of Tokyo Press, pp. 55–79.

Byrne, P.M., S.S. Park, M. Beaty, M. Sharp, L. Gonzalez, and T. Abdoun (2004). "Numerical Modeling of Liquefaction and Comparison with Centrifuge Tests". In: *Canadian Geotechnical Journal* 41.2, pp. 193–211. DOI: 10/b7f2x4. eprint: https://doi.org/10.1139/t03-088.

Cole, David A. and Poul V. Lade (1984). “Influence Zones in Alluvium over Dip-Slip Faults”. In: *Journal of Geotechnical Engineering* 110.5, pp. 599–615. DOI: 10/b6d7q3. eprint: https://ascelibrary.org/doi/pdf/10.1061/%28ASCE%290733-9410%281984%29110%3A5%28599%29.

Garcia, Fernando E. and Jonathan D. Bray (2018a). “Distinct Element Simulations of Earthquake Fault Rupture through Materials of Varying Density”. In: *Soils and Foundations* 58.4, pp. 986–1000. ISSN: 0038-0806. DOI: 10/gfhgvk.

Garcia, Fernando E. and Jonathan D. Bray (2018b). “Distinct Element Simulations of Shear Rupture in Dilatant Granular Media”. In: *International Journal of Geomechanics* 18.9, p. 04018111. DOI: 10/gdxmwk.

Hecker, S., N. A. Abrahamson, and K. E. Wooddell (2013). “Variability of Displacement at a Point: Implications for Earthquake-Size Distribution and Rupture Hazard on FaultsVariability of Displacement at a Point: Implications for Earthquake-Size Distribution and Rupture Hazard on Faults”. In: *Bulletin of the Seismological Society of America* 103 (2A), p. 651. DOI: 10/f4srkj. eprint: /gsw/content_public/journal/bssa/103/2a/10.1785_0120120159/3/651.pdf.

Moss, R.E.S. and Z.E. Ross (2011). “Probabilistic Fault Displacement Hazard Analysis for Reverse Faults”. In: *Bulletin of the Seismological Society of America* 101, pp. 1542–1553. DOI: 10/dd8d5r.

Oettle, N.K. and J.D. Bray (2017). “Numerical Procedures for Simulating Earthquake Fault Rupture Propagation”. In: *International Journal of Geomechanics* 17.1. DOI: 10/f9mw2d. eprint: https://ascelibrary.org/doi/pdf/10.1061/%28ASCE%29GM.1943-5622.0000661.

Oettle, N.K., J.D. Bray, and D.S. Dreger (2015). “Dynamic Effects of Surface Fault Rupture Interaction with Structures”. In: *Soil Dynamics and Earthquake Engineering* 72, pp. 37–47. DOI: 10/f69md5.

Oettle, Nicolas K. and Jonathan D. Bray (2013). “Geotechnical Mitigation Strategies for Earthquake Surface Fault Rupture”. In: *Journal of Geotechnical and Geoenvironmental Engineering* 139.11, pp. 1864–1874. DOI: 10/f5dsd9. eprint: https://ascelibrary.org/doi/pdf/10.1061/%28ASCE%29GT.1943-5606.0000933.

Petersen, M.D., T.E. Dawson, R. Chen, T. Cao, C.J. Wills, D.P. Schwartz, and A.D. Frankel (2011). “Fault Displacement Hazard for Strike-Slip Faults”. In: *Bulletin of the Seismological Society of America* 101, pp. 805–825. DOI: 10/czxb37.

Šmilauer, V. (2015). *Yade Documentation 2nd Ed*. The Yade Project. DOI: 10.5281/zenodo.34073.

Wells, Donald L and Vikram S Kulkarni (2014). “Probabilistic Fault Displacement Hazard Analysis–Sensitivity Analyses and Recommended Practices for Developing Design Fault Displacements”. In: *Proceedings, 10th National Conference in Earthquake Engineering, EERI*, pp. 21–25.

Youngs, Robert R. et al. (2003). “A Methodology for Probabilistic Fault Displacement Hazard Analysis (PFDHA)”. In: *Earthquake Spectra* 19, pp. 191–219. DOI: 10/dkk9k7.

Hazards: Earthquake - Soil Liquefaction

Andrus, R.D. and K.H. Stokoe II (2000). "Liquefaction Resistance of Soils from Shear-Wave Velocity". In: *Journal of Geotechnical and Geoenvironmental Engineering* 126.11, pp. 1015–1025. DOI: 10/c349gg.

Boulanger, RW and IM Idriss (2014). *CPT and SPT Based Liquefaction Triggering Procedures*. UCD/CGM.-14. UC Davis. URL: https://facultysand.engineering.ucdavis.edu/boulanger/wp-content/uploads/sites/71/2014/09/Boulanger_Idriss_CPT_and_SPT_Liq_triggering_CGM-14-01_20141.pdf.

Brandenberg, Scott J et al. (2020). "Next-Generation Liquefaction Database". In: *Earthquake Spectra*, p. 8755293020902477. DOI: 10/ghghsg.

Bray, Jonathan D and Jorge Macedo (2017). "6th Ishihara Lecture: Simplified Procedure for Estimating Liquefaction-Induced Building Settlement". In: *Soil Dynamics and Earthquake Engineering* 102, pp. 215–231. DOI: 10/gcgmnp.

Bray, Jonathan D et al. (2017). *U.S. – New Zealand – Japan International Workshop on Liquefaction-Induced Ground Movements Effects.* 2017/02. Pacific Earthquake Engineering Research Center.

Cetin, K Onder and Raymond B Seed (2004). "Nonlinear Shear Mass Participation Factor (Rd) for Cyclic Shear Stress Ratio Evaluation". In: *Soil Dynamics and Earthquake Engineering* 24.2, pp. 103–113. DOI: 10/ftdkdk.

Cetin, K Onder, Raymond B Seed, Robert E Kayen, Robb ES Moss, H Tolga Bilge, Makbule Ilgac, and Khaled Chowdhury (2018). "SPT-Based Probabilistic and Deterministic Assessment of Seismic Soil Liquefaction Triggering Hazard". In: *Soil Dynamics and Earthquake Engineering* 115, pp. 698–709. DOI: 10/ghkftx.

Chen, Qiushi, Chaofeng Wang, and C Hsein Juang (2016). "Probabilistic and Spatial Assessment of Liquefaction-Induced Settlements through Multiscale Random Field Models". In: *Engineering Geology* 211, pp. 135–149. DOI: 10/f82cxq.

Cubrinovski, M. et al. (2011). "Geotechnical Aspects of the 22 February 2011 Christchurch Earthquake". In: *Bulletin of the New Zealand Society for Earthquake Engineering* 44.4, pp. 205–226. DOI: 10/ghghsm.

Cubrinovski, Misko, J Bray, C de la Torre, M Olsen, B Bradley, Chiaro G, Stock E, and Wotherspoon L (2017). "Liquefaction Effects and Associated Damages Observed at the Wellington Centreport from the 2016 Kaikoura Earthquake". In: *Bulletin of the New Zealand Society for Earthquake Engineering* 50.2, pp. 152–173. ISSN: 1174-9857. DOI: 10/ghghsh.

Fotopoulou, Stavroula, Stella Karafagka, and Kyriazis Pitilakis (2018). "Vulnerability Assessment of Low-Code Reinforced Concrete Frame Buildings Subjected to Liquefaction-Induced Differential Displacements". In: *Soil Dynamics and Earthquake Engineering* 110, pp. 173–184. DOI: 10/gdpxr9.

Holzer, Thomas L, Michael J Bennett, Thomas E Noce, Amy C Padovani, and John C Tinsley III (2006). "Liquefaction Hazard Mapping with LPI in the Greater Oakland, California, Area". In: *Earthquake Spectra* 22.3, pp. 693–708. DOI: 10/b2jkcm.

Idriss, I. (1999). “An Update to the Seed-Idriss Simplified Procedure for Evaluating Liquefaction Potential”. In: *Proc., TRB Worshop on New Approaches to Liquefaction*. Worshop on New Approaches to Liquefaction. Federal Highway Administration, pp. 99–165. URL: http://www.ce.memphis.edu/7137/PDFs/IDRISS.pdf.

Idriss, I.M. and R.W. Boulanger (2008). *Soil Liquefaction during Earthquakes*. Earthquake Engineering Research Institute.

Kavazanjian, Edward et al. (2016). *State of the Art and Practice in the Assessment of Earthquake-Induced Soil Liquefaction and Its Consequences*. Washington, D.C.: National Academies Press, p. 23474. ISBN: 978-0-309-44027-1. DOI: 10.17226/23474.

Kayen, R., R. Moss, E. Thompson, R. Seed, K. Cetin, A.D. Kiureghian, Y. Tanaka, and K. Tokimatsu (2013). “Shear-Wave Velocity–Based Probabilistic and Deterministic Assessment of Seismic Soil Liquefaction Potential”. In: *Journal of Geotechnical and Geoenvironmental Engineering* 139.3, pp. 407–419. DOI: 10/gfsh6j.

Khoshnevisan, Sara, Hsein Juang, Yan-Guo Zhou, and Wenping Gong (2015). “Probabilistic Assessment of Liquefaction-Induced Lateral Spreads Using CPT—Focusing on the 2010–2011 Canterbury Earthquake Sequence”. In: *Engineering Geology* 192, pp. 113–128. DOI: 10/ghghsj.

Moss, RE, Raymond B Seed, Robert E Kayen, Jonathan P Stewart, Armen Der Kiureghian, and K Onder Cetin (2006). “CPT-Based Probabilistic and Deterministic Assessment of in Situ Seismic Soil Liquefaction Potential”. In: *Journal of Geotechnical and Geoenvironmental Engineering* 132.8, pp. 1032–1051. DOI: 10/cwmmgv.

Robertson, P.K. and C.E. Wride (1998). “Evaluating Cyclic Liquefaction Potential Using the Cone Penetration Test”. In: *Canadian Geotechnical Journal* 35, pp. 442–459. DOI: 10/cz2348.

Robertson, Peter K (2009). “Interpretation of Cone Penetration Tests—a Unified Approach”. In: *Canadian geotechnical journal* 46.11, pp. 1337–1355. DOI: 10/b4n873.

Seed, H.B. and I.M. Idriss (1971). “Simplified Procedure for Evaluating Soil Liquefaction Potential”. In: *Journal of Soil Mechanics & Foundations Div*.

Stewart, JP et al. (2016). “PEER-NGL Project: Open Source Global Database and Model Development for the next-Generation of Liquefaction Assessment Procedures”. In: *Soil Dynamics and Earthquake Engineering* 91, pp. 317–328. DOI: 10/ghghsk.

Wang, C and Q Chen (2018). “A Hybrid Geotechnical and Geological Data-Based Framework for Multiscale Regional Liquefaction Hazard Mapping”. In: *Géotechnique* 68.7, pp. 614–625.

Wang, Chaofeng, Qiushi Chen, Mengfen Shen, and C Hsein Juang (2017). “On the Spatial Variability of CPT-Based Geotechnical Parameters for Regional Liquefaction Evaluation”. In: *Soil Dynamics and Earthquake Engineering* 95, pp. 153–166. DOI: 10/f93b78.

Youd, T. Leslie and David M. Perkins (Nov. 1, 1987). “Mapping of Liquefaction Severity Index”. In: *Journal of Geotechnical Engineering* 113.11, pp. 1374–1392. ISSN: 0733-9410. DOI: 10/ctxpdp.

Youd, T.L. and I.M. Idriss (2001). “Liquefaction Resistance of Soils: Summary Report from the 1996 NCEER and 1998 NCEER/NSF Workshops on Evaluation of Liquefaction Resistance of

Soils". In: *Journal of Geotechnical and Geoenvironmental Engineering* 127.4, pp. 297–313. DOI: 10/ckhqrq.

Zhu, Jing, Laurie G Baise, and Eric M Thompson (2017a). "An Updated Geospatial Liquefaction Model for Global ApplicationAn Updated Geospatial Liquefaction Model for Global Application". In: *Bulletin of the Seismological Society of America* 107.3, pp. 1365–1385. DOI: 10/gbjbdd.

Hazards: Earthquake - Slope Stability and Landslides

Boulanger, Ross and Katerina Ziotopoulou (Mar. 2017). *PM4Sand Version 3.1: A Sand Plasticity Model for Earthquake Engineering Applications*. UC Davis.

Boulanger, Ross and Katerina Ziotopoulou (2018). *PM4Silt (Version 1): A Silt Plasticity Model for Earthquake Engineering Applications.* University of California, Davis.

Bray, J.D., E.M. Rathje, A.J. Augello, and S.M. Merry (1998). "Simplified Seismic Design Procedure for Geosynthetic-Lined, Solid-Waste Landfills". In: *Geosynthetics International* 5.1-2, pp. 203–235. DOI: 10/ghghnf. eprint: https://doi.org/10.1680/gein.5.0119.

Bray, J.D. and T. Travasarou (2007). "Simplified Procedure for Estimating Earthquake-Induced Deviatoric Slope Displacements". In: *Journal of Geotechnical and Geoenvironmental Engineering* 133, pp. 381–392. DOI: 10/dg2f3j.

Bray, J.D. and T. Travasarou (2009). "Pseudostatic Coefficient for Use in Simplified Seismic Slope Stability Evaluation". In: *Journal of Geotechnical and Geoenvironmental Engineering* 135.9, pp. 1336–1340. DOI: 10/dpp6vz.

Bray, Jonathan D. and Jorge Macedo (2019). "Procedure for Estimating Shear-Induced Seismic Slope Displacement for Shallow Crustal Earthquakes". In: *Journal of Geotechnical and Geoenvironmental Engineering* 145.12, p. 04019106. DOI: 10/ghghnd.

Bray, Jonathan D., Jorge Macedo, and Thaleia Travasarou (Mar. 2018). "Simplified Procedure for Estimating Seismic Slope Displacements for Subduction Zone Earthquakes". In: *Journal of Geotechnical and Geoenvironmental Engineering* 144.3, p. 04017124. ISSN: 1090-0241, 1943-5606. DOI: 10/gczxxf.

Bray, Jonathan D et al. (2017). *U.S. – New Zealand – Japan International Workshop on Liquefaction-Induced Ground Movements Effects.* 2017/02. Pacific Earthquake Engineering Research Center.

Byrne, P.M., S.S. Park, M. Beaty, M. Sharp, L. Gonzalez, and T. Abdoun (2004). "Numerical Modeling of Liquefaction and Comparison with Centrifuge Tests". In: *Canadian Geotechnical Journal* 41.2, pp. 193–211. DOI: 10/b7f2x4. eprint: https://doi.org/10.1139/t03-088.

Grant, Alex, Joseph Wartman, and Grace Abou-Jaoude (2016). "Multimodal Method for Coseismic Landslide Hazard Assessment". In: *Engineering Geology* 212, pp. 146–160. ISSN: 0013-7952. DOI: 10/f87hmx.

Hynes-Griffin, M.E. and A.G. Franklin (1984). *Rationalizing the Seismic Coefficient Method*. Army Engineer Waterways Experiment Station Vicksburg Ms Geotechnical Lab.

Jibson, R.W. (2007). “Regression Models for Estimating Coseismic Landslide Displacement”. In: *Engineering Geology* 91.2, pp. 209–218. ISSN: 0013-7952. DOI: 10/cjtp88.

Jibson, Randall W, Ellen M Rathje, Matthew W Jibson, and Yong W Lee (2013). *SLAMMER: Seismic Landslide Movement Modeled Using Earthquake Records*. US Geological Survey. *SLAMMER*. URL: https://www.usgs.gov/software/slammer-seismic-landslide-movement-modeled-using-earthquake-records.

Kramer, Steven Lawrence (1996). *Geotechnical Earthquake Engineering*. Prentice-Hall, Inc.

Macedo, Jorge, Jonathan Bray, Norman Abrahamson, and Thaleia Travasarou (2018). “Performance-Based Probabilistic Seismic Slope Displacement Procedure”. In: *Earthquake Spectra* 34.2, pp. 673–695. DOI: 10/gd2trk. eprint: https://doi.org/10.1193/122516EQS251M.

Makdisi, F.I. and H.B. Seed (1978). “Simplified Procedure for Estimating Dam and Embankment Earthquake-Induced Deformations”. In: *Journal of Geotechnical and Geoenvironmental Engineering* 104.

Rathje, E.M., Y. Wang, P.J. Stafford, G. Antonakos, and G. Saygili (2014). “Probabilistic Assessment of the Seismic Performance of Earth Slopes”. In: *Bulletin of Earthquake Engineering* 12.3, pp. 1071–1090. ISSN: 1573-1456. DOI: 10/f55g79.

Saygili, G. and E.M. Rathje (2008). “Empirical Predictive Models for Earthquake-Induced Sliding Displacements of Slopes”. In: *Journal of Geotechnical and Geoenvironmental Engineering* 134, pp. 790–803. DOI: 10/cggvhx.

Seed, H. Bolton (1979). “Considerations in the Earthquake-Resistant Design of Earth and Rockfill Dams”. In: *Géotechnique* 29.3, pp. 215–263. DOI: 10/d99zzf. eprint: https://doi.org/10.1680/geot.1979.29.3.215.

Yang, Z., A. Elgamal, and E. Parra (2003). “Computational Model for Cyclic Mobility and Associated Shear Deformation”. In: *Journal of Geotechnical and Geoenvironmental Engineering* 129, pp. 1119–1127. DOI: 10/bm7w49.

Hazards: Tropical Cyclone - Wind

Barbato, Michele, Francesco Petrini, Vipin U Unnikrishnan, and Marcello Ciampoli (2013). “Performance-Based Hurricane Engineering (PBHE) Framework”. In: *Structural Safety* 45, pp. 24–35. DOI: 10/ghghns.

Batts, M.E., E. Simiu, and L.R. Russell (1980). “Hurricane Wind Speeds in the United States”. In: *Journal of the Structural Division, ASCE* 106.10, pp. 2001–2016.

Chavas, D.R. and N. Lin (2016). “A Model for the Complete Radial Structure of the Tropical Cyclone Wind Field. Part II: Wind Field Variability”. In: *Journal of the Atmospheric Sciences* 73.8, pp. 3093–3113. DOI: 10/f8xn94.

Chavas, D.R., N. Lin, and K. Emanuel (2015). “A Model for the Complete Radial Structure of the Tropical Cyclone Wind Field. Part I: Comparison with Observed Structure”. In: *Journal of the Atmospheric Sciences* 72.9, pp. 3647–3662. DOI: 10/f7qqnz.

Chen, Y. and Z. Duan (2018). “A Statistical Dynamics Track Model of Tropical Cyclones for Assessing Typhoon Wind Hazard in the Coast of Southeast China”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 172, pp. 325–340. DOI: 10/gcwzqp.

Chow, S.-h (1971). “A Study of the Wind Field in the Planetary Boundary Layer of a Moving Tropical Cyclone”. M.S. Thesis. New York, N.Y: New York University.

Chuang, W.-C. and S.M.J. Spence (2019). “An Efficient Framework for the Inelastic Performance Assessment of Structural Systems Subject to Stochastic Wind Loads”. In: *Engineering Structures* 179, pp. 92–105. DOI: 10/ghgjk6.

Council, Applied Technology (2020). *ATC Hazards by Location*. URL: https://hazards.atcouncil.org/.

Davis, C. et al. (2008). “Prediction of Landfalling Hurricanes with the Advanced Hurricane WRF Model”. In: *Monthly Weather Review* 136.6, pp. 1990–2005. DOI: 10/b58xn3.

Emanuel, K. (2004). *Tropical Cyclone Energetics and Structure." Atmospheric Turbulence and Mesoscale Meteorology: Scientific Research Inspired By*. Ed. by B.Stevens Doug Lilly, E. Fedorovich, and R. Rotunno. Cambridge: Cambridge University Press, pp. 165–192.

Emanuel, K. (2005). “Increasing Destructiveness of Tropical Cyclones over the Past 30 Years”. In: *Nature* 436.7051, pp. 686–688. DOI: 10/b9bcx2.

Emanuel, K. (2011). “Self-Stratification of Tropical Cyclone Outflow. Part II: Implications for Storm Intensification”. In: *Journal of the Atmospheric Sciences* 69.3, pp. 988–996. DOI: 10/cqkm63.

Emanuel, K. (2017). “A Fast Intensity Simulator for Tropical Cyclone Risk Analysis”. In: *Natural Hazards* 88.2, pp. 779–796. DOI: 10/gbrtmj.

Emanuel, K., C. DesAutels, C. Holloway, and R. Korty (2004). “Environmental Control of Tropical Cyclone Intensity”. In: *Journal of the Atmospheric Sciences* 61.7, pp. 843–858. DOI: 10/d3tcfj.

Emanuel, K., S. Ravela, E. Vivant, and C. Risi (2006). “A Statistical Deterministic Approach to Hurricane Risk Assessment”. In: *Bull. Amer. Meteorol. Soc* 87.3, pp. 299–314. DOI: 10/dzrp9p.

Emanuel, K. and R. Rotunno (2011). “Self-Stratification of Tropical Cyclone Outflow. Part I: Implications for Storm Structure”. In: *Journal of the Atmospheric Sciences* 68.10, pp. 2236–2249. DOI: 10/brp455.

Emanuel, K., R. Sundararajan, and J. Williams (2008). “Hurricanes and Global Warming: Results from Downscaling IPCC AR4 Simulations”. In: *Bull. Amer. Meteorol. Soc* 89.3, pp. 347–368. DOI: 10/d2kz2w.

Emanuel, K.A. (1988). “The Maximum Intensity of Hurricanes”. In: *Journal of the Atmospheric Sciences* 45.7, pp. 1143–1155. DOI: 10/btvmbz.

Engineering Sciences Data Unit (2008). *Strong Winds in the Atmospheric Boundary Layer. Part 2: Discrete Gust Speeds.* ESDU 83045. London: ESDU International plc. ISBN: 978-0-85679-460-5.

Fang, G., L. Zhao, S. Cao, Y. Ge, and W. Pang (2018a). “A Novel Analytical Model for Wind Field Simulation under Typhoon Boundary Layer Considering Multi-Field Correlation and

Height-Dependency”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 175, pp. 77–89. DOI: 10/gdh25v.

Fang, G., L. Zhao, L. Song, X. Liang, L. Zhu, S. Cao, and Y. Ge (2018b). “Reconstruction of Radial Parametric Pressure Field near Ground Surface of Landing Typhoons in Northwest Pacific Ocean”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 183, pp. 223–234. DOI: 10/ghgjk7.

Fernandez-Caban, P.L. et al. (2019). “Observing Hurricane Harvey’s Eyewall at Landfall”. In: *Bulletin of the American Meteorological Society* 100.5, pp. 759–775. DOI: 10/ghkn63.

Georgiou, P.N. (1986). “Design Wind Speeds in Tropical Cyclone-Prone Regions”. Ph. D., University of Western Ontario.

Hamid, S., B.M. Golam Kibria, S. Gulati, M. Powell, B. Annane, S. Cocke, J.-P. Pinelli, K. Gurley, and S.-C. Chen (2010). “Predicting Losses of Residential Structures in the State of Florida by the Public Hurricane Loss Evaluation Model”. In: *Statistical Methodology* 7.5, pp. 552–573.

Holland, G. (2008). “A Revised Hurricane Pressure–Wind Model”. In: *Monthly Weather Review* 136.9, pp. 3432–3445. DOI: 10/cpcs93.

Holland, G.J. (1980). “An Analytic Model of the Wind and Pressure Profiles in Hurricanes”. In: *Monthly Weather Review* 108.8, pp. 1212–1218. DOI: 10/c882cm.

Holland, G.J., J.I. Belanger, and A. Fritz (2010). “A Revised Model for Radial Profiles of Hurricane Winds”. In: *Monthly Weather Review* 138.12, pp. 4393–4401. DOI: 10/b4wq6n.

Hu, L., Y.-L. Xu, Q. Zhu, A. Guo, and A. Kareem (2017). “Tropical Storm–Induced Buffeting Response of Long-Span Bridges: Enhanced Nonstationary Buffeting Force Model”. In: *Journal of Structural Engineering* 143.6, p. 04017027. DOI: 10/f955fq.

Huang, W.F. and Y.L. Xu (2013). “Prediction of Typhoon Design Wind Speed and Profile over Complex Terrain”. In: *Struct. Eng. Mech* 45.1, pp. 1–18. DOI: 10/f5cqx4.

Ishihara, T., K.K. Siang, C.C. Leong, and Y. Fujino (2005). “Wind Field Model and Mixed Probability Distribution Function for Typhoon Simulation”. In: *The Sixth Asia-Pacific Conference on Wind Engineering (APCWE-VI)*. Seoul, Korea.

Kaplan, J. and M. DeMaria (1995). “A Simple Empirical Model for Predicting the Decay of Tropical Cyclone Winds after Landfall”. In: *Journal of Applied Meteorology* 34.11, pp. 2499–2512. DOI: 10/fxfmbg.

Kaplan, J. and M. DeMaria (2001). “On the Decay of Tropical Cyclone Winds after Landfall in the New England Area”. In: *Journal of Applied Meteorology* 40.2, pp. 280–286. DOI: 10/c4gzj5.

Kareem, A., L. Hu, Y. Guo, and D.K. Kwon (2019). “Generalized Wind Loading Chain: A Time-Frequency Modeling Framework for Nonstationary Winds Effects on Structures”. In: *Journal of Structural Engineering* 145.10, p. 04019092.

Kepert, J. (2001). “The Dynamics of Boundary Layer Jets within the Tropical Cyclone Core. Part I: Linear Theory”. In: *Journal of the Atmospheric Sciences* 58.17, pp. 2469–2484. DOI: 10/bkj8vh.

Kepert, J. and Y. Wang (2001). “The Dynamics of Boundary Layer Jets within the Tropical Cyclone Core. Part II: Nonlinear Enhancement”. In: *Journal of the Atmospheric Sciences* 58.17, pp. 2485–2501. DOI: 10/ccrpxg.

Kepert, J.D. (2006). “Observed Boundary Layer Wind Structure and Balance in the Hurricane Core. Part II: Hurricane Mitch”. In: *Journal of the Atmospheric Sciences* 63.9, pp. 2194–2211.

Kepert, J.D. (2010a). “Slab- and Height-resolving Models of the Tropical Cyclone Boundary Layer. Part I: Comparing the Simulations”. In: *Quarterly Journal of the Royal Meteorological Society* 136.652, pp. 1686–1699. DOI: 10/bq3mv5.

Kepert, J.D. (2010b). “Slab- and Height-resolving Models of the Tropical Cyclone Boundary Layer. Part II: Why the Simulations Differ”. In: *Quarterly Journal of the Royal Meteorological Society* 136.652, pp. 1700–1711. DOI: 10/cjhj2s.

Kepert, J.D. (2011). “Choosing a Boundary Layer Parameterization for Tropical Cyclone Modeling”. In: *Monthly Weather Review* 140.5, pp. 1427–1445. DOI: 10/fzpfsh.

Kepert, J.D. (2013). “How Does the Boundary Layer Contribute to Eyewall Replacement Cycles in Axisymmetric Tropical Cyclones?” In: *Journal of the Atmospheric Sciences* 70.9, pp. 2808–2830. DOI: 10/f4744w.

Kepert, J.D. and D.S. Nolan (2014). “Reply to “Comments on ‘How Does the Boundary Layer Contribute to Eyewall Replacement Cycles in Axisymmetric Tropical Cyclones?”’” In: *Journal of the Atmospheric Sciences* 71.12, pp. 4692–4704. DOI: 10/ghgjmc.

Kwon, D.-K. and A. Kareem (2009). “Gust-Front Factor: A New Framework for Wind Load Effects on Structures”. In: *Journal of Structural Engineering, ASCE*. DOI: 10/fsfn5m.

Langousis, A. (2008). “Extreme Rainfall Intensities and Long-Term Rainfall Risk from Tropical Cyclones”. Ph. D., Massachusetts Institute of Technology.

Lauren, M., W. Yue, L. Chris, and R. David (2014). “Assessing Climate Change Impact on the U.S. East Coast Hurricane Hazard: Temperature, Frequency, and Track”. In: *Natural Hazards Review* 15.3.

Li, L. and P. Chakraborty (2020). “Slower Decay of Landfalling Hurricanes in Warming World”. In: *Nature* 587, pp. 230–234. DOI: 10/ghkn65.

Li, L., A. Kareem, J. Hunt, Y. Xiao, C. Zhou, and L. Song (2015a). “Turbulence Spectra for Boundary-Layer Winds in Tropical Cyclones: A Conceptual Framework and Field Measurements at Coastlines”. In: *Boundary-Layer Meteorol* 154.2, pp. 243–263. DOI: 10/f6w5tb.

Li, L., A. Kareem, J. Hunt, F. Xing, P. Chan, Y. Xiao, and C. Li (2019a). “Observed Sub-Hectore-Scale Low Level Jets in Surface-Layer Velocity Profiles of Landfalling Typhoons”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 190, pp. 151–165. DOI: 10/ghkn64.

Li, L., A. Kareem, Y. Xiao, L. Song, and C. Zhou (2015b). “A Comparative Study of Field Measurements of the Turbulence Characteristics of Typhoon and Hurricane Winds”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 140, pp. 49–66. DOI: 10/f67kdj.

Li, S.H., Z.D. Duan, and H.P. Hong (2016). “Typhoon Wind Hazard Estimation and Mapping for Coastal Region in Mainland China”. In: *Natural Hazards Review* 17.2.

Li, S.H. and H.P. Hong (2015). “Observations on a Hurricane Wind Hazard Model Used to Map Extreme Hurricane Wind Speed”. In: *Journal of Structural Engineering* 141.10, p. 04014238. DOI: 10/f7r7m9.

Li, S.H. and H.P. Hong (2016). “Typhoon Wind Hazard Estimation for China Using an Empirical Track Model”. In: *Natural Hazards* 82.2, pp. 1009–1029. DOI: 10/f8pg53.

Lin, N. (2015). “An Integrated Approach to Assess and Manage Hurricane Risk in a Changing Climate”. In: *The Bridge* 45.4, pp. 46–51.

Lin, N. and D. Chavas (2012). “On Hurricane Parametric Wind and Applications in Storm Surge Modeling”. In: *Journal of Geophysical Research: Atmospheres* 117.D9. DOI: 10/ghgjmd.

Liu, F. (2014). “Projections of Future US Design Wind Speeds Cue to Climate Change for Estimating Hurricane Losses”. Ph.D., Clemson University.

Liu, Y., D.-L. Zhang, and M.K. Yau (1997). “A Multiscale Numerical Study of Hurricane Andrew”. In: *Monthly Weather Review* 125.12, pp. 3073–3093. DOI: 10/fcvwwg.

Masters, F.J., P.J. Vickery, P. Bacon, and E.N. Rappaport (2010). “TOWARD OBJECTIVE, STANDARDIZED INTENSITY ESTIMATES FROM SURFACE WIND SPEED OBSERVATIONS”. In: *Bull. Amer. Meteorol. Soc* 91.12, pp. 1665–1681. DOI: 10/bggc78.

Meng, Y., M. Matsui, and K. Hibi (1995). “An Analytical Model for Simulation of the Wind Field in a Typhoon Boundary Layer”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 56.2, pp. 291–310. DOI: 10/bgjr9r.

Meng, Y., M. Matsui, and K. Hibi (1997). “A Numerical Study of the Wind Field in a Typhoon Boundary Layer”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 67-68, pp. 437–448. DOI: 10/c7z8rr.

Montgomery, M.T., S.F. Abarca, R.K. Smith, C.-C. Wu, and Y.-H. Huang (2014). “Comments on “How Does the Boundary Layer Contribute to Eyewall Replacement Cycles in Axisymmetric Tropical Cyclones?”” In: *Journal of the Atmospheric Sciences* 71.12, pp. 4682–4691. DOI: 10/ghgjmg.

Mudd, L., P. Vickery, and P. Sarathi (2015). “Development of a New Synthetic Hurricane Model for Deriving MetOcean Design Criteria for the Gulf of Mexico”. In: *Offshore Technology Conference, Offshore Technology Conference*. Houston, Texas, USA. DOI: 10/ghgjmj.

Mudd, L. and P.J. Vickery (2015). “Advancements in Synthetic Hurricane Track Modeling in the Gulf of Mexico”. In: *14th International Conference on Wind Engineering,Porto*. Alegre, Brazil.

NOAA (2018). *Reanalysis Data*. URL: www.aoml.noaa.gov/hrd/data_sub/re_anal.html.

Powell, M., G. Soukup, S. Cocke, S. Gulati, N. Morisseau-Leroy, S. Hamid, N. Dorst, and L. Axe (2005). “State of Florida Hurricane Loss Projection Model: Atmospheric Science Component”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 93.8, pp. 651–674. DOI: 10/cj5xk8.

Powell, M.D., P.J. Vickery, and T.A. Reinhold (2003). “Reduced Drag Coefficient for High Wind Speeds in Tropical Cyclones”. In: *Nature* 422, p. 279. DOI: 10/cd66wx.

Russell, L.R. (1971). “Probability Distributions for Hurricane Effects”. In: *Journal of the Waterways, Harbors and Coastal Engineering Division, ASCE* 97.1, pp. 139–154.

Shapiro, L.J. (1983). “The Asymmetric Boundary Layer Flow under a Translating Hurricane”. In: *Journal of the Atmospheric Sciences* 40.8, pp. 1984–1998. DOI: 10/c36wt8.

Smith, R.K. (1968). “The Surface Boundary Layer of a Hurricane”. In: *Tellus* 20.3, pp. 473–484.

Smith, R.K., M.T. Montgomery, and G.L. Thomsen (2014). “Sensitivity of Tropical-Cyclone Models to the Surface Drag Coefficient in Different Boundary-Layer Schemes”. In: *Quarterly Journal of the Royal Meteorological Society* 140.680, pp. 792–804. DOI: 10/f52m46.

Smith, R.K., M.T. Montgomery, and S. Vogl (2008). “A Critique of Emanuel’s Hurricane Model and Potential Intensity Theory”. In: *Quarterly Journal of the Royal Meteorological Society* 134.632, pp. 551–561. DOI: 10/b29dnx.

Smith, R.K. and S. Vogl (2008). “A Simple Model of the Hurricane Boundary Layer Revisited”. In: *Quarterly Journal of the Royal Meteorological Society* 134.631, pp. 337–351. DOI: 10/b662xv.

Snaiki, R. and T. Wu (2017). “A Linear Height-Resolving Wind Field Model for Tropical Cyclone Boundary Layer”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 171, pp. 248–260. DOI: 10/gctgcp.

Snaiki, R. and T. Wu (2018). “A Semi-Empirical Model for Mean Wind Velocity Profile of Landfalling Hurricane Boundary Layers”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 180, pp. 249–261. DOI: 10/gfbtb3.

Song, L.L., W.C. Chen, B.L. Wang, S.Q. Zhi, and A.J. Liu (2016). “Characteristics of Wind Profiles in the Landfalling Typhoon Boundary Layer”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 149, pp. 77–88. DOI: 10/f7945b.

Spence, S.M.J. and A. Kareem (2014). “Performance-Based Design and Optimization of Uncertain Wind-Excited Dynamic Building Systems”. In: *Engineering Structures* 78, pp. 133–144. DOI: 10/f6qh64.

Unnikrishnan, V.U. and M. Barbato (2016). “Performance-Based Comparison of Different Storm Mitigation Techniques for Residential Buildings”. In: *Journal of Structural Engineering* 142.6, p. 12. DOI: 10/f8pfxd.

Vickery, P., J. Lin, P. Skerlj, L. Twisdale, and K. Huang (2006a). “HAZUS-MH Hurricane Model Methodology. I: Hurricane Hazard, Terrain, and Wind Load Modeling”. In: *Natural Hazards Review* 7.2, pp. 82–93. DOI: 10/cc72n8.

Vickery, P., P. Skerlj, A. Steckley, and L. Twisdale (2000a). “Hurricane Wind Field Model for Use in Hurricane Simulations”. In: *Journal of Structural Engineering* 126.10, pp. 1203–1221. DOI: 10/crr2nc.

Vickery, P. and L. Twisdale (1995). “Wind-Field and Filling Models for Hurricane Wind-Speed Predictions”. In: *Journal of Structural Engineering* 121.11, pp. 1700–1709.

Vickery, P., D. Wadhera, and J. Stear (2010). “A Synthetic Model for Gulf of Mexico Hurricanes”. In: *Offshore Technology Conference, Offshore Technology Conference*. Houston, Texas, USA.

Vickery, P.J. (2005). “Simple Empirical Models for Estimating the Increase in the Central Pressure of Tropical Cyclones after Landfall along the Coastline of the United States”. In: *Journal of Applied Meteorology* 44.12, pp. 1807–1826. DOI: 10/bgsk6s.

Vickery, P.J., F.J. Masters, M.D. Powell, and D. Wadhera (2009a). “Hurricane Hazard Modeling: The Past, Present, and Future”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 97.7-8, pp. 392–405. DOI: 10/c2qqn8.

Vickery, P.J., P.F. Skerlj, and L.A. Twisdale (2000b). “Simulation of Hurricane Risk in the US Using Empirical Track Model”. In: *Journal of Structural Engineering-ASCE* 126.10, pp. 1222–1237. DOI: 10/crszwm.

Vickery, P.J. and D. Wadhera (2008). “Statistical Models of Holland Pressure Profile Parameter and Radius to Maximum Winds of Hurricanes from Flight-Level Pressure and H*Wind Data”. In: *Journal of Applied Meteorology and Climatology* 47.10, pp. 2497–2517. DOI: 10/ckr3kb.

Vickery, P.J., D. Wadhera, M.D. Powell, and Y. Chen (2009b). “A Hurricane Boundary Layer and Wind Field Model for Use in Engineering Applications”. In: *Journal of Applied Meteorology and Climatology* 48.2, pp. 381–405. DOI: 10/fks8jq.

Vickery, P.J., D. Wadhera, L.A. Twisdale, and F.M. Lavelle (2009c). “U.S. Hurricane Wind Speed Risk and Uncertainty”. In: *Journal of Structural Engineering* 135.3, pp. 301–320. DOI: 10/cswbrr.

Wang, H., T. Wu, T. Tao, A. Li, and A. Kareem (2016). “Measurements and Analysis of Non-Stationary Wind Characteristics at Sutong Bridge in Typhoon Damrey”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 151, pp. 100–106. DOI: 10/f8gwph.

Wills, J.A.B., B.E. Lee, and T.A. Wyatt (2000). “A Review of Tropical Cyclone Wind Field Models”. In: *Wind and Structures* 3.2, pp. 133–142. DOI: 10/ghgjmk.

Wurman, Joshua and Karen Koshiba (2017). “Damage in Hurricane Harvey”. In: *Monthly Weather Review*.

Xiao, Y.F., Z.D. Duan, Y.Q. Xiao, J.P. Ou, L. Chang, and Q.S. Li (2011). “Typhoon Wind Hazard Analysis for Southeast China Coastal Regions”. In: *Structural Safety* 33.4, pp. 286–295. DOI: 10/dhttn6.

Yau, S.C., N. Lin, and E. Vanmarcke (2011). “Hurricane Damage and Loss Estimation Using an Integrated Vulnerability Model”. In: *Natural Hazards Review* 12.4, pp. 184–189. DOI: 10/dcf4vn.

Yu, B., A. Chowdhury, and F.J. Masters (2008). “Hurricane Wind Power Spectra, Co-Spectra, and Integral Length Scales.” In: *Boundary Layer Meteorology* 129.3, pp. 411–430. DOI: 10/fd588d.

Yu, B. and G.A. Chowdhury (2009). “Gust Factors and Turbulence Intensities for the Tropical Cyclone Environment”. In: *Journal of Applied Meteorology and Climatology* 48.3, pp. 534–552. DOI: 10/dc9r4x.

Zhao, L., A. Lu, L. Zhu, S. Cao, and Y. Ge (2013). “Radial Pressure Profile of Typhoon Field near Ground Surface Observed by Distributed Meteorologic Stations”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 122, pp. 105–112. DOI: 10/f5hcnn.

Hazards: Tropical Cyclone - Storm Surge

Berger, M.J., D. George, R.J. LeVeque, and K.T. Mandli (2011). "The GeoClaw Software for Depth-Averaged Flows with Adaptive Refinement". In: *Advances in Water Resources* 34.9, pp. 1195–1206. DOI: 10/cqptn7.

Chen, C.S., H.D. Liu, and R.C. Beardsley (2003). "An Unstructured Grid, Finite-Volume, Three-Dimensional, Primitive Equations Ocean Model: Application to Coastal Ocean and Estuaries". In: *Journal of Atmospheric and Oceanic Technology* 20.1, pp. 159–186. DOI: 10/fw62c8. *FVCOM*. URL: http://fvcom.smast.umassd.edu/fvcom/.

Demirbilek, Z., O.G. Nwogu, D.L. Ward, A. Sanchez, and A. (2009). *Wave Transformation over Reefs: Evaluation of One Dimensional Numerical Models*. Report ERDC/CHL TR-09-1, US Army Corps of Engineers.

Dietrich, J.C. et al. (2011). "Modeling Hurricane Waves and Storm Surge Using Integrally-Coupled, Scalable Computations". In: *Coastal Engineering* 58, pp. 45–65. DOI: 10/cqfdnd.

Hu, K., Q. Chen, and H. Wang (2015). "A Numerical Study of Vegetation Impact on Reducing Storm Surge by Wetlands in a Semi-Enclosed Estuary". In: *Coastal Engineering* 95, pp. 66–76. DOI: 10/f6vsjd.

Jacob, K. et al. (2011). "Responding to Climate Change in New York State: The ClimAID Integrated Assessment for Effective Climate Change Adaptation in New York State: Transportation". In: *Annals of the New York Academy of Sciences* 1244.1, pp. 299–362.

Jelesnianski, Chester P., Jye Chen, and Wilson A. Shaffer (Apr. 1992). *SLOSH: Sea, Lake and Overland Surges from Hurricanes*. NWS 48. NOAA, Silver Spring, MD. URL: https://www.hsdl.org/?view&did=779560. *SLOSH*. *SLOSH: Sea, Lake, and Overland Surges from Hurricanes*. URL: https://www.nhc.noaa.gov/surge/slosh.php.

Jia, Gaofeng and Alexandros A. Taflanidis (2013). "Kriging Metamodeling for Approximation of High-Dimensional Wave and Surge Responses in Real-Time Storm/Hurricane Risk Assessment". In: *Computer Methods in Applied Mechanics and Engineering* 261-262, pp. 24–38. DOI: 10/gbdcg4.

Kennedy, A.B., Q. Chen, J.T. Kirby, and R.A. Dalrymple (2000). "Boussinesq Modeling of Wave Transformation, Breaking and Runup. I: 1D". In: *J. Waterway, Port, Coastal and Ocean Eng.-ASCE* 126, pp. 39–47. DOI: 10/fcnxn7.

Kennedy, A.B., D. Wirasaet, A. Begmohammadi, T. Sherman, D. Bolster, and J.C. Dietrich (2019). "Subgrid Theory for Storm Surge Modeling". In: *Ocean Modelling* 144.101491. DOI: 10/ghgjk4.

Kennedy, A.B. et al. (2011). "Origin of the Hurricane Ike Forerunner Surge". In: *Geophysical Research Letters* L08805.

Kennedy, A.B. et al. (2012). "Tropical Cyclone Inundation Potential on the Hawaiian Islands of Oahu and Kauai". In: *Ocean Modelling* 52-53, pp. 54–68. DOI: 10/ghgjmb.

Kerr, P. C. et al. (Oct. 2013). "U.S. IOOS Coastal and Ocean Modeling Testbed: Inter-Model Evaluation of Tides, Waves, and Hurricane Surge in the Gulf of Mexico: IOOS TESTBED: INTER-MODEL EVALUATION". In: *Journal of Geophysical Research: Oceans* 118.10, pp. 5129–5172. ISSN: 21699275. DOI: 10/gcz48r.

Kijewski-Correa, T., N. Smith, A. Taflanidis, A. Kennedy, C. Liu, M. Krusche, and C. Vardeman (2014). "CyberEye: Development of Integrated Cyber-Infrastructure to Support Rapid Hurricane Risk Assessment". In: *Journal of Wind Engineering and Industrial Aerodynamics* 133, pp. 211–224. DOI: 10/f6mhdd.

LeVeque, R. (2002). *Finite Volume Methods for Hyperbolic Problems, Cambridge Texts in Applied Mathematics*. Cambridge University Press.

Luettich, R.A., J.J. Westerink, and N.W. Scheffner (1992). *ADCIRC: An Advanced Three-Dimensional Circulation Model for Shelves, Coasts, and Estuaries*. Dredging research program technical report DRP-92-6. Vicksburg, MS: U.S Army Engineers Waterways Experiment Station. *ADCIRC*. URL: https://adcirc.org/ (visited on 10/24/2020).

Lynett, P.J., T.R. Wu, and P.L.-F. Liu (2002). "Modeling Wave Runup with Depth-Integrated Equations". In: *Coastal Engineering* 46.2, pp. 89–107. DOI: 10/fh66sv.

Mandli, K.T., A.J. Ahmadia, M. Berger, D. Calhoun, D.L. George, Y. Hadjimichael, D.I. Ketcheson, G.I. Lemoine, and R.J. LeVeque (2016). "Clawpack: Building an Open Source Ecosystem for Solving Hyperbolic PDEs". In: *J. Computer Science* 2.3.

Mandli, Kyle T. and Clint N. Dawson (Mar. 1, 2014). "Adaptive Mesh Refinement for Storm Surge". In: *Ocean Modelling* 75, pp. 36–50. ISSN: 1463-5003. DOI: 10/f5tztb.

Nadal-Caraballo, N.C, J.A. Melby, V.M. Gonzalez, and A.T. Cox (2015). *North Atlantic Coast Comprehensive Study – Coastal Storm Hazards from Virginia to Maine, ERDC/CHL TR-15-5 U.S*. Vicksburg, MS: Army Engineer Research and Development Center.

NJcoast (2018). *Implementation Report*. URL: https://njcoast.us/documents/164/download/.

Nwogu, O. and Z. Demirbilek (2010). "Infragravity Wave Motions and Runup over Shallow Fringing Reefs". In: *J. Waterway, Port, Coastal and Ocean Eng.-ASCE* 136, pp. 295–305. DOI: 10/fb92jz.

Rego, J.L. and C.Y. Li (2010). "Storm Surge Propagation in Galveston Bay during Hurricane Ike". In: *Journal of Marine Systems* 82.4, pp. 265–279. DOI: 10/cqxzsk.

Resio, D.T. and J.J. Westerink (2008). "Modeling of the Physics of Storm Surges". In: *Physics Today* 61, pp. 33–38. DOI: 10/dqf54v.

Roelvink, D., A. Reniers, A. Dongeren, J.V. Vries, R. McCall, and J. Lescinski (2009). "Modelling Storm Impacts on Beaches, Dunes, and Barrier Islands". In: *Coastal Engineering* 56.11-12, pp. 1133–1152. DOI: 10/bq5rbm.

Smith, J.M., T. Hesser, A. Roland, and M. Bryant (2018). "Validation of Unstructured Wavewatch III for Nearshore Waves". In: *Proc. 36th Conf*. Ed. by P. Lynett. Baltimore, ASCE: Coastal Eng. DOI: 10/ghgjk5.

Smith, J.M., A.R. Sherlock, and D.T. Resio (2001). *STWAVE: Steady-State Spectral Wave Model User's Manual for STWAVE, Version 3.0*. DTIC Document.

Taflanidis, A.A., J. Zhang, N.C. Nadal-Caraballo, and J.A. Melby (2017). "Advances in Surrogate Modeling for Hurricane Risk Assessment: Storm Selection and Climate Change Impact"". In: *In Proceedings of 12th International Conference on Structural Safety & Reliability*. Vienna, Austria, pp. 6–10.

USACE (2015). *North Atlantic Coast Comprehensive Study: Resilient Adaptation to Increasing Risk, U.S.* Vicksburg, MS: Army Engineer Research and Development Center.

Vousdoukas, M.I., E. Voukouvalas, A. Annunziato, A. Giardino, and L. Feyen (2016). "Projections of Extreme Storm Surge Levels along Europe". In: *Climate Dynamics* 47.9, pp. 3171–3190. DOI: 10/bc6v.

Zhang, K., Y. Li, and B. Zachry (2017a). "Transition of the Coastal and Estuarine Storm Tide Model to an Operational Model for Forecasting Storm Surges". In: *Abstracts, 33rd Conference on Hurricanes and Tropical Meteorology*. Ponte Vedra, Paper7B.4. URL: https://ams.confex.com/ams/33HURRICANE/webprogram/Paper340466.html.

Zijlema, M. (2010). "Computation of Wind-Wave Spectra in Coastal Waters with SWAN on Unstructured Grids". In: *Coastal Engineering* 57, pp. 267–277. DOI: 10/fxfjfx. *SWAN*. Delft University of Technology. URL: http://swanmodel.sourceforge.net/.

Hazards: Tsunami - Inundation

Ash, Cale (Apr. 17, 2015). "Design of a Tsunami Vertical Evacuation Refuge Structure in Westport, Washington". In: *Structures Congress 2015*, pp. 1530–1537. DOI: 10/gh2tst.

Berger, M.J., D. George, R.J. LeVeque, and K.T. Mandli (2011). "The GeoClaw Software for Depth-Averaged Flows with Adaptive Refinement". In: *Advances in Water Resources* 34.9, pp. 1195–1206. DOI: 10/cqptn7.

Biscarini, C. (2010). "Computational Fluid Dynamics Modelling of Landslide Generated Water Waves". In: *Landslides* 7.2, pp. 117–124. DOI: 10/dfgbzw.

Choi, B.H., D.C. Kim, E. Pelinovsky, and S.B. Woo (2007). "Three-Dimensional Simulation of Tsunami Run-up around Conical Island". In: *Coastal Engineering* 54.8, pp. 618–629. DOI: 10/b3qf5f.

George, D. (2008). "Augmented Riemann Solvers for the Shallow Water Equations over Variable Topography with Steady States and Inundation". In: *Journal of Computational Physics* 227.6, pp. 3089–3113. DOI: 10/fdg4mx.

George, David L. (2004). "Numerical Approximation of the Nonlinear Shallow Water Equations with Topography and Dry Beds : A Godunov-Type Scheme". Masters Thesis. University of Washington. URL: https://faculty.washington.edu/rjl/students/dgeorge/dgeorgemasters.pdf.

González, F.I., R.J. LeVeque, and L.M. Adams (2013). *Tsunami Hazard Assessment of the Ocosta School Site in Westport, WA*. University of Washington.

Hu, K., C.G. Mingham, and D.M. Causon (2000). *Numerical Simulation of Wave Overtopping of Coastal Structures Using the Non-Linear Shallow Water Equations*. Coastal Engineering.

Hubbard, M.E. and N. Dodd (2002). "A 2D Numerical Model of Wave Run-up and Overtopping". In: *Coastal Engineering* 47.1, pp. 1–26. DOI: 10/fkj2jm.

Kim, D.H., P.J. Lynett, and S.A. Socolofsky (2009). "A Depth-Integrated Model for Weakly Dispersive, Turbulent, and Rotational Fluid Flows". In: *Ocean Modelling, Elsevier Ltd* 27.3–4, pp. 198–214. DOI: 10/d44qbh.

Kim, J., G.K. Pedersen, F. Løvholt, and R.J. LeVeque (2017). "A Boussinesq Type Extension of the GeoClaw Model - a Study of Wave Breaking Phenomena Applying Dispersive Long Wave Models". In: *Coastal Engineering, Elsevier* 122 (January), pp. 75–86. DOI: 10/f96bb5.

Larsen, B.E., D.R. Fuhrman, C. Baykal, and B.M. Sumer (2017). "Tsunami-Induced Scour around Monopile Foundations". In: *Coastal Engineering, Elsevier Ltd* 129 (August), pp. 36–49. DOI: 10/gcgr9m.

Lynett, P.J., J.A. Melby, and D.H. Kim (2010). "An Application of Boussinesq Modeling to Hurricane Wave Overtopping and Inundation". In: *Ocean Engineering, Elsevier* 37.1, pp. 135–153. DOI: 10/cjcb3p.

Macías, J., A. Mercado, J.M. González-Vida, S. Ortega, and M.J. Castro (2016). "Comparison and Computational Performance of Tsunami-Hysea and MOST Models for LANTEX 2013 Scenario: Impact Assessment on Puerto Rico Coasts". In: *Pure and Applied Geophysics* 173.12, pp. 3973–3997. DOI: 10/f9c6xk.

Madsen, P.A. and O.R. Sørensen (1992). "A New Form of the Boussinesq Equations with Improved Linear Dispersion Characteristics. Part 2. A Slowly-Varying Bathymetry". In: *Coastal Engineering* 18.3–4, pp. 183–204. DOI: 10/bw5pv3.

Madsen, P.a, H.B. Bingham, and H.a Schaffer (2003). "Boussinesq-Type Formulations for Fully Nonlinear and Extremely Dispersive Water Waves: Derivation and Analysis". In: *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* 459.2033, pp. 1075–1104. DOI: 10/bxkqfn.

Mayer, S. and P.A. Madsen (2000). "Simulation of Breaking Waves in the Surf Zone Using a Navier-Stokes Solver". In: *Proceeding to Coastal Engineering Conference*. Vol. I, pp. 928–941. DOI: 10.1061/40549(276)72.

Montagna, F., G. Bellotti, and M. Di Risio (2011). "3D Numerical Modeling of Landslide-Generated Tsunamis around a Conical Island". In: *Natural Hazards* 58.1, pp. 591–608. DOI: 10/btmx93.

Motley, Michael R., Hin Kei Wong, Xinsheng Qin, Andrew O. Winter, and Marc O. Eberhard (May 1, 2016). "Tsunami-Induced Forces on Skewed Bridges". In: *Journal of Waterway, Port, Coastal, and Ocean Engineering* 142.3, p. 04015025. DOI: 10/f8jtc3.

Popinet, S. (2012). "Adaptive Modelling of Long-Distance Wave Propagation and Fine-Scale Flooding during the Tohoku Tsunami". In: *Natural Hazards and Earth System Science* 12.4, pp. 1213–1227. DOI: 10/f3zqpr.

Qin, X., M. Motley, R. Leveque, F. Gonzalez, and K. Mueller (2018). "A Comparison of a Two-Dimensional Depth-Averaged Flow Model and a Three-Dimensional RANS Model for Predicting Tsunami Inundation and Fluid Forces". In: *Natural Hazards and Earth System Sciences* 18.9, pp. 2489–2506. DOI: 10/gfbrxc.

Qin, X., M.R. Motley, and N. Marafi (2016). "Three-Dimensional Modeling of Tsunami Forces on Coastal Communities". In: *Coastal Engineering*.

Sarfaraz, M. and A. Pak (2017). "SPH Numerical Simulation of Tsunami Wave Forces Impinged on Bridge Superstructures". In: *Coastal Engineering, Elsevier* 121, pp. 145–157. DOI: 10/f9vvht.

Shi, F., J.T. Kirby, J.C. Harris, J.D. Geiman, and S.T. Grilli (2012). “A High-Order Adaptive Time-Stepping TVD Solver for Boussinesq Modeling of Breaking Waves and Coastal Inundation”. In: *Ocean Modelling, Elsevier Ltd* 43–44, pp. 36–51. DOI: 10/d273xk.

Titov, V.V. and F.I. Gonzalez (1997). “Implementation and Testing of the Method of Splitting Tsunami (MOST) Model”. In: *NOAA Technical Memorandum ERL PMEL-112*.

Wei, Zhao, Tao Tao, Ding ZhuoShu, and Enrico Zio (2013). “A Dynamic Particle Filter-Support Vector Regression Method for Reliability Prediction”. In: *Reliability Engineering & System Safety* 119, pp. 109–116. DOI: 10/f49wsg.

Williams, I.A. and D.R. Fuhrman (2016). “Numerical Simulation of Tsunami-Scale Wave Boundary Layers”. In: *Coastal Engineering, Elsevier B.V* 110, pp. 17–31. DOI: 10/f8dvsw.

Response: Structural Systems

Álvarez, Rodolfo, José I. Restrepo, Marios Panagiotou, and Sergio E. Godínez (Oct. 1, 2020). “Analysis of Reinforced Concrete Coupled Structural Walls via the Beam-Truss Model”. In: *Engineering Structures* 220, p. 111005. ISSN: 0141-0296. DOI: 10/ghnr47.

Ancheta, T.D. et al. (2014). “NGA-West2 Database”. In: *Earthquake Spectra* 30.3, pp. 989–1005. DOI: 10/f6jfjj.

Ataei, N. and J.E. Padgett (2015). “Fragility Surrogate Models for Coastal Bridges in Hurricane Prone Zones”. In: *Engineering Structures* 103, pp. 203–213. DOI: 10/f7vs9d.

Attary, N., J.W. Lindt, V.U. Unnikrishnan, A.R. Barbosa, and D.T. Cox (2016). “Methodology for Development of Physics-Based Tsunami Fragilities”. In: *Jl. Struct.Engrg., ASCE* 143.5, p. 04016223.

Aviram, A., K.R. Mackie, and B. Stojadinovic (2008). *Guidelines for Nonlinear Analysis of Bridge Structures in California*. PEER Report 2008/03. Berkeley: Pacific Earthquake Engineering Research Center.

Carreño, R., K. H. Lotfizadeh, J. P. Conte, and J. I. Restrepo (Feb. 1, 2020). “Material Model Parameters for the Giuffrè-Menegotto-Pinto Uniaxial Steel Stress-Strain Model”. In: *Journal of Structural Engineering* 146.2, p. 04019205. ISSN: 1943-541X. DOI: 10/ghqvm3.

Deierlein, G.G., A.M. Reinhorn, and M.R. Willford (2010). “Nonlinear Structural Analysis for Seismic Design”. In: *NEHRP Seismic Design Technical Brief No. 4, NIST GCR*, pp. 10–917–5.

Dettmer, W. and S. Reese (2004). “On the Theoretical and Numerical Modelling of Armstrong-Frederick Kinematic Hardening in the Finite Strain Regime”. In: *Computer Methods in Applied Mechanics and Engineering, Elsevier* 193.1-2, pp. 87–116. DOI: 10/bhqr2t.

Dhakal, R.P. and K. Maekawa (2002). “Path-Dependent Cyclic Stress-Strain Relationship of Reinforcing Bar Including Buckling”. In: *Engineering Structures, Elsevier* 24, pp. 1383–1396. DOI: 10/dczgnx.

Do, Thanh N. and Filip C. Filippou (2018). “A Damage Model for Structures with Degrading Response”. In: *Earthquake Engineering & Structural Dynamics* 47.2, pp. 311–332. ISSN: 1096-9845. DOI: 10/gcwp7m.

Dodd, L.L. and J.I. Restrepo-Posada (1995). “Model for Predicting Cyclic Behavior of Reinforcing Steel”. In: *Jl. Struct. Engrg., ASCE* 121.3, pp. 433–445. DOI: 10/fgs3ct.

Folz, Bryan and André Filiatrault (2001). *SAWS - Version 1.0, A Computer Program for the Seismic Analysis of Woodframe Structures*. SSRP-2001/09. La Jolla, CA: University of California, San Diego.

Hube, M.A. and K.M. Mosalam (2008). *Experimental and Computational Evaluation of Current and Innovative In-Span Hinge Details in Reinforced Concrete Box-Girder Bridges*. PEER report 2008/103, Berkeley: Pacific Earthquake Engineering Research Center, University of California.

Hutchinson, T.C., R.W. Boulanger, Y.H. Chai, and I.M. Idriss (2001). *Inelastic Seismic Response of Extended Pile Shaft Supported Bridge Structures*. PEER report 2002/14, Berkeley: Pacific Earthquake Engineering Research Center, University of California.

Ibarra, Luis F., Ricardo A. Medina, and Helmut Krawinkler (2005). “Hysteretic Models That Incorporate Strength and Stiffness Deterioration”. In: *Earthquake Engineering & Structural Dynamics* 34.12, pp. 1489–1511. ISSN: 1096-9845. DOI: 10/bkfq6n.

Kaviani, P., F. Zareian, and E. Taciroglu (2012). “Seismic Behavior of Reinforced Concrete Bridges with Skew-Angled Abutments”. In: *Engineering Structures* 45, pp. 137–150. DOI: 10/f4chwq.

Kaviani, P., F. Zareian, and E. Taciroglu (2014). *Performance-Based Seismic Assessment of Skewed Bridges*. PEER report no. 2014/1, Berkeley, CA: Pacific Earthquake Engineering Research Center.

Khalili-Tehrani, P., E. Ahlberg, C.S. Rha, J.P. Stewart, E. Taciroglu, and J.W. Wallace (2014). “Nonlinear Load-Deflection Behavior of Reinforced Concrete Drilled Piles in Stiff Clay”. In: *Journal of Geotechnical & Geoenvironmental Engineering, ASCE* 140.3, p. 04013022. DOI: 10/gbf38x.

Kunnath, S.K., Y. Heo, and J.F. Mohle (2009). “Nonlinear Uniaxial Material Model for Reinforcing Steel Bars”. In: *Jl. Struct. Engrg., ASCE* 135.4, pp. 335–343. DOI: 10/crx3kp.

Lee, J. and G.L. Fenves (1998). “Plastic-Damage Model for Cyclic Loading of Concrete Structures”. In: *Jl. Engrg. Mech., ASCE* 124.8, pp. 892–900. DOI: 10/c6tqw6.

Lemaitre, J. and J.L. Chaboche (1990). “Mechanics of Solid Materials”. In: *Cambridge University Press* (BN-13), pp. 978–0521328531.

Lemnitzer, Anne, Payman Khalili-Tehrani, Eric R. Ahlberg, Changsoon Rha, Ertugrul Taciroglu, John W. Wallace, and Jonathan P. Stewart (Dec. 1, 2010). “Nonlinear Efficiency of Bored Pile Group under Lateral Loading”. In: *Journal of Geotechnical and Geoenvironmental Engineering* 136.12, pp. 1673–1685. ISSN: 1090-0241. DOI: 10/cwmsgq.

Lowes, Laura N. and Arash Altoontash (Dec. 1, 2003). “Modeling Reinforced-Concrete Beam-Column Joints Subjected to Cyclic Loading”. In: *Journal of Structural Engineering* 129.12, pp. 1686–1697. ISSN: 0733-9445. DOI: 10/dp6sqn.

Lu, Yuan and Marios Panagiotou (Mar. 1, 2014). “Three-Dimensional Cyclic Beam-Truss Model for Nonplanar Reinforced Concrete Walls”. In: *Journal of Structural Engineering* 140.3, p. 04013071. ISSN: 1943-541X. DOI: 10/f54kbg.

Madurapperuma, M. A. K. M. and Anil C. Wijeyewickrema (Nov. 1, 2013). “Response of Reinforced Concrete Columns Impacted by Tsunami Dispersed 20′ and 40′ Shipping Containers”. In: *Engineering Structures* 56, pp. 1631–1644. ISSN: 0141-0296. DOI: 10/f5qd5c.

Maekawa, K., A. Pimanmas, and H. Okamura (2003). *Nonlinear Mechanics of Reinforced Concrete*. NY: Spon Press, Tylor & Francis Group.

Malley, J.O., G.G. Deierlein, H. Krawinkler, J.R. Maffei, M. Pourzanjani, J. Wallace, and J.A. Heintz (2010). *Modeling and Acceptance Criteria for Seismic Design and Analysis of Tall Buildings*. PEER report 2010/11,

Mander, J. B., M. J. N. Priestley, and R. Park (Aug. 1, 1988). “Theoretical Stress-Strain Model for Confined Concrete”. In: *Journal of Structural Engineering* 114.8, pp. 1804–1826. ISSN: 0733-9445. DOI: 10/cwzrtg.

McKenna, F. (2011). “OpenSees: A Framework for Earthquake Engineering Simulation”. In: *Computing in Science & Engineering* 13.4, pp. 58–66. DOI: 10/cd3djt.

Menegotto, M. and P.E. Pinto (1973). “Method of Analysis of Cyclically Loaded RC Plane Frames Including Changes in Geometry and Non-Elastic Behavior of Elements under Normal Force and Bending"”. In: *Preliminary Report for Symposium on Resistance and Ultimate Deformability of Structures, IABSE*. Vol. 13, pp. 15–22.

Miller, M., S. Cortes, D. Ory, and J.W. Baker (2015). “Estimating Impacts of Catastrophic Network Damage from Earthquakes Using an Activity-Based Travel Model”. In: *Transportation Research Board 94th Annual Meeting*. Washington DC.

Minjie, Z., I. Elkhetali, and M.H. Scott (2018). “Validation of OpenSees for Tsunami Loading on Bridge Superstructures"”. In: *J. Bridge Eng., ASCE* 23.4, p. 04018015.

Minjie, Zhu and M.H. Scott (2014). “Modeling Fluid–Structure Interaction by the Particle Finite Element Method in OpenSees”. In: *Computers & Structures* 132, pp. 12–21. DOI: 10/f5r5g4.

N.I.S.T. (2017a). *Guidelines for Nonlinear Structural Analysis for Design of Buildings: Part I – General*. NIST GCR 17-917-46v1,

N.I.S.T. (2017b). *Guidelines for Nonlinear Structural Analysis for Design of Buildings: Part Ib – Concrete Moment Frames*. NIST GCR 17-917-46v3,

N.I.S.T. (2017c). *Guidelines for Nonlinear Structural Analysis for Design of Buildings: Part IIa – Steel Moment Frames*. NIST GCR 17-917-46v2,

N.I.S.T.-A.T.C. (2018). *Blind Prediction Contenst on Deep, Wide-Flange Structural Steel Beam-Columns*. URL: https://www.atcouncil.org/atc-106-blind-contest.

NBI (2016). *National Bridge Inventory System, US Department of Transportation*. Federal Highway Administration. URL: https://catalog.data.gov/dataset/national-bridge-inventory-system-nbi-1992-b9105..

Nurbaiah, M.N., L. Liberatore, F. Mollaioli, and S. Tesfamariam (17). “Modelling of Masonry Infilled RC Frames Subjected to Cyclic Loads: State of the Art Review and Modelling with OpenSees"”. In: *Engineering Structures, Elsevier* 150, pp. 599–621.

Omrani, R., B. Mobasher, X. Liang, S. Gunay, K.M. Mosalam, F. Zareian, and E. Taciroglu (2015). "Guidelines for Nonlinear Seismic Analysis of Ordinary Bridges: Version 2.0". In: *Caltrans Final Report* (15-65A0454).

Omrani, R., B. Mobasher, F. Zareian, and E. Taciroglu (2017). "Variability in the Predicted Seismic Performance of a Typical Seat-Type Bridge Due to Epistemic Uncertainties in Its Abutment Backfill and Shear-Key Models". In: *Engineering Structures* 148C, pp. 718–738. DOI: 10/gbzfws.

Petrone, C., T. Rossetto, and K. Goda (2017). "Fragility Assessment of a RC Structure under Tsunami Actions via Nonlinear Static and Dynamic Analyses". In: *Engineering Structures* 136, pp. 36–53. DOI: 10/f9263h.

Shamsabadi, A., P. Khalili-Tehrani, J.P. Stewart, and E. Taciroglu (2010). "Validated Simulation Models for Lateral Response of Bridge Abutments with Typical Backfills". In: *ASCE Journal of Bridge Engineering* 15.3, pp. 302–311. DOI: 10/d65qzh.

Silva, P.F., S. Megally, and F. Seible (2009). "Seismic Performance of Sacrificial Exterior Shear Keys in Bridge Abutments". In: *Earthquake Spectra* 25.3, pp. 1–11. DOI: 10/dpvnwf.

Spacone, E. and S. El-Tawil (2004). "Nonlinear Analysis of Steel-Concrete Composite Structures: State of the Art". In: *Jl. Struct. Engrg., ASCE* 130.2.

Taciroglu, Ertugrul, ChangSoon Rha, and John W. Wallace (Oct. 1, 2006). "A Robust Macroelement Model for Soil–Pile Interaction under Cyclic Loads". In: *Journal of Geotechnical and Geoenvironmental Engineering* 132.10, pp. 1304–1314. ISSN: 1090-0241. DOI: 10/dxkvhk.

Terzic, V., M.J. Schoettler, J.I. Restrepo, and S.A. Mahin (2015). *Concrete Column Blind Prediction Contest 2010: Outcomes and Observations*. PEER-2015/1. Berkeley, CA: Pacific Earthquake Engineering Research Center.

TPU (2020). *Aerodynamic Database*. Tokyo Polytechnic University. URL: http://wind.arch.t-kougei.ac.jp/system/eng/contents/code/tpu.

Xu, S.-Y. and J. Zhang (2011). "Hysteretic Shear-Flexure Interaction Model of Reinforced Concrete Columns for Seismic Response Assessment of Bridges". In: *Earthquake Engineering & Structural Dynamics* 40.3, pp. 315–337. DOI: 10/cgsctn.

Zhang, Jian and Nicos Makris (2002). "Kinematic Response Functions and Dynamic Stiffnesses of Bridge Embankments". In: *Earthquake Engineering & Structural Dynamics* 31.11, pp. 1933–1966. ISSN: 1096-9845. DOI: 10/fq2hnw.

Zhang, Peizhou, José I. Restrepo, Joel P. Conte, and Jinping Ou (Nov. 1, 2017b). "Nonlinear Finite Element Modeling and Response Analysis of the Collapsed Alto Rio Building in the 2010 Chile Maule Earthquake". In: *The Structural Design of Tall and Special Buildings* 26.16, e1364. ISSN: 1541-7794. DOI: 10/ghnrx7.

Response: Geotechnical Systems

Institute, American Petroleum (2007). *Recommended Practice for Planning, Designing and Constructing Fixed Offshore Platforms–Working Stress Design*. 21st. manual. American Petroleum Institute (API). API Recommended Practice 2A-WSD (RP 2A-WSD).

Arduino, P. Macari E.J. (2001). “Implementation of a Porous Media Formulation for Geomaterials”. In: *ASCE Journal of Engineering Mechanics* 127.2, pp. 157–166. DOI: 10/djz8ph.

Bielak, J., K. Loukakis, Y. Hisada, and C. Yoshimura (2003). “Domain Reduction Method for Three-Dimensional Earthquake Modeling in Localized Regions, Part I: Theory”. In: *Bulletin of the Seismological Society of America* 93.2, pp. 817–824. DOI: 10/bhkvzv.

Biot, M. A. (1941). “General Theory of Three Dimensional Consolidation”. In: *Journal of Applied Physics* 12, pp. 155–164. DOI: 10/fg8sfb.

Biot, M. A. (1956). “Theory of Propagation of Elastic Waves in a Fluid Saturated Porous Solid”. In: *Journal of the Acoustical Society of America* 28, pp. 168–191.

Biot, M. A. (1962). “Mechanics of Deformation and Acoustic Propagation in Porous Media”. In: *Journal of Applied Physics* 33, pp. 1482–1498. DOI: 10/dz7cmr.

Borja, R. I. (2006). “On the Mechanical Energy and Effective Stress in Saturated and Unsaturated Porous Continua”. In: *International Journal of Solids and Structures* 43, pp. 1764–1786. DOI: 10/c889mh.

Borja, R. I. (2013). *Plasticity, Modeling and Computation*. Springer.

Boulanger, Ross and Katerina Ziotopoulou (Mar. 2017). *PM4Sand Version 3.1: A Sand Plasticity Model for Earthquake Engineering Applications*. UC Davis.

Boulanger, Ross and Katerina Ziotopoulou (2018). *PM4Silt (Version 1): A Silt Plasticity Model for Earthquake Engineering Applications.* University of California, Davis.

Dafalias, Y. F. (1986). “Bounding Surface Plasticity I: Mathematical Foundation and Hypoplasticity”. In: *Journal of Engineering Mechanics* 112.9, pp. 966–987. DOI: 10/bsjpm9.

Dafalias, Y. F. and M. T. Manzari (2004). “Simple Plasticity Sand Model Accounting for Fabric Change Effects”. In: *Journal of Engineering Mechanics* 130.6, pp. 622–634. DOI: 10/dwv68j.

Ehlers, W. (2002). *Porous Media - Theory, Experiments and Numerical Application*. Ed. by W. Ehlers and J. Buhm. Berlin: Springer-Verlag, pp. 3–86.

Elgamal, Ahmed, Zhaohui Yang, Ender Parra, and Ahmed Ragheb (2003). “Modeling of Cyclic Mobility in Saturated Cohesionless Soils”. In: *International Journal of Plasticity* 19.6, pp. 883–905. DOI: 10/bsxchn.

Ghofrani, A. (2018). *Development of Numerical Tools for the Evaluation of Pile Response to Laterally Spreading Soil*. University of Washington: Ph.D. Dissertation.

Iai, S., T. Tobita, O. Ozutsumi, and K. Ueda (2011). “Dilatancy of Granular Materials in a Strain Space Multiple Mechanism Model”. In: *International Journal for Numerical and Analytical Methods in Geomechanics* 35.3, pp. 360–392. DOI: 10/dr6ss8.

Iai, S., K. Ueda, T. Tobita, and O. Ozutsumi (2013). “Finite Strain Formulation of a Strain Space Multiple Mechanism Model for Granular Materials”. In: *International Journal for Numerical and Analytical Methods in Geomechanics* 37.9, pp. 1189–1212. DOI: 10/f42d35.

Joyner, W. B. and A. T. F. Chen (1975). “Calculation of Nonlinear Ground Response in Earthquakes”. In: *Bulletin of the Seismological Society of America* 65.5, pp. 1315–1336.

Kawamoto, Reid, Edward Andò, Gioacchino Viggiani, and José E. Andrade (2018). "All You Need Is Shape: Predicting Shear Banding in Sand with LS-DEM". In: *Journal of the Mechanics and Physics of Solids* 111, pp. 375–392. DOI: 10/gc25z7.

Laursen, Tod A (2002). *Computational Contact and Impact Mechanics: Fundamentals of Modelling Interfacial Phenomena in Nonlinear Finite Element Analysis*. Springer, Berlin.

Lysmer, J. and A. M. Kuhlemeyer (1969). "Finite Dynamic Model for Infinite Media". In: *Journal of the Engineering Mechanics Division, ASCE* 95, pp. 859–877.

Mast, C., P. Arduino, G. Miller, and P. Mackenzie-Helnwein (2015). "Simulating Granular Column Collapse Using the Material Point Method". In: *Acta Geotechnica* 10.1, pp. 101–116. DOI: 10/f6xr3m.

McGann, C. R., P. P. Arduino, and Mackenzie-Helnwein (2015). "Stabilized Single-Point 8-Node Hexahedral Element for Dynamic Analysis of Fluid Saturated Porous Media". In: *Computers and Geotechnics* 66, pp. 126–141. DOI: 10/f67dcg.

McGann, C.R., P. Arduino, and P. Mackenzie-Helnwein (2012). "Stabilized Single-Point 4-Node Quadrilateral Element for Dynamic Analysis of Fluid Saturated Porous Media". In: *Acta Geotechnica* 7.4, pp. 297–311. DOI: 10/ghhz5h.

McKenna, F. (2011). "OpenSees: A Framework for Earthquake Engineering Simulation". In: *Computing in Science & Engineering* 13.4, pp. 58–66. DOI: 10/cd3djt.

Petek, K. A. (2006). *Development and Application of Mixed Beam-Solid Models for Analysis of Soil-Pile Interaction Problems*. University of Washington: Ph.D. Dissertation.

Prevost, J. H. (1977). "Mathematical Modeling of Monotonic and Cyclic Undrained Clay Behavior". In: *International Journal for Numerical and Analytical Methods in Geomechanics* 1, pp. 195–216. DOI: 10/dm2664.

Prevost, J. H. (1985). "A Simple Plasticity Theory for Frictional Cohesionless Soils". In: *Soil Dynamics and Earthquake Engineering* 4, pp. 9–17. DOI: 10/dc3zhv.

Yoshimura, C., J. Bielak, Y. Hisada, and A. Fernández (2003). "Domain Reduction Method for Three-Dimensional Earthquake Modeling in Localized Regions, Part II: Verification and Applications". In: *Bulletin of the Seismological Society of America* 93.2, pp. 825–840. DOI: 10/bt8k78.

Zhang, W., E. Esmaeilzadeh Seylabi, and E. Taciroglu (2019b). "An ABAQUS Toolbox for Soil-Structure Interaction Analysis". In: *Computers and Geotechnics* 114, pp. 103–143. ISSN: 0266-352X. DOI: 10/ghhz5f.

Zienkiewicz, OC and T Shiomi (1984). "Dynamic Behaviour of Saturated Porous Media; the Generalized Biot Formulation and Its Numerical Solution". In: *International journal for numerical and analytical methods in geomechanics* 8.1, pp. 71–96. DOI: 10/c4j3sn.

Response: Computational Fluid Dynamics - Wind

American institute of aeronautics and astronautics (1998). *Guide for the Verification and Validation of Computational Fluid Dynamics Simulations*. AIAA G-077-1998. American Institute of Aeronautics and Astronautics.

Beran, P., B. Stanford, and C. Schrock (2017). “Uncertainty Quantification in Aeroelasticity”. In: *Annual Review of Fluid Mechanics, Vol 43* 49, pp. 361–386. DOI: 10/ghk56w.

Bervida, M., L. Paturno, S. Stanič, and S. de Miranda (2020). “Synthetic Generation of the Atmospheric Boundary Layer for Wind Loading Assessment Using Spectral Methods”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 196, p. 104040. DOI: 10/ghk2xz.

Bose, S.T. and G.I. Park (2018). “Wall-Modeled Large-Eddy Simulation for Complex Turbulent Flows”. In: *Annual Review of Fluid Mechanics* 50, pp. 535–561. DOI: 10/ghk2x2.

Collins, K.B. (2008). *A Multi-Fidelity Framework for Physics Based Rotor Blade Simulation and Optimization*. Georgia Institute of Technology.

Ding, F. and A. Kareem (2020). “Tall Buildings with Dynamic Façade under Winds”. In: *Engineering*. DOI: 10/ghk54t.

Ding, F., A. Kareem, and J. Wan (2018). “Aerodynamic Tailoring of Structures Using Computational Fluid Dynamics”. In: *Structural Engineering International*. DOI: 10/ghk56t.

Ding, F and A. Kareem (2019). “Inflow and Model-Form Uncertainty Quantification in CFD-Enabled Aerodynamic Shape Optimization”. In: EMI. MIT.

Ding, Fei and Ahsan Kareem (2018). “A Multi-Fidelity Shape Optimization via Surrogate Modeling for Civil Structures”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 178, pp. 49–56. DOI: 10/gdtdx9.

Ferziger, J.H. and M. Peric (2012). *Computational Methods for Fluid Dynamics*. Berlin: Springer Science and Business Media.

Forrester, A.I.J., A. Sóbester, and A.J. Keane (2007). “Multi-Fidelity Optimization via Surrogate Modelling”. In: *PRoy SocA-Math Phy* 463.

Gorlé, C., C. Garcia-Sanchez, and G. Iaccarino (2015). “Quantifying Inflow and RANS Turbu-Lence Model Form Uncertainties for Wind Engineering Flows”. In: *Journal of Wind Engineering and Industrial Aerodynamics* 144, pp. 202–212.

Hoarau, Y., S.-H. Peng, D. Schwamborn, and A. Revell (2016). “Progress in Hybrid RANS-LES Modelling”. In: *Methods-a Companion to Methods in Enzymology* 26.

Hoshiya, M. (1972). “Simulation of Multi-Correlated Random Processes and Application to Structural Vibration Problems”. In: *P Jpn Soc Civil Eng* 204, pp. 121–128. DOI: 10/bhrp5h.

Jarrin, N., S. Benhamadouche, D. Laurence, and R. Prosser (2006). “A Synthetic-Eddy-Method for Generating Inflow Conditions for Large-Eddy Simulations”. In: *Int J Heat Fluid Flow* 27.4, pp. 585–593. DOI: 10/btk8vb.

Kareem, A. (2017). “Computational Modeling and Simulation of Wind Effects on Built Environment at NSF’s NHERI SimCenter and Its Role in EFs” (Florida International University). URL: https://www.youtube.com/watch?v=j0DUvdKTWXg.

Kareem, A. (2020). “Emerging Frontiers in Wind Engineering: Computing, Stochastics, Machine Learning and Beyond”. In: *Journal of Wind Engineering and Industrial Aerodynamics*. DOI: 10/ghk54z.

Kareem, A., L. Hu, Y. Guo, and D.K. Kwon (2019). “Generalized Wind Loading Chain: A Time-Frequency Modeling Framework for Nonstationary Winds Effects on Structures”. In: *Journal of Structural Engineering* 145.10, p. 04019092.

Klein, M., A. Sadiki, and J. Janicka (2003). "A Digital Filter Based Generation of Inflow Data for Spatially Developing Direct Numerical or Large Eddy Simulations". In: *Journal of Computational Physics* 186.2, pp. 652–665. DOI: 10/cstkxs.

Kraichnan, R.H. (1970). "Diffusion by a Random Velocity Field". In: *Physics of Fluids* 13.1, pp. 22–31. DOI: 10/fpbx84.

Kutz, J.N. (2017). "Deep Learning in Fluid Dynamics". In: *Journal of Fluid Mechanics* 814, pp. 1–4. DOI: 10/gfxr5h.

Lamberti, Giacomo, Clara Garcia-Sanchez, Sousa Jorge, and Catherine Gorlé (2018). "Optimizing Turbulent Inflow Conditions for Large-Eddy Simulations of the Atmospheric Boundary Layer". In: *Journal of Wind Engineering and Industrial Aerodynamics* 177, pp. 32–44. DOI: 10/gdvhks.

Leary, S.J., A. Bhaskar, and A.J. Keane (2003). "A Knowledge-Based Approach to Response Surface Modelling in Multifidelity Optimization". In: *Journal of Global Optimization* 26.3, pp. 297–319. DOI: 10/d4m2cc.

Ling, J., A. Kurzawski, and J. Templeton (2016b). "Reynolds Averaged Turbulence Modelling Using Deep Neural Networks with Embedded Invariance." In: *Journal of Fluid Mechanics* 807, pp. 155–166. DOI: 10/f88zp4.

Liu, W., J. Fang, S. Rolfo, C. Moulinec, and D.R. Emerson (2020). *An Iterative Machine-Learning Framework for RANS Turbulence Modeling*. arXiv: 1910.01232v3 [physics.flu-dyn].

Luo, X. and A. Kareem (2019). "Deep Convolution Neural Networks for Uncertainty Propagation in Random Fields". In: *Computer-Aided Civil and Infrastructure Engineering*. DOI: 10/ghk54x.

Luo, X and A. Kareem (2020). "Bayesian Deep Learning with Hierarchical Prior: Predictions from Limited and Noisy Data". In: *Structural Safety* 84, p. 101918. DOI: 10/ghk54w.

Mao, Z, A.D. Jagtap, and G.E. Karniadakis (2020). "Physics-Informed Neural Networks for High-Speed Flows". In: *Computer Methods in Applied Mechanics and Engineering* 360.1, p. 112789.

Molinaro, R., J-S. Singh, S. Catsoulis, C. Narayanan, and D. Lakehal (2021). "Embedding Data Analytics and CFD into the Digital Twin Concept". In: *Computers & Fluids* 214, p. 104759. DOI: 10/ghk54v.

Oberkampf, W.L. and C. Roy (2004). "Verification and Validation in Computational Simulation". In: AIAA Professional Development Short-Course, pp. 6–7.

Oberkampf, W.L. and T.G. Trucano (2008). "Verification and Validation Benchmarks". In: *Nuclear Engineering and Design* 238.3, pp. 716–743. DOI: 10/bt6kkq.

Parente, A., J. Gorle, J. van Beeck, and C. Benocci (2011). "A Comprehensive Modelling Approach for the Neutral Atmospheric Boundary Layer: Consistent Inflow Conditions, Wall Function and Turbulence Model Closure". In: *Boundary-Layer Meteorology* 140.3, pp. 411–428. DOI: 10/dkmzx9.

Roache, P.J. (1998). *Verification and Validation in Computational Science and Engineering*. Hermosa.

Roy, C.J. and W.L. Oberkampf (2011). “A Comprehensive Framework for Verification, Validation, and Uncertainty Quantification in Scientific Computing”. In: *Comput Methods Appl Mech Eng* 200.25-28, pp. 2131–2144. DOI: 10/b5bt9z.

Spalart, P. (2010). “Reflections on RANS Modelling”. In: *Progress in Hybrid RANS-LES Modelling*, pp. 7–24.

Tompson, J., K. Schlachter, P. Sprechmann, and K. Perlin (2016). “Accelerating Eulerian Fluid Simulation With Convolutional Networks.” In: *Proceedings of the 34th International Conference on Machine Learning*.

TPU (2020). *Aerodynamic Database*. Tokyo Polytechnic University. URL: http://wind.arch.t-kougei.ac.jp/system/eng/contents/code/tpu.

Wu, X. (2017). “Inflow Turbulence Generation Methods”. In: *Annual Review of Fluid Mechanics, Vol 43* 49.1, pp. 23–49. DOI: 10/ghk56x.

Yu, D., K. Butler, A. Kareem, J. Glimm, and J. Sun (2013). “Simulation of the Influence of Aspect Ratio on the Aerodynamics of Rectangular Prisms”. In: *J Eng Mech* 139.4, pp. 429–438. DOI: 10/ggcxrw.

Yu, D. and A. Kareem (1998). “Parametric Study of Flow around Rectangular Prisms Using LES”. In: *J Wind Eng Ind Aerodyn* 77-78, pp. 653–662. DOI: 10/dvqnfp.

Response: Computational Fluid Dynamics - Water

Brackbill, J.U., D.B. Kothe, and C. Zemach (1992). “A Continuum Method for Modeling Surface Tension”. In: *Journal of Computational Physics* 100, pp. 335–354. DOI: 10/bvbwqk.

Chen, S. and G.D. Doolen (1998). “Lattice Boltzmann Method for Fluid Flows”. In: *Annual Review of Fluid Mechanics* 30, pp. 329–364. DOI: 10/czwgk5.

Chou, P.Y. (1945). “On Velocity Correlations and the Solutions of the Equations of Turbulent Fluctuation”. In: *Quarterly of Applied Mathematics* 3, pp. 38–54. DOI: 10/gf7rfj.

Darrigol, O. (2005). *Worlds of Flow: A History of Hydrodynamics from the Bernoullis to Prandtl*. Oxford: Oxford University Press.

Deardorff, J. (1970). “A Numerical Study of Three-Dimensional Turbulent Channel Flow at Large Reynolds Numbers”. In: *Journal of Fluid Mechanics* 41, pp. 453–480. DOI: 10/bdw49r.

Gao, Xifeng, Wenzel Jakob, Marco Tarini, and Daniele Panozzo (July 20, 2017). “Robust Hex-Dominant Mesh Generation Using Field-Guided Polyhedral Agglomeration”. In: *ACM Transactions on Graphics* 36.4, 114:1–114:13. ISSN: 0730-0301. DOI: 10/gbxfzd.

Geuzaine, Christophe and Jean-François Remacle (2009). “Gmsh: A 3-D Finite Element Mesh Generator with Built-in Pre- and Post-Processing Facilities”. In: *International Journal for Numerical Methods in Engineering* 79.11, pp. 1309–1331. ISSN: 1097-0207. DOI: 10/dkdqqc.

Giles, Michael B. (Dec. 1, 1990). “Nonreflecting Boundary Conditions for Euler Equation Calculations”. In: *AIAA Journal* 28.12, pp. 2050–2058. ISSN: 0001-1452. DOI: 10/fhw6p5.

Gingold, R.A. and J.J. Monaghan (1977). "Smoothed Particle Hydrodynamics: Theory and Application to Non-Spherical Stars". In: *Monthly Notices of the Royal Astronomical Society* 181, pp. 375–389. DOI: 10/gf3kk6.

Higuera, P., J.L. Lara, and I.J. Losada (2013a). "Realistic Wave Generation and Active Wave Absorption for Navier-Stokes Models. Application to OpenFOAM". In: *Coastal Engineering* 71, pp. 102–118. DOI: 10/gdvqhj.

Higuera, P., J.L. Lara, and I.J. Losada (2013b). "Simulating Coastal Engineering Processes with OpenFOAM". In: *Coastal Engineering* 71, pp. 119–134. DOI: 10/gdvqhh.

Higuera, P., J.L. Lara, and I.J. Losada (2014a). "Three-Dimensional Interaction of Waves and Porous Coastal Structures Using OpenFOAM. Part I: Formulation and Validation". In: *Coastal Engineering* 83, pp. 243–258.

Higuera, P., J.L. Lara, and I.J. Losada (2014b). "Three-Dimensional Interaction of Waves and Porous Coastal Structures Using OpenFOAM. Part II: Application". In: *Coastal Engineering* 83, pp. 259–270.

Higuera, P., J.L. Lara, and I.J. Losada (2015). "Three-Dimensional Numerical Wave Generation with Moving Boundaries". In: *Coastal Engineering* 101, pp. 35–47. DOI: 10/f7jd9d.

Hirt, C.W. and B.D. Nichols (1981). "Volume of Fluid (VOF) Method for the Dynamics of Free Boundaries". In: *Journal of Computational Physics* 39, pp. 201–225. DOI: 10/bxm88h.

Jasak, H. (1996). "Analysis and Estimation for the Finite Volume Method with Applications to Fluid Flows". Imperial College of Science, Technology and Medicine, London.

Lind, S.J., B.D. Rogers, and P.K. Stansby (2020). "Review of Smoothed Particle Hydrodynamics: Towards Converged Lagrangian Flow Modelling". In: *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* 476, p. 20190801. DOI: 10/ghndg2.

Lucy, L.B. (1977). "A Numerical Approach to the Testing of the Fission Hypothesis". In: *Astronomical Journal* 82, pp. 1013–1024. DOI: 10/fw9nk4.

Miquel, Adria Moreno, Arun Kamath, Mayilvahanan Alagan Chella, Renata Archetti, and Hans Bihs (June 2018). "Analysis of Different Methods for Wave Generation and Absorption in a CFD-Based Numerical Wave Tank". In: *Journal of Marine Science and Engineering* 6.2, p. 73. DOI: 10/gf2zzn.

Orszag, S.A. (1970). "Analytical Theories of Turbulence". In: *Journal of Fluid Mechanics* 41, pp. 363–386. DOI: 10/fkdbdq.

Peskin, C.S. (1972). "Flow Patterns around Heart Valves: A Numerical Method". In: *Journal of Computational Physics* 10, pp. 252–271. DOI: 10/c7r2hc.

Peskin, C.S. (1977). "Numerical Analysis of Blood Flow in the Heart". In: *Journal of Computational Physics* 25, pp. 220–252. DOI: 10/bxj2kh.

Peskin, C.S. (2002). "The Immersed Boundary Method". In: *Acta Numerica* 11, pp. 479–517. DOI: 10/c2f9cs.

Reynolds, O. (1895). "On the Dynamical Theory of Incompressible Viscous Fluids and the Determination of the Criterion". In: *Philosophical Transactions of the Royal Society A* 186, pp. 123–164.

Ubbink, H. (2002). “Computational Fluid Dynamics of Dispersed Two-Phase Flows at High Phase Fractions”. Imperial College of Science, Technology and Medicine, London.

Ubbink, O. (1997). “Numerical Prediction of Two Fluid Systems with Sharp Interfaces”. Imperial College of Science, Technology and Medicine, London.

Verhetsel, Kilian, Jeanne Pellerin, and Jean-François Remacle (July 12, 2019). “Finding Hexahedrizations for Small Quadrangulations of the Sphere”. In: *ACM Transactions on Graphics* 38.4, 53:1–53:13. ISSN: 0730-0301. DOI: 10/ghntfm.

Yamakawa, Soji and Kenji Shimada (2003). “Fully-Automated Hex-Dominant Mesh Generation with Directionality Control via Packing Rectangular Solid Cells”. In: *International Journal for Numerical Methods in Engineering* 57.15, pp. 2099–2129. ISSN: 1097-0207. DOI: 10/d35tbp.

Performance: Buildings

Agency, Federal Emergency Management (1997). *NEHRP Guidelines for the Seismic Rehabilitation Ofbuildings*. FEMA 273. Washington, D.C.

Akiyama, Mitsuyoshi and Dan M. Frangopol (July 7, 2014). “Reliability of Bridges under Seismic and Tsunami Hazards”. In: *Vulnerability, Uncertainty, and Risk*, pp. 1696–1705. DOI: 10/ghngf3.

Applied Technology Council (1985). *ATC-13: Earthquake Damage Evaluation Data for California*. California, ATC, Redwood City, CA, USA.

Applied Technology Council (2012). *Seismic Performance Assessment of Buildings*. First Edition. Federal Emergency Management Agency.

Applied Technology Council (Dec. 2018a). *Methodology*. Second Edition. Vol. 1. Seismic Performance Assessment of Buildings P-58-1. Federal Emergency Management Agency. URL: https://www.fema.gov/media-library-data/1557508320921-d67f745e88e04e54a1f40f8e94835042/FEMA_P-58-1-SE_Volume1_Methodology.pdf.

ARUP (2013). *Resilience-Based Earthquake Design Initiative for the next Generation of Buildings*. ARUP, USA.

Aslani, Hesameddin and Eduardo Miranda (July 1, 2005). “Probability-Based Seismic Response Analysis”. In: *Engineering Structures* 27.8, pp. 1151–1163. ISSN: 0141-0296. DOI: 10/fhwkvz.

Attary, N., V.U. Unnikrishnan, J.W. Lindt, D.T. Cox, and A.R. Barbosa (2017). “Performance-Based Tsunami Engineering Methodology for Risk Assessment of Structures”. In: *Engineering Structures* 141, pp. 676–686. DOI: 10/f97zq4.

Baker, J.W., B.A. Bradley, and P.J. Stafford (2021). *Seismic Hazard and Risk Analysis*. Cambridge, England: Cambridge University Press.

Barbato, Michele, Francesco Petrini, Vipin U Unnikrishnan, and Marcello Ciampoli (2013). “Performance-Based Hurricane Engineering (PBHE) Framework”. In: *Structural Safety* 45, pp. 24–35. DOI: 10/ghghns.

Bernardini, Enrica, Seymour M. J. Spence, Dae-Kun Kwon, and Ahsan Kareem (Oct. 1, 2015). "Performance-Based Design of High-Rise Buildings for Occupant Comfort". In: *Journal of Structural Engineering* 141.10, p. 04014244. ISSN: 1943-541X. DOI: 10/f7r5wz.

Bradley, B.A., D.S. Lee, R. Broughton, and C. Price (2010). "Efficient Evaluation of Performance-Based Earthquake Engineering Equations". In: *Structural Safety*. DOI: 10.1016/j.strusafe.2008.03.003.

Bradley, Brendon A. (Sept. 2013). "A Critical Examination of Seismic Response Uncertainty Analysis in Earthquake Engineering". In: *Earthquake Engineering & Structural Dynamics* 42.11, pp. 1717–1729. ISSN: 00988847. DOI: 10/f462v3.

Bruneau, Michel, Michele Barbato, Jamie E. Padgett, Arash E. Zaghi, Judith Mitrani-Reiser, and Yue Li (Oct. 1, 2017). "State of the Art of Multihazard Design". In: *Journal of Structural Engineering* 143.10, p. 03117002. ISSN: 1943-541X. DOI: 10/gg3ss5.

Carey, Trevor J., H. Benjamin Mason, Andre R. Barbosa, and Michael H. Scott (Apr. 1, 2019). "Multihazard Earthquake and Tsunami Effects on Soil–Foundation–Bridge Systems". In: *Journal of Bridge Engineering* 24.4, p. 04019004. DOI: 10/ghngf2.

Chmielewski, H., R. Guidotti, T. McAllister, and P. Gardoni (2016). "Response of Water Systems under Extreme Events: A Comprehensive Approach to Modeling Water System Resilience". In: *Proc. 16th World Environmental and Water Resources Congress*, pp. 475–486.

Choe, Do-Eun, Paolo Gardoni, David Rosowsky, and Terje Haukaas (Mar. 1, 2008). "Probabilistic Capacity Models and Seismic Fragility Estimates for RC Columns Subject to Corrosion". In: *Reliability Engineering & System Safety*. Probabilistic Modelling of Structural Degradation 93.3, pp. 383–393. ISSN: 0951-8320. DOI: 10/bhjb7r.

Council, Applied Technology (Dec. 2018b). *Implementation Guide*. Second. Vol. 2. Seismic Performance Assessment of Buildings P-58-2. Federal Emergency Management Agency. URL: https://www.fema.gov/media-library-data/1557508320921-d67f745e88e04e54a1f40f8e94835042/FEMA_P-58-1-SE_Volume1_Methodology.pdf. *PACT*. URL: https://femap58.atcouncil.org/pact.

Crowley, Helen, Miriam Colombi, and Vitor Silva (2014). "Epistemic Uncertainty in Fragility Functions for European RC Buildings". In: *SYNER-G: Typology Definition and Fragility Functions for Physical Elements at Seismic Risk: Buildings, Lifelines, Transportation Networks and Critical Facilities*. Ed. by K. Pitilakis, H. Crowley, and A.M. Kaynia. Geotechnical, Geological and Earthquake Engineering. Dordrecht: Springer Netherlands, pp. 95–109. ISBN: 978-94-007-7872-6. URL: https://doi.org/10.1007/978-94-007-7872-6_4 (visited on 12/08/2020).

Deierlein, Gregory G., Frank McKenna, Adam Zsarnóczay, Tracy Kijewski-Correa, Ahsan Kareem, Wael Elhaddad, Laura Lowes, Matthew J. Schoettler, and Sanjay Govindjee (2020). "A Cloud-Enabled Application Framework for Simulating Regional-Scale Impacts of Natural Hazards on the Built Environment". In: *Frontiers in Built Environment* 6. ISSN: 2297-3362. DOI: 10/ghms27.

Elgamal, Ahmed, Linjun Yan, Zhaohui Yang, and Joel P. Conte (July 1, 2008). "Three-Dimensional Seismic Response of Humboldt Bay Bridge-Foundation-Ground System". In: *Journal of Structural Engineering* 134.7, pp. 1165–1176. ISSN: 0733-9445. DOI: 10/bkpmjs.

"Performance-Based Seismic Design Concepts and Implementation" (2004). In: *Proceedings of an International Workshop*. Ed. by P. Fajfar and H. Krawinkler. Bled Slovenia.

Federal Emergency Management Agency (2011a). *Hazus–MH 2.1: Earthquake Technical Manual*. Washington, D.C.: FEMA, p. 718.

Federal Emergency Management Agency (Nov. 2017). *Hazus Tsunami Model Technical Guidance*. Washington D.C.

Federal Emergency Management Agency (2018a). *Earthquake Model Technical Manual*. HAZUS – Multi-Hazard Loss Estimation Methodology 2.1. Washington, D.C.

Federal Emergency Management Agency (2018b). *Hurricane Model User Manual*. FEMA. URL: https://www.fema.gov/sites/default/files/2020-09/fema_hazus_hurricane-model_user-manual_2.1.pdf.

Filiatrault, Andre and Timothy Sullivan (Aug. 1, 2014). "Performance-Based Seismic Design of Nonstructural Building Components: The next Frontier of Earthquake Engineering". In: *Earthquake Engineering and Engineering Vibration* 13.1, pp. 17–46. ISSN: 1993-503X. DOI: 10/ghnv9j.

Gavrilovic, Stevan and Terje Haukaas (Nov. 22, 2020). "Multi-Model Probabilistic Analysis of the Lifecycle Cost of Buildings". In: *Sustainable and Resilient Infrastructure* 0.0, pp. 1–19. ISSN: 2378-9689. DOI: 10/ghnv9m.

Gill, Joel C. and Bruce D. Malamud (2014). "Reviewing and Visualizing the Interactions of Natural Hazards". In: *Reviews of Geophysics* 52.4, pp. 680–722. ISSN: 1944-9208. DOI: 10/ghch8m.

Guan, Xingquan, Henry Burton, and Thomas Sabol (Dec. 1, 2020). "Python-Based Computational Platform to Automate Seismic Design, Nonlinear Structural Model Construction and Analysis of Steel Moment Resisting Frames". In: *Engineering Structures* 224, p. 111199. ISSN: 0141-0296. DOI: 10/ghnv9h.

Hinkel, Jochen et al. (Mar. 4, 2014). "Coastal Flood Damage and Adaptation Costs under 21st Century Sea-Level Rise". In: *Proceedings of the National Academy of Sciences* 111.9, pp. 3292–3297. ISSN: 0027-8424, 1091-6490. DOI: 10/f52nkt.

Karaman, H., M. Şahin, and A.S. Elnashai (2008). "Earthquake Loss Assessment Features of Maeviz-Istanbul (Hazturk)". In: *Journal of Earthquake Engineering* 12, pp. 175–186. DOI: 10.1080/13632460802014006. *HAZturk*.

Kircher, Charles A., Robert V. Whitman, and William T. Holmes (May 1, 2006). "HAZUS Earthquake Loss Estimation Methods". In: *Natural Hazards Review* 7.2, pp. 45–59. ISSN: 1527-6988. DOI: 10/bhg5zh.

Kojima, Satoru et al. (Mar. 1, 2014). "Large-Scale Landslides in Toyama Prefecture, Central Japan, and Their Probable Relationship with Earthquakes". In: *Environmental Earth Sciences* 71.6, pp. 2753–2763. ISSN: 1866-6299. DOI: 10/ghngf4.

Lange, D., S. Devaney, and A. Usmani (2014). "An Application of the PEER Performance Based Earthquake Engineering Framework to Structures in Fire". In: *Engineering Structures* 66, pp. 100–115. DOI: 10/f52dq6.

Lin, Ning, Erik Vanmarcke, and Siu-Chung Yau (2010). "Windborne Debris Risk Analysis - Part II. Application to Structural Vulnerability Modeling". In: *Wind and Structures* 13.2, pp. 207–220. ISSN: 1226-6116. DOI: 10/ghngfz.

Moehle, J. and G. Deierlein (2004). "A Framework Methodology for Performance-Based Earthquake Engineering". In: *13th World Conference on Earthquake Engineering*. Vancouver BC, Canada.

Nazari, N., J. W. van de Lindt, and Y. Li (Feb. 1, 2015). "Effect of Mainshock-Aftershock Sequences on Woodframe Building Damage Fragilities". In: *Journal of Performance of Constructed Facilities* 29.1, p. 04014036. ISSN: 1943-5509. DOI: 10/f6w2qg.

Ouyang, Zhicheng and Seymour M. J. Spence (May 1, 2020). "A Performance-Based Wind Engineering Framework for Envelope Systems of Engineered Buildings Subject to Directional Wind and Rain Hazards". In: *Journal of Structural Engineering* 146.5, p. 04020049. ISSN: 1943-541X. DOI: 10/ghnsqx.

Park, Sangki, John W. van de Lindt, and Yue Li (Apr. 1, 2014). "ABV Procedure Combined with Mechanistic Response Modeling for Roof- and Surge-Loss Estimation in Hurricanes". In: *Journal of Performance of Constructed Facilities* 28.2, pp. 206–215. DOI: 10/ghngfx.

Pita, G., J. -P. Pinelli, S. Cocke, K. Gurley, J. Mitrani-Reiser, J. Weekes, and S. Hamid (May 1, 2012). "Assessment of Hurricane-Induced Internal Damage to Low-Rise Buildings in the Florida Public Hurricane Loss Model". In: *Journal of Wind Engineering and Industrial Aerodynamics*. 13th International Conference on Wind Engineering 104-106, pp. 76–87. ISSN: 0167-6105. DOI: 10/gbbj4j.

Pitilakis, K. (2014). *SYNER-G: Systemic Seismic Vulnerability and Risk Assessment of Complex Urban, Utility, Lifeline Systems and Critical Facilities*. New York: Springer. ISBN: 978-94-017-8834-2.

Pitilakis, K. D., S. T. Karapetrou, and S. D. Fotopoulou (Aug. 1, 2014). "Consideration of Aging and SSI Effects on Seismic Vulnerability Assessment of RC Buildings". In: *Bulletin of Earthquake Engineering* 12.4, pp. 1755–1776. ISSN: 1573-1456. DOI: 10/f6gpck.

Porter, K.A., A.S. Kiremidjian, and J.S. LeGrue (2001). "Assembly-Based Vulnerability of Buildings and Its Use in Performance Evaluation". In: *Earthquake Spectra* 17, pp. 291–312. DOI: 10/c9x2kk.

Ramirez, C.M. (2009). *Building-Specific Loss Estimation Methods & Tools for Simplified Performance-Based Earthquake Engineering*. Ph.D. Dissertation. Stanford University.

Reese, S., B.A. Bradley, J. Bind, G. Smart, W. Power, and J. Sturman (2011). "Empirical Building Fragilities from Observed Damage in the 2009 South Pacific Tsunami". In: *Earth-Science Reviews* 107, pp. 156–173. DOI: 10/ckqs3t.

Schotanus, M. I. J., P. Franchin, A. Lupoi, and P. E. Pinto (Oct. 1, 2004). "Seismic Fragility Analysis of 3D Structures". In: *Structural Safety* 26.4, pp. 421–441. ISSN: 0167-4730. DOI: 10/fjkpsz.

Shome, N. and P. Bazzurro (2009). "Comparison of Vulnerability of New High-Rise Concrete Moment Frame Structure Using HAZUS and Nonlinear Dynamic Analysis". In: *Proceedings of the 10th ICOSSAR*. Osaka, Japan.

Silva, Vitor et al. (Nov. 1, 2019). “Current Challenges and Future Trends in Analytical Fragility and Vulnerability Modeling”. In: *Earthquake Spectra* 35.4, pp. 1927–1952. ISSN: 8755-2930. DOI: 10/ghnsrw.

Vickery, Peter J., Peter F. Skerlj, Jason Lin, Lawrence A. Twisdale, Michael A. Young, and Francis M. Lavelle (May 1, 2006b). “HAZUS-MH Hurricane Model Methodology. II: Damage and Loss Estimation”. In: *Natural Hazards Review* 7.2, pp. 94–103. ISSN: 1527-6988. DOI: 10/b4xkjn.

Welch, D.P. (2016). *Non-Structural Element Considerations for Contemporary Performance-Based Earthquake Engineering*. Doctoral Dissertation. University of Pavia.

Werner, S.D., S. Cho, C.E. Taylor, J-P. Lavoie, C. Huyck, and R.T. Eguchi (2006). *REDARS 2 Demonstration Project for Seismic Risk Analysis of Highway Systems*. Sacramento, California: California Department of Transportation.

Xiong, Chen, Xinzheng Lu, Hong Guan, and Zhen Xu (Apr. 1, 2016). “A Nonlinear Computational Model for Regional Seismic Simulation of Tall Buildings”. In: *Bulletin of Earthquake Engineering* 14.4, pp. 1047–1069. ISSN: 1573-1456. DOI: 10.1007/s10518-016-9880-0.

Zaghi, Arash E., Jamie E. Padgett, Michel Bruneau, Michele Barbato, Yue Li, Judith Mitrani-Reiser, and Amanda McBride (Dec. 1, 2016). “Establishing Common Nomenclature, Characterizing the Problem, and Identifying Future Opportunities in Multihazard Design”. In: *Journal of Structural Engineering* 142.12, H2516001. ISSN: 1943-541X. DOI: 10/ghngf5.

Zhang, Sherong, Gaohui Wang, and Wenqi Sa (July 1, 2013). “Damage Evaluation of Concrete Gravity Dams under Mainshock–Aftershock Seismic Sequences”. In: *Soil Dynamics and Earthquake Engineering* 50, pp. 16–27. ISSN: 0267-7261. DOI: 10/f4znmw.

Zou, J., D.P. Welch, A. Zsarnóczay, A. Taflanidis, and G.G. Deierlein (2020). “Surrogate Modeling for the Seismic Response Estimation of Residential Wood Frame Structures”. In: *Proceedings of the 17th World Conference on Earthquake Engineering*.

Zsarnóczay, A. and G.G. Deierlein (2020). “PELICUN - A Computational Framework for Estimating Damage, Loss and Community Resilience”. In: 17th World Conference on Earthquake Engineering, p. 12.

Performance: Transportation Networks

Argyroudis, Sotiris and Amir M. Kaynia (2014). “Fragility Functions of Highway and Railway Infrastructure”. In: *SYNER-G: Typology Definition and Fragility Functions for Physical Elements at Seismic Risk: Buildings, Lifelines, Transportation Networks and Critical Facilities*. Ed. by K. Pitilakis, H. Crowley, and A.M. Kaynia. Geotechnical, Geological and Earthquake Engineering. Dordrecht: Springer Netherlands, pp. 299–326. ISBN: 978-94-007-7872-6. URL: https://doi.org/10.1007/978-94-007-7872-6_10 (visited on 12/08/2020).

Balomenos, Georgios P., Sabarethinam Kameshwar, and Jamie E. Padgett (Apr. 1, 2020). “Parameterized Fragility Models for Multi-Bridge Classes Subjected to Hurricane Loads”. In: *Engineering Structures* 208, p. 110213. ISSN: 0141-0296. DOI: 10/ghnwc7.

Bjarnadottir, Sigridur, Yue Li, and Mark G. Stewart (Nov. 2, 2014). “Regional Loss Estimation Due to Hurricane Wind and Hurricane-Induced Surge Considering Climate Variability”.

In: *Structure and Infrastructure Engineering* 10.11, pp. 1369–1384. ISSN: 1573-2479. DOI: 10/ghnwc8.

Chang, Stephanie E (2000). "Transportation Performance, Disaster Vulnerability, and Long-Term Effects of Earthquakes". In: *Second euroconference on global change and catastrophe risk management*.

Choi, E., R. DesRoches, and Nielson B (2004). "Seismic Fragility of Typical Bridges in Moderate Seismic Zones". In: *Engineering Structures* 26, pp. 187–199. DOI: 10/cv7t57.

Federal Emergency Management Agency (2018a). *Earthquake Model Technical Manual*. HAZUS – Multi-Hazard Loss Estimation Methodology 2.1. Washington, D.C.

Federal Emergency Management Agency (Oct. 2020). *Hazus Earthquake Model Technical Manual*.

Gidaris, I. and J.E. Padgett (2017). "Probabilistic Fragility Analysis and Resilience Assessment of Bridges Subjected to Earthquake Mainshocks and Aftershocks". In: *Proceedings of the 16th World Conference on Earthquake Engineering*. Santiago, Chile.

Han, Y. and R.A. Davidson (2012). "Probabilistic Seismic Hazard Analysis for Spatially Distributed Infrastructure". In: *Earthq Eng Struct Dyn* 41, pp. 2141–2158. DOI: 10/ghghnt.

Jacob, K. et al. (2011). "Responding to Climate Change in New York State: The ClimAID Integrated Assessment for Effective Climate Change Adaptation in New York State: Transportation". In: *Annals of the New York Academy of Sciences* 1244.1, pp. 299–362.

Kameshwar, Sabarethinam and Jamie E. Padgett (Nov. 1, 2014). "Multi-Hazard Risk Assessment of Highway Bridges Subjected to Earthquake and Hurricane Hazards". In: *Engineering Structures*. Performance Based Engineering: Current Advances and Applications 78, pp. 154–166. ISSN: 0141-0296. DOI: 10/f6qjkx.

Kiremidjian, A.S., J. Moore, Y.Y. Fan, N. Basoz, O. Yazali, and M. Williams (2006). *Pacific Earthquake Engineering Research Center Highway Demonstration Project*. PEER Report 2006/02. PEER: Pacific Earthquake Engineering Research Center.

Koc, E., B. Cetiner, A. Rose, L. Soibelman, E. Taciroglu, and D. Wei (2020). "CRAFT: Comprehensive Resilience Assessment Framework for Transportation Systems in Urban Areas". In: *Advanced Engineering Informatics* 46, p. 101159. DOI: 10/ghmf7r.

Lagaros, Nikos D., Yiannis Tsompanakis, Prodromos N. Psarropoulos, and Evaggelos C. Georgopoulos (Oct. 1, 2009). "Computationally Efficient Seismic Fragility Analysis of Geostructures". In: *Computers & Structures*. Civil-Comp Special Issue 87.19, pp. 1195–1203. ISSN: 0045-7949. DOI: 10/b9n65h.

Lee, R. and A.S. Kiremidjian (2007). "Uncertainty and Correlation for Loss Assessment of Spatially Distributed Systems, under Review Earthquake Spectra". In: *Earthquake Spectra* 23.4, pp. 753–770.

Loth, C. and J.W. Baker (2013). "A Spatial Cross-Correlation Model of Ground Motion Spectral Accelerations at Multiple Periods". In: *Earthquake Engineering & Structural Dynamics* 42.3, pp. 397–417. DOI: 10/f4pdhp.

Mangalathu, S., F. Soleimani, and J.-S. Jeon (2017). "Bridge Classes for Regional Seismic Risk Assessment: Improving HAZUS Models". In: *Engineering Structures* 148, pp. 755–766. DOI: 10/gbzb99.

Miller-Hooks, Elise, Xiaodong Zhang, and Reza Faturechi (July 1, 2012). "Measuring and Maximizing Resilience of Freight Transportation Networks". In: *Computers & Operations Research* 39.7, pp. 1633–1643. ISSN: 0305-0548. DOI: 10/bzg7kb.

Miller, M. and J. Baker (2015). "Ground-Motion Intensity and Damage Map Selection for Probabilistic Infrastructure Network Risk Assessment Using Optimization". In: *Earthquake Engineering & Structural Dynamics* 44.7, pp. 1139–1156. ISSN: 1096-9845. DOI: 10/f68t47.

Miller, M., S. Cortes, D. Ory, and J.W. Baker (2015). "Estimating Impacts of Catastrophic Network Damage from Earthquakes Using an Activity-Based Travel Model". In: *Transportation Research Board 94th Annual Meeting*. Washington DC.

Nielson, Bryant G. and Reginald DesRoches (2007). "Seismic Fragility Methodology for Highway Bridges Using a Component Level Approach". In: *Earthquake Engineering & Structural Dynamics* 36.6, pp. 823–839. ISSN: 1096-9845. DOI: 10/bgkw2t.

Park, Y.-J. and H-S Ang (1985). "Mechanistic Seismic Damage Model for Reinforced Concrete". In: *Journal of structural engineering* 111.4, pp. 722–739.

Simon, József and László Gergely Vigh (Nov. 1, 2016). "Seismic Fragility Assessment of Integral Precast Multi-Span Bridges in Areas of Moderate Seismicity". In: *Bulletin of Earthquake Engineering* 14.11, pp. 3125–3150. ISSN: 1573-1456. DOI: 10/ghnwc6.

Stergiou, E and A.S. Kiremidjian (2006). "Treatment of Uncertainties in Seismic Risk Analysis of Transportation Systems. The John a". In: *Blume Earthquake Engineering Center* 156.

Yin, C., J. Shi, F. Liu, W. Tian, and W. Tian (2017). "Embankment Seismic Fragility Assessment Based on IDA-PSDA". In: *China Journal of Highway and Transport* 30.5, pp. 28–37. ISSN: 1001-7372. URL: http://zgglxb.chd.edu.cn/CN/abstract/abstract2526.shtml (visited on 12/08/2020).

Performance: Water, Sewer, and Gas Pipelines

Dueñas-Osorio, L., J.I. Craig, and B.J. Goodno (2007). "Seismic Response of Critical Interdependent Networks". In: *Earthquake engineering & structural dynamics* 36.2, pp. 285–306. DOI: 10/b8ttkk.

Environmental Protection, New York City Department of (Oct. 2013). *NYC Wastewater Resiliency Plan*. New York City Department of Environmental Protection, p. 266. URL: https://www1.nyc.gov/assets/dep/downloads/pdf/climate-resiliency/climate-plan-single-page.pdf.

Fan, C., C. Zhang, A. Yahja, and A. Mostafavi (2019). "Disaster City Digital Twin: A Vision for Integrating Artificial and Human Intelligence for Disaster Management". In: *International Journal of Information Management* 102049.

G&E Engineering Systems (May 1994). *NIBS Earthquake Loss Estimation Methods, Technical Manual*.

He, X. (2019). "Disaster Risk Management of Interdependent Infrastructure Systems for Community Resilience Planning". (doctoral dissertation, University of Illinois at Urbana-Champaign.

Isoyama, R. and T Katayama (1982). *Reliability Evaluation of Water Supply Systems during Earthquakes*.

Johansen, C. and I. Tien (2018). "Probabilistic Multi-Scale Modeling of Interdependencies between Critical Infrastructure Systems for Resilience". In: *Sustainable and Resilient Infrastructure* 3.1, pp. 1–15. DOI: 10/ghghnw.

Johansen, Chloe, Jennifer Horney, and Iris Tien (June 1, 2017). "Metrics for Evaluating and Improving Community Resilience". In: *Journal of Infrastructure Systems* 23.2, p. 04016032. ISSN: 1943-555X. DOI: 10/f96mwg.

Jun, L. and Y. Guoping (2013). "Iterative Methodology of Pressure-Dependent Demand Based on EPANET for Pressure-Deficient Water Distribution Analysis". In: *Journal of Water Resources Panning and Management, ASCE* 139.1, pp. 34–44. DOI: 10/fzjgpw.

Khater, M. and F. Waisman (1999). *Potable Water System Analysis Model (POWSAM)*. National institute of Building Sciences.

Markov, I., M. Grigoriu, and T.D. O'Rourke (1994). *An Evaluation of Seismic Serviceability of Water Supply Networks with Application to San Francisco Auxiliary Water Supply System*. NCEER report no. 94-0001,

N.I.S.T. and T.D. O'Rourke (2016). *Critical Assessment of Lifeline System Performance: Understanding Societal Needs in Disaster Recovery*. NIST CGR 16-917-39, GCR 16-917-39. Redwood City, CA: Applied Technology Council. URL: http://dx.doi.org/10.6028/NIST.GCR.16-917-39.

O'Rourke, T.D. (2010). "Geohazards and Large Geographically Distributed Systems". In: *Geotechnique* LX.7, pp. 503–543.

O'Rourke, T.D. (2014). "Earthquake-Resilient Lifelines: NEHRP Research, Development and Implementation Roadmap". In: *NIST GCR 14-917-33, NEHRP Consultants Joint Venture*. Redwood City, CA.

Ouyang, M. (2014). "Review on Modeling and Simulation of Interdependent Critical Infrastructure Systems". In: *Reliability Engineering and System Safety* 121, pp. 43–60. DOI: 10/gfvdfx.

Romero, N., T.D. O'Rourke, L.K. Nozick, and C.A. Davis (2010). "Seismic Hazards and Water Supply Performance". In: *Journal of Earthquake Engineering* 14, pp. 1022–1043. DOI: 10/b7fjn7.

Sayyed, M.A.H., R. Gupta, and T.T. Tanyimboh (2014). "Modelling Pressure Deficient Water Distribution Networks in EPANET", 16th Conf. on Water Distr". In: *Sys, Analysis, Procedia Engineering* 89, pp. 626–631. DOI: 10/ghghnz.

Tabucchi, T., R. Davidson, and S. Brink (2010). "Simulation of Post-Earthquake Water Supply System Restoration". In: *Civil Engineering and Environmental Systems* 27.4, pp. 263–279. DOI: 10/ftj58h.

Tomar, A., H.V. Burton, A. Mosleh, and J. Yun Lee (2020). "Hindcasting the Functional Loss and Restoration of the Napa Water System Following the 2014 Earthquake Using Discrete-Event Simulation". In: *Journal of Infrastructure Systems* 26.4, p. 04020035. DOI: 10/ghghn2.

Wang, Y. and T.D. O'Rourke (2008). *Seismic Performance Evaluation of Water Supply Systems*. MCEER technical report 08-0015. Buffalo, NY: MCEER. *GIRAFFE*.

Performance: Electrical Transmission Substations and Lines

Moore, J.E., R.G. Little, S. Cho, and S. Lee (2005). *Using Regional Economic Models to Estimate the Costs of Infrastructure Failures: The Cost of a Limited Interruption in Electric Power in the Los Angeles Region*. Keston Institute for Infrastructure, University of Southern California.

Zimmerman, R. D., C. E. Murillo-Sánchez, and R. J. Thomas (Feb. 2011). "MATPOWER: Steady-State Operations, Planning, and Analysis Tools for Power Systems Research and Education". In: *IEEE Transactions on Power Systems* 26.1, pp. 12–19. ISSN: 1558-0679. DOI: 10/b94mfs. *MatPower*. URL: https://matpower.org/.

Recovery: Communities

Costa, Rodrigo C. (2019). "A Computer Simulation Framework for Assessing Disaster Recovery in Urban Communities". University of British Columbia.

Costa, Rodrigo, Terje Haukaas, and Stephanie E Chang (2020a). "Agent-Based Model for Post-Earthquake Housing Recovery". In: *Earthquake Spectra (in press)*. DOI: 10/ghhz4s.

Costa, Rodrigo, Terje Haukaas, and Stephanie E Chang (2020b). "Predicting Population Displacements after Earthquakes". In: *Sustainable and Resilient Infrastructure*, pp. 1–19. DOI: 10/ghhz4t.

Cutter, Susan L et al. (2013). "Disaster Resilience: A National Imperative". In: *Environment: Science and Policy for Sustainable Development* 55.2, pp. 25–29.

Deshmukh, Abhijeet and Makarand Hastak (2012). "A Framework for Enhancing Resilience of Community by Expediting Post Disaster Recovery". In: *International Institute for Infrastructure Resilience and Reconstruction (I3R2). Kumamoto, Japan*, pp. 1–9.

Ellingwood, Bruce R., Harvey Cutler, Paolo Gardoni, Walter Gillis Peacock, John W. van de Lindt, and Naiyu Wang (2016). "The Centerville Virtual Community: A Fully Integrated Decision Model of Interacting Physical and Social Infrastructure Systems". In: *Sustainable and Resilient Infrastructure* 1.3-4, pp. 95–107. DOI: 10/ghbg42.

Kwasinski, Alexis, Joseph Trainor, Brian Wolshon, and Francis M Lavelle (2016). "A Conceptual Framework for Assessing Resilience at the Community Scale". In: *Gaithersburg, MD: National Institute of Standards and Technology*, pp. 16–001.

Miles, Scott B. and Stephanie E. Chang (2006). "Modeling Community Recovery from Earthquakes". In: *Earthquake Spectra* 22.2, pp. 439–458. ISSN: 87552930. DOI: 10/bzrvz7.

Miles, Scott B, Henry V Burton, and Hua Kang (2019). "Community of Practice for Modeling Disaster Recovery". In: *Natural Hazards Review* 20.1, p. 04018023. DOI: 10/ghhz4p.

Miles, Scott B and Stephanie E Chang (2003). *Urban Disaster Recovery: A Framework and Simulation Model*. MCEER-03-0005. Multi-disciplinary Center for Earthquaker Engineering Research.

Moradi, Saeed (2020). "RecovUS: An Agent-Based Model of Post-Disaster Housing Recovery". Texas Tech University.

Recovery: Infrastructure Systems

Achour, Nebil, Masakatsu Miyajima, Federica Pascale, and Andrew D.F. Price (2014). "Hospital Resilience to Natural Hazards: Classification and Performance of Utilities". In: *Disaster Prevention and Management: An International Journal* 23.1, pp. 40–52. ISSN: 0965-3562. DOI: 10/f5pfcb.

Agency, Federal Emergency Management (2015). *Hazus–MH 2.1: Earthquake Technical Manual*. Federal Emergency Management Agency, p. 718. URL: www.fema.gov/plan/prevent/hazus.

Aghapour, Amir Hossein, Maziar Yazdani, Fariborz Jolai, and Mohammad Mojtahedi (2019). "Capacity Planning and Reconfiguration for Disaster-Resilient Health Infrastructure". In: *Journal of Building Engineering* 26, p. 100853. DOI: 10/ghhz4f.

Bambaren, C (2011). "(A3) Health Care Facilities Affected by the Earthquake in Chile". In: *Prehospital and Disaster Medicine* 26.S1, s1–s2.

Boarnet, Marlon G (1998). "Business Losses, Transportation Damage and the Northridge Earthquake". In: *Journal of Transportation and Statistics* 1.2, pp. 49–64.

Ceferino, Luis, Anne Kiremidjian, and Greg Deierlein (2018a). "Probabilistic Model for Regional Multiseverity Casualty Estimation Due to Building Damage Following an Earthquake". In: *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* 4.3, p. 04018023. DOI: 10/ghhz4h.

Ceferino, Luis, Anne Kiremidjian, and Gregory Deierlein (2018b). "Regional Multiseverity Casualty Estimation Due to Building Damage Following a Mw 8.8 Earthquake Scenario in Lima, Peru". In: *Earthquake Spectra* 34.4, pp. 1739–1761. DOI: 10/ghhz4j.

Ceferino, Luis, Judith Mitrani-Reiser, Anne Kiremidjian, Gregory Deierlein, and Celso Bambarén (2020). "Effective Plans for Hospital System Response to Earthquake Emergencies". In: *Nature Communications*. DOI: 10.1038/s41467-020-18072-w.

Chang, Liang (2010a). *Transportation System Modeling and Applications in Earthquake Engineering*.

Chang, Stephanie E (2000). "Transportation Performance, Disaster Vulnerability, and Long-Term Effects of Earthquakes". In: *Second euroconference on global change and catastrophe risk management*.

Cimellaro, G. P. and M. Pique (2016). "Resilience of a Hospital Emergency Department under Seismic Event". In: *Advances in Structural Engineering* 19.5, pp. 825–836. ISSN: 1369-4332. DOI: 10/f8nbvx.

Cimellaro, Gian Paolo, Andrei M Reinhorn, and Michel Bruneau (2011). “Performance-Based Metamodel for Healthcare Facilities”. In: *Earthquake Engineering & Structural Dynamics* 40.11, pp. 1197–1217. DOI: 10/cjx995.

Cimellaro, GP, A Zamani-Noori, O Kammouh, V Terzic, and SA Mahin (2016). *Resilience of Critical Structures, Infrastructure, and Communities*. PEER Report 2016/08. Pacific Earthquake Engineering Research Center.

Cooper, Thomas W and Thomas W Cooper (1997). *A Study of the Performance of Petroleum Storage Tanks during Earthquakes, 1933-1995*. US National Institute of Standards and Technology USA.

DHS (2020). *Department of Homeland Security: Critical Infrastructure Sectors*. URL: https://www.cisa.gov/critical-infrastructure-sectors.

Eidinger, John and Craig A Davis (2012). *Recent Earthquakes: Implications for US Water Utilities*. Water Research Foundation.

Eusgeld, Irene and Wolfgang Kroger (2008). “Comparative Evaluation of Modeling and Simulation Techniques for Interdependent Critical Infrastructures”. In: *9th International Conference on Probabilistic Safety Assessment and Management 2008, PSAM 2008* 1 (August), pp. 484–491.

Guidotti, R, P Gardoni, and Y Chen (2017). “Multi-Layer Heterogeneous Network Model for Interdependent Infrastructure Systems”. In: *Proceedings of the 12th International Conference on Structural Safety & Reliability (ICOSSAR 2017)*. TU Wien Vienna, Austria.

Gul, Muhammet and Ali Fuat Guneri (2015). “A Comprehensive Review of Emergency Department Simulation Applications for Normal and Disaster Conditions”. In: *Computers & Industrial Engineering* 83, pp. 327–344. DOI: 10/f699n9.

Hallsworth, Alan and Rodney Tolley (2000). “Urban Hysteria & Panic in the Streets–the British Fuel Blockade September 2000–a Social Interpretation”. In: *World Transport Policy & Practice* 6.3, pp. 5–10. URL: http://www.ecoplan.org/library/wt6-3.pdf.

Hamby, Leigh and Sarah W Fraser (2004). “Using Patient Waiting-Time Data to Improve the Hospital Bed-Assignment Process”. In: *The Joint Commission Journal on Quality and Safety* 30.1, pp. 42–46. DOI: 10/ghhz5d.

Hardin, Garrett (2009). “The Tragedy of the Commons”. In: *Journal of Natural Resources Policy Research* 1.3, pp. 243–253. DOI: 10/d5wrd6.

Helbing, Dirk, Hendrik Ammoser, and Christian Kühnert (2006). “Disasters as Extreme Events and the Importance of Network Interactions for Disaster Response Management”. In: *Extreme Events in Nature and Society*. Springer, pp. 319–348.

Hiete, Michael, Mirjam Merz, and Frank Schultmann (2011). “Scenario-based Impact Analysis of a Power Outage on Healthcare Facilities in Germany”. In: *International Journal of Disaster Resilience in the Built Environment* 2.3, pp. 222–244. DOI: 10/b6xjsm.

Hines, P., E. Cotilla-Sanchez, and S. Blumsack (2010). “Do Topological Models Provide Good Information about Electricity Infrastructure Vulnerability?” In: *Chaos* 20.3, pp. 1–11. ISSN: 10541500. pmid: 20887062.

Holguin-Veras, J., E. Taniguchi, M. Jaller, F. Aros-Vera, F. Ferreira, and R. G. Thompson (2014). “The Tohoku Disasters: Chief Lessons Concerning the Post Disaster Humanitarian Logistics

Response and Policy Implications". In: *Transportation Research Part A: Policy and Practice* 69, pp. 86–104. ISSN: 09658564. DOI: 10/ghhz4b.

Jacques, Caitlin C, Jason McIntosh, Sonia Giovinazzi, Thomas D Kirsch, Thomas Wilson, and Judith Mitrani-Reiser (2014). "Resilience of the Canterbury Hospital System to the 2011 Christchurch Earthquake". In: *Earthquake Spectra* 30.1, pp. 533–554. DOI: 10/f53bgr.

Johnston, David et al. (2014). "The 2010/2011 Canterbury Earthquakes: Context and Cause of Injury". In: *Natural Hazards* 73.2, pp. 627–637. DOI: 10/f6dv8g.

Jun, QIU, Guo-dong Liu, Su-xing Wang, Xiu-zhu Zhang, Liang Zhang, LI Yang, Dan-Feng Yuan, Zhi-huan Yang, and Ji-Hong Zhou (2010). "Analysis of Injuries and Treatment of 3 401 Inpatients in 2008 Wenchuan Earthquake—Based on Chinese Trauma Databank". In: *Chinese Journal of Traumatology (English Edition)* 13.5, pp. 297–303.

Karlaftis, Matthew G, Konstantinos L Kepaptsoglou, and Sergios Lambropoulos (2007). "Fund Allocation for Transportation Network Recovery Following Natural Disasters". In: *Journal of Urban Planning and Development* 133.1, pp. 82–89. DOI: 10/cxbzzc.

Liu, Haibin, Rachel A Davidson, and Tatiyana V Apanasovich (2007). "Statistical Forecasting of Electric Power Restoration Times in Hurricanes and Ice Storms". In: *IEEE Transactions on Power Systems* 22.4, pp. 2270–2279. DOI: 10/dc3fs7.

McDaniels, Timothy, Stephanie Chang, Darren Cole, Joseph Mikawoz, and Holly Longstaff (2008). "Fostering Resilience to Extreme Events within Infrastructure Systems: Characterizing Decision Contexts for Mitigation and Adaptation". In: *Global Environmental Change* 18.2, pp. 310–318. ISSN: 09593780. DOI: 10/cdtq2v.

Miles, Scott B, Henry V Burton, and Hua Kang (2019). "Community of Practice for Modeling Disaster Recovery". In: *Natural Hazards Review* 20.1, p. 04018023. DOI: 10/ghhz4p.

Mitrani-Reiser, Judith, Michael Mahoney, William T Holmes, Juan Carlos De La Llera, Rick Bissell, and Thomas Kirsch (2012). "A Functional Loss Assessment of a Hospital System in the Bío-Bío Province". In: *Earthquake Spectra* 28 (1_suppl1), pp. 473–502. DOI: 10/f38w6t.

O'Rourke, Michael J and Pak So (2000). "Seismic Fragility Curves for On-Grade Steel Tanks". In: *Earthquake spectra* 16.4, pp. 801–815. DOI: 10/fc7s32.

Ouyang, M. (2014). "Review on Modeling and Simulation of Interdependent Critical Infrastructure Systems". In: *Reliability Engineering and System Safety* 121, pp. 43–60. DOI: 10/gfvdfx.

Ouyang, Min and Leonardo Duenas-Osorio (2014). "Multi-Dimensional Hurricane Resilience Assessment of Electric Power Systems". In: *Structural Safety* 48, pp. 15–24. DOI: 10/f57c73.

Padgett, Jamie E and Reginald DesRoches (2007). "Bridge Functionality Relationships for Improved Seismic Risk Assessment of Transportation Networks". In: *Earthquake Spectra* 23.1, pp. 115–130. DOI: 10/bzxgfh.

Rinaldi, Steven M, James P Peerenboom, and Terrence K Kelly (2001). "Identifying, Understanding, and Analyzing Critical Infrastructure Interdependencies". In: *IEEE control systems magazine* 21.6, pp. 11–25. DOI: 10/c7qpp9.

Shen, Xuesi (2017). "Development of a Hybrid Simulation Model for Understanding Community Resilience to Fuel Disruption". University of British Columbia. DOI: http://dx.doi.org/10.14288/1.0357249.

Smythe, T. C. (2013). *Assessing the Impacts of Hurricane Sandy on the Port of New York and New Jersey's Maritime Responders and Response Infrastructure*. University of Colorado Natural Hazards Center, pp. 1–22.

Sun, Li, Bozidar Stojadinovic, and Giovanni Sansavini (2019). "Resilience Evaluation Framework for Integrated Civil Infrastructure–Community Systems under Seismic Hazard". In: *Journal of Infrastructure Systems* 25.2, p. 04019016. DOI: 10/ghhz39.

Tomar, A., H.V. Burton, A. Mosleh, and J. Yun Lee (2020). "Hindcasting the Functional Loss and Restoration of the Napa Water System Following the 2014 Earthquake Using Discrete-Event Simulation". In: *Journal of Infrastructure Systems* 26.4, p. 04020035. DOI: 10/ghghn2.

Vieth, Teri L and Karin V Rhodes (2006). "The Effect of Crowding on Access and Quality in an Academic ED". In: *The American journal of emergency medicine* 24.7, pp. 787–794. DOI: 10/dg6f9s.

Vugrin, Eric D, Mark A Turnquist, and Nathanael JK Brown (2014). "Optimal Recovery Sequencing for Enhanced Resilience and Service Restoration in Transportation Networks". In: *International Journal of Critical Infrastructures* 10.3-4, pp. 218–246. DOI: 10/ghhz4d.

Vugrin, Eric D, Stephen J Verzi, Patrick D Finley, Mark A Turnquist, Anne R Griffin, Karen A Ricci, and Tamar Wyte-Lake (2015). "Modeling Hospitals' Adaptive Capacity during a Loss of Infrastructure Services". In: *Journal of healthcare engineering* 6. DOI: 10/f66vcw.

Wheeler, Gregory (2020). "Bounded Rationality". In: *The Stanford Encyclopedia of Philosophy*. Ed. by Edward N. Zalta. Spring 2020. Metaphysics Research Lab, Stanford University. URL: https://plato.stanford.edu/archives/spr2020/entries/bounded-rationality/.

Yavari, Soheil, Stephanie E Chang, and Kenneth J Elwood (2010). "Modeling Post-Earthquake Functionality of Regional Health Care Facilities". In: *Earthquake Spectra* 26.3, pp. 869–892. DOI: 10/czsrj7.

Yi, Pengfei (2005). *Real-Time Generic Hospital Capacity Estimation under Emergency Situations*. State University of New York at Buffalo.

Zhang, Weili and Naiyu Wang (2016). "Resilience-Based Risk Mitigation for Road Networks". In: *Structural Safety* 62, pp. 57–65. DOI: 10/f82c8c.

Recovery: Housing

Airriess, Christopher A, Wei Li, Karen J Leong, Angela Chia-Chen Chen, and Verna M Keith (2008). "Church-Based Social Capital, Networks and Geographical Scale: Katrina Evacuation, Relocation, and Recovery in a New Orleans Vietnamese American Community". In: *Geoforum* 39.3, pp. 1333–1346.

Aldrich, Daniel P (2010). "Fixing Recovery: Social Capital in Post-Crisis Resilience". In: *Journal of Homeland Security, Forthcoming*.

Aldrich, Daniel P (2011). "The Power of People: Social Capital's Role in Recovery from the 1995 Kobe Earthquake". In: *Natural hazards* 56.3, pp. 595–611.

Aldrich, Daniel P (2012). *Building Resilience: Social Capital in Post-Disaster Recovery*. University of Chicago Press.

Almufti, Ibrahim and Michael Willford (2013). *REDi Rating System: Resilience Based Earthquake Design Initiative for the next Generation of Buildings. Version 1.0*. Arup / Arup. URL: https://www.arup.com/-/media/arup/files/publications/r/redi_final-version_october-2013-arup-website.pdf.

Bilau, Abdulquadri Ade, Emlyn Witt, and Irene Lill (2015). “A Framework for Managing Post-Disaster Housing Reconstruction”. In: *Procedia Economics and Finance* 21, pp. 313–320. DOI: 10/ggqn8k.

Bilau, Abdulquadri, Emlyn Witt, and Irene Lill (2018). “Practice Framework for the Management of Post-Disaster Housing Reconstruction Programmes”. In: *Sustainability* 10.11, p. 3929. DOI: 10/gfr7hq.

Binder, Sherri Brokopp, Charlene K Baker, and John P Barile (2015). “Rebuild or Relocate? Resilience and Postdisaster Decision-Making after Hurricane Sandy”. In: *American journal of community psychology* 56.1-2, pp. 180–196.

Boiser, Andresito, A Wilkinson, and A Yan Chang (2011). *Skills Availability for Housing Repair and Reconstruction in Christchurch*. The University of Auckland.

Bolin, Robert (1985). “Disasters and Long-Term Recovery Policy: A Focus on Housing and Families”. In: *Review of Policy Research* 4.4, pp. 709–715. DOI: 10/fpmz7r.

Bolin, Robert C and Patricia Bolton (1983). “Recovery in Nicaragua and the USA”. In: *International Journal of Mass Emergencies and Disasters* 1.1, pp. 125–144.

Bothara, Jitendra K, RP Dhakal, D Dizhur, and JM Ingham (2016). “The Challenges of Housing Reconstruction after the April 2015 Gorkha, Nepal Earthquake”. In: *Technical Journal of Nepal Engineers’ Association, Special Issue on Gorkha Earthquake 2015, XLIII-EC30* 1, pp. 121–134.

Bullard, Robert D and Beverly Wright (2009). *Race, Place, and Environmental Justice after Hurricane Katrina: Struggles to Reclaim, Rebuild, and Revitalize New Orleans and the Gulf Coast*. PERSEUS BOOKS.

Burton, Christopher G (2015). “A Validation of Metrics for Community Resilience to Natural Hazards and Disasters Using the Recovery from Hurricane Katrina as a Case Study”. In: *Annals of the Association of American Geographers* 105.1, pp. 67–86. DOI: 10/gf7qvw.

Burton, Henry V., Scott B. Miles, and Hua Kang (2018). “Integrating Performance-Based Engineering and Urban Simulation to Model Post-Earthquake Housing Recovery”. In: *Earthquake Spectra* 34.4, pp. 1763–1785. DOI: 10/gftcg8.

Chamlee-Wright, Emily and Virgil Henry Storr (2009). ““There’s No Place like New Orleans”: Sense of Place and Community Recovery in the Ninth Ward after Hurricane Katrina”. In: *Journal of Urban Affairs* 31.5, pp. 615–634.

Chang, Yan, Suzanne Wilkinson, Regan Potangaroa, and Erica Seville (2011). “Identifying Factors Affecting Resource Availability for Post-Disaster Reconstruction: A Case Study in China”. In: *Construction Management and Economics* 29.1, pp. 37–48. DOI: 10/bvzm7c.

Comerio, Mary C (2006). “Estimating Downtime in Loss Modeling”. In: *Earthquake Spectra* 22.2, pp. 349–365. DOI: 10/cwmmdp.

Comerio, Mary C (2013). *Housing Recovery in Chile: A Qualitative Mid-Program Review*. Pacific Earthquake Engineering Research Center.

Comerio, Mary C (2014). "Disaster Recovery and Community Renewal: Housing Approaches". In: *Cityscape (Washington, D.C.)* 16.2, pp. 51–68. ISSN: 1936007X.

Costa, Rodrigo C. (2019). "A Computer Simulation Framework for Assessing Disaster Recovery in Urban Communities". University of British Columbia.

Costa, Rodrigo, Terje Haukaas, and Stephanie E Chang (2020a). "Agent-Based Model for Post-Earthquake Housing Recovery". In: *Earthquake Spectra (in press)*. DOI: 10/ghhz4s.

Cutter, Susan L, Christopher G Burton, and Christopher T Emrich (2010). "Disaster Resilience Indicators for Benchmarking Baseline Conditions". In: *Journal of homeland security and emergency management* 7.1.

Dacy, Douglas C and Howard Kunreuther (1969). *Economics of Natural Disasters; Implications for Federal Policy*. Free Press.

Davidson, Rachel A (2015). "Integrating Disciplinary Contributions to Achieve Community Resilience to Natural Disasters". In: *Civil Engineering and Environmental Systems* 32.1-2, pp. 55–67. DOI: 10/gc3f96.

Di Ludovico, Marco, Andrea Prota, Claudio Moroni, Gaetano Manfredi, and Mauro Dolce (2017a). "Reconstruction Process of Damaged Residential Buildings Outside Historical Centres after the L'Aquila Earthquake: Part I–Light Damage Reconstruction". In: *Bulletin of Earthquake Engineering* 15.2, pp. 667–692.

Di Ludovico, Marco, Andrea Prota, Claudio Moroni, Gaetano Manfredi, and Mauro Dolce (2017b). "Reconstruction Process of Damaged Residential Buildings Outside Historical Centres after the L'Aquila Earthquake: Part II—"heavy Damage" Reconstruction". In: *Bulletin of Earthquake Engineering* 15.2, pp. 693–729.

Ellingwood, Bruce R, Naiyu Wang, James Robert Harris, and Therese P McAllister (2018). "Performance-Based Engineering to Achieve Community Resilience". In: *Routledge Handbook of Sustainable and Resilient Infrastructure*, pp. 94–112. DOI: 10/ghhz47.

Fussell, Elizabeth, Narayan Sastry, and Mark VanLandingham (2010). "Race, Socioeconomic Status, and Return Migration to New Orleans after Hurricane Katrina". In: *Population and environment* 31.1-3, pp. 20–42. DOI: 10/ctrx78.

Hamideh, Sara, Walter G Peacock, and Shannon Van Zandt (2018). "Housing Recovery after Disasters: Primary versus Seasonal/Vacation Housing Markets in Coastal Communities". In: *Natural Hazards Review*. DOI: 10/gc9ktk.

Henderson, Tammy L, Karen A Roberto, and Yoshinori Kamo (2010). "Older Adults' Responses to Hurricane Katrina: Daily Hassles and Coping Strategies". In: *Journal of Applied Gerontology* 29.1, pp. 48–69. DOI: 10/frhwrc.

Hwang, Sungjoo, Moonseo Park, Hyun-Soo Lee, SangHyun Lee, and Hyunsoo Kim (2015). "Postdisaster Interdependent Built Environment Recovery Efforts and the Effects of Governmental Plans: Case Analysis Using System Dynamics". In: *Journal of construction engineering and management* 141.3, p. 04014081. DOI: 10/f63ngm.

Kamel, Nabil MO and Anastasia Loukaitou-Sideris (2004). "Residential Assistance and Recovery Following the Northridge Earthquake". In: *Urban Studies* 41.3, pp. 533–562. DOI: 10/bqmp6j.

Kang, Hua, Henry V Burton, and Haoxiang Miao (2018). "Replicating the Recovery Following the 2014 South Napa Earthquake Using Stochastic Process Models". In: *Earthquake Spectra* 34.3, pp. 1247–1266.

Kick, Edward L, James C Fraser, Gregory M Fulkerson, Laura A McKinney, and Daniel H De Vries (2011). "Repetitive Flood Victims and Acceptance of FEMA Mitigation Offers: An Analysis with Community–System Policy Implications". In: *Disasters* 35.3, pp. 510–539.

Lee, Ji Yun, Jie Zhao, Yue Li, and Yue-Jun Yin (2019). "Quantitative Impact of Catastrophe Risk Insurance on Community Resilience". In: *13th International Conference on Applications of Statistics and Probability in Civil Engineering* (Seoul, South Korea, May 26–30, 2019).

Li, Wei, Christopher A Airriess, Angela Chia-Chen Chen, Karen J Leong, and Verna Keith (2010). "Katrina and Migration: Evacuation and Return by African Americans and Vietnamese Americans in an Eastern New Orleans Suburb". In: *The professional geographer* 62.1, pp. 103–118.

Loukaitou-Sideris, Anastasia and Nabil M. Kamel (2004). *Residential Recovery from the Northridge Earthquake: An Evaluation of Federal Assistance Programs*. CALIFORNIA POLICY RESEARCH CENTER. URL: http://pdfwww.china-up.com:8080/international/case/case/905.pdf.

Masoomi, Hassan and John W van de Lindt (2018). "Community-Resilience-Based Design of the Built Environment". In: *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* 5.1, p. 04018044. DOI: 10/ghhz46.

Mayer, Joshua, Saeed Moradi, Ali Nejat, Souparno Ghosh, Zhen Cong, and Daan Liang (2020). "Drivers of Post-Disaster Relocations: The Case of Moore and Hattiesburg Tornados". In: *International Journal of Disaster Risk Reduction*, p. 101643. DOI: 10/ghhz5b.

McNeil, Sue, Kelsey Mininger, Alex Greer, and Joseph Trainor (2015). *Household Residential Decision-Making in the Wake of Disaster: Report of Results Prepared for Sea Bright Residents*. Disaster Research Center.

Miles, Scott B. and Stephanie E. Chang (2011). "ResilUS: A Community Based Disaster Resilience Model". In: *Cartography and Geographic Information Science* 38.1, pp. 36–51. DOI: 10/b22zmv.

Moradi, Saeed (2020). "RecovUS: An Agent-Based Model of Post-Disaster Housing Recovery". Texas Tech University.

Myers, Candice A, Tim Slack, and Joachim Singelmann (2008). "Social Vulnerability and Migration in the Wake of Disaster: The Case of Hurricanes Katrina and Rita". In: *Population and Environment* 29.6, pp. 271–291.

Nejat, Ali (2018). "Perceived Neighborhood Boundaries: A Missing Link in Modeling Post-Disaster Housing Recovery". In: *International journal of disaster risk reduction* 28, pp. 225–236. DOI: 10/gdhw67.

Nejat, Ali, Sherri Brokopp Binder, Alex Greer, and Mehdi Jamali (2018). "Demographics and the Dynamics of Recovery: A Latent Class Analysis of Disaster Recovery Priorities after the 2013 Moore, Oklahoma Tornado." In: *International Journal of Mass Emergencies & Disasters* 36.1.

Nejat, Ali and Ivan Damnjanovic (2012). "Agent-Based Modeling of Behavioral Housing Recovery Following Disasters". In: *Computer-Aided Civil and Infrastructure Engineering* 27.10, pp. 748–763. DOI: 10/f4cdm4.

Nejat, Ali and Souparno Ghosh (2016). "LASSO Model of Postdisaster Housing Recovery: Case Study of Hurricane Sandy". In: *Natural Hazards Review* 17.3, pp. 1–13. ISSN: 15276988. DOI: 10/f8zqmf.

Nejat, Ali, Roxana J Javid, Souparno Ghosh, and Saeed Moradi (2020). "A Spatially Explicit Model of Postdisaster Housing Recovery". In: *Computer-Aided Civil and Infrastructure Engineering* 35.2, pp. 150–161. DOI: 10/ghhz4k.

Nejat, Ali, Saeed Moradi, and Souparno Ghosh (2019). "Anchors of Social Network Awareness Index: A Key to Modeling Postdisaster Housing Recovery". In: *Journal of Infrastructure Systems* 25.2, p. 04019004. DOI: 10/ghhz44.

Ngo, Ehren B (2001). "When Disasters and Age Collide: Reviewing Vulnerability of the Elderly". In: *Natural Hazards Review* 2.2, pp. 80–89. DOI: 10/ffvdzb.

Olshansky, Robert B. (2006). "Planning after Hurricane Katrina". In: *Journal of the American Planning Association* 72.2, pp. 147–153. DOI: 10/bxzscz.

Peacock, Walter Gillis, Shannon Van Zandt, Yang Zhang, and Wesley E Highfield (2014). "Inequities in Long-Term Housing Recovery after Disasters". In: *Journal of the American Planning Association* 80.4, pp. 356–371. DOI: 10/gfdb6v.

Ranghieri, Federica and Mikio Ishiwatari (2014). *Learning from Megadisasters: Lessons from the Great East Japan Earthquake*. The World Bank. URL: https://www.gfdrr.org/sites/default/files/publication/Learning%20from%20Megadisasters%20%20Lessons%20from%20the%20Great%20East%20Japan%20Earthquake.pdf.

Reid, Karen and Ruth Beilin (2015). "Making the Landscape "Home": Narratives of Bushfire and Place in Australia". In: *Geoforum* 58, pp. 95–103.

Rosenheim, Nathanael, Roberto Guidotti, Paolo Gardoni, and Walter Gillis Peacock (2019). "Integration of Detailed Household and Housing Unit Characteristic Data with Critical Infrastructure for Post-Hazard Resilience Modeling". In: *Sustainable and Resilient Infrastructure*, pp. 1–17. DOI: 10/ghhz4v.

Rust, Edward B and Kerry Killinger (2006). *The Financial Services Roundtable Blue Ribbon Commission on Mega-Catastrophes: A Call to Action*. Financial Services Roundtable.

Sadri, Arif Mohaimin, Satish V Ukkusuri, Seungyoon Lee, Rosalee Clawson, Daniel Aldrich, Megan Sapp Nelson, Justin Seipel, and Daniel Kelly (2018). "The Role of Social Capital, Personal Networks, and Emergency Responders in Post-Disaster Recovery and Resilience: A Study of Rural Communities in Indiana". In: *Natural hazards* 90.3, pp. 1377–1406. DOI: 10/ghhz5c.

Sanders, Sara, Stan L Bowie, and Yvonne Dias Bowie (2004). "Chapter 2 Lessons Learned on Forced Relocation of Older Adults: The Impact of Hurricane Andrew on Health, Mental Health, and Social Support of Public Housing Residents". In: *Journal of Gerontological Social Work* 40.4, pp. 23–35. DOI: 10/dcnsh6.

Sutley, Elaina J, Lori Peek, and John W van de Lindt (2017). “Community-Level Framework for Seismic Resilience. I: Coupling Socioeconomic Characteristics and Engineering Building Systems”. In: *Natural Hazards Review* 18.3, p. 4016014. DOI: 10/ghhz48.

Wang, Ying, Zhenhua Zou, and Juan Li (2015). “Influencing Factors of Households Disadvantaged in Post-Earthquake Life Recovery: A Case Study of the Wenchuan Earthquake in China”. In: *Natural Hazards* 75.2, pp. 1853–1869. DOI: 10/f6ss2b.

Wood, Amy, Ilan Now, and Miles Parker (2016). *The Canterbury Rebuild Five Years on from the Christchurch Earthquake*. 3. Reserve Bank of New Zealand / Bank of New Zealand. URL: http://www.rbnz.govt.nz/research-and-publications/reserve-bank-bulletin (visited on 06/16/2018).

Wu, Jie Ying (2004). “A Comparative Study of Housing Reconstruction after Two Major Earthquakes: The 1994 Northridge Earthquake in the United States and the 1999 Chi-Chi Earthquake in Taiwan”. Texas A&M University.

Zhang, Yang and Walter Gillis Peacock (2009). “Planning for Housing Recovery? Lessons Learned from Hurricane Andrew”. In: *Journal of the American Planning Association* 76.1, pp. 5–24. DOI: 10/bf8m4b.

Recovery: Business

Aghababaei, Mohammad, Maria Koliou, Maria Watson, and Yu Xiao (2020). “Quantifying Post-Disaster Business Recovery through Bayesian Methods”. In: *Structure and Infrastructure Engineering*, pp. 1–19.

Alesch, Daniel J, James N Holly, Elliott Mittler, and Robert Nagy (2001). *Organizations at Risk: What Happens When Small Businesses and Not-for-Profits Encounter Natural Disasters*. Fairfax, VA: Public Entity Risk Institute.

Bolin, Robert C and Patricia Bolton (1983). “Recovery in Nicaragua and the USA”. In: *International Journal of Mass Emergencies and Disasters* 1.1, pp. 125–144.

Brown, Charlotte (2019). “Business Recovery from Disaster: A Research Update for Practitioners”. In: *The Australasian Journal of Disaster and Trauma Studies* 23.2.

Brown, Charlotte, Erica Seville, and John Vargo (2017). “Efficacy of Insurance for Organisational Disaster Recovery: Case Study of the 2010 and 2011 Canterbury Earthquakes”. In: *Disasters* 41.2, pp. 388–408. DOI: 10/ghhz4r.

Brown, Charlotte, Joanne Stevenson, Sonia Giovinazzi, Erica Seville, and John Vargo (2015). “Factors Influencing Impacts on and Recovery Trends of Organisations: Evidence from the 2010/2011 Canterbury Earthquakes”. In: *International Journal of Disaster Risk Reduction* 14, pp. 56–72. DOI: 10/ghhz4q.

Chang, Stephanie E (2010b). “Urban Disaster Recovery: A Measurement Framework and Its Application to the 1995 Kobe Earthquake”. In: *Disasters* 34.2, pp. 303–327. DOI: 10/cwx45s.

Chang, Stephanie E and Anthony Falit-Baiamonte (2002). “Disaster Vulnerability of Businesses in the 2001 Nisqually Earthquake”. In: *Global Environmental Change Part B: Environmental Hazards* 4.2, pp. 59–71. DOI: 10/bddprz.

Dahlhamer, James M and Kathleen J Tierney (1998). "Rebounding from Disruptive Events: Business Recovery Following the Northridge Earthquake". In: *Sociological spectrum* 18.2, pp. 121–141.

Friedman, Jerome, Trevor Hastie, and Robert Tibshirani (2001). *The Elements of Statistical Learning*. Vol. 1. 10. Springer series in statistics New York.

Kachali, H, ZR Whitman, JR Stevenson, J Vargo, E Seville, and Trevor Wilson (2015). "Industry Sector Recovery Following the Canterbury Earthquakes". In: *International Journal of Disaster Risk Reduction* 12, pp. 42–52. DOI: 10/ghhz4m.

Marshall, Maria I, Linda S Niehm, Sandra B Sydnor, and Holly L Schrank (2015). "Predicting Small Business Demise after a Natural Disaster: An Analysis of Pre-Existing Conditions". In: *Natural Hazards* 79.1, pp. 331–354.

Morrish, Sussie C and Rosalind Jones (2020). "Post-Disaster Business Recovery: An Entrepreneurial Marketing Perspective". In: *Journal of Business Research* 113, pp. 83–92.

Morrish, Sussie and Sussie C Morrish (2011). "Entrepreneurial Marketing: A Strategy for the Twenty-First Century?" In: *Journal of Research in Marketing and Entrepreneurship*.

Stevenson, JR, Y Chang-Richards, D Conradson, S Wilkinson, J Vargo, E Seville, and D Brunsdon (2014). "Organizational Networks and Recovery Following the Canterbury Earthquakes". In: *Earthquake Spectra* 30.1, pp. 555–575. DOI: 10/f53csr.

Wang, Ying, Zhenhua Zou, and Juan Li (2015). "Influencing Factors of Households Disadvantaged in Post-Earthquake Life Recovery: A Case Study of the Wenchuan Earthquake in China". In: *Natural Hazards* 75.2, pp. 1853–1869. DOI: 10/f6ss2b.

Watson, Maria, Yu Xiao, Jennifer Helgeson, and Maria Dillard (2020). "Importance of Households in Business Disaster Recovery". In: *Natural Hazards Review* 21.4, p. 05020008.

Webb, Gary R, Kathleen J Tierney, and James M Dahlhamer (2000). "Businesses and Disasters: Empirical Patterns and Unanswered Questions". In: *Natural Hazards Review* 1.2, pp. 83–90.

Webb, Gary R, Kathleen J Tierney, and James M Dahlhamer (2002). "Predicting Long-Term Business Recovery from Disaster: A Comparison of the Loma Prieta Earthquake and Hurricane Andrew". In: *Global Environmental Change Part B: Environmental Hazards* 4.2, pp. 45–58. DOI: 10/b5r3gw.

Xiao, Yu and Walter Gillis Peacock (2014). "Do Hazard Mitigation and Preparedness Reduce Physical Damage to Businesses in Disasters? Critical Role of Business Disaster Planning". In: *Natural Hazards Review* 15.3, p. 04014007. DOI: 10/ghhz4n.

Cross-Cutting: Uncertainty Quantification

Abbiati, Giuseppe, Imad Abdallah, Stefano Marelli, Bruno Sudret, and Bozidar Stojadinovic (2017). "Hierarchical Kriging Surrogate of the Seismic Response of a Steel Piping Network Based on Multi-Fidelity Hybrid and Computational Simulators". In: *7th International Conference on Advances in Experimental Structural Engineering (7AESE)*.

Adams, Brian M, WJ Bohnhoff, KR Dalbey, JP Eddy, MS Eldred, DM Gay, K Haskell, Patricia D Hough, and Laura P Swiler (2009). *DAKOTA, a Multilevel Parallel Object-Oriented*

Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis: Version 5.0 User's Manual. Tech. Rep. SAND2010-2183. Sandia National Laboratories. *Dakota*. Sandia. URL: https://dakota.sandia.gov/.

Akiyama, Mitsuyoshi, Dan M Frangopol, and Hiroki Ishibashi (2020). "Toward Life-Cycle Reliability-, Risk-and Resilience-Based Design and Assessment of Bridges and Bridge Networks under Independent and Interacting Hazards: Emphasis on Earthquake, Tsunami and Corrosion". In: *Structure and Infrastructure Engineering* 16.1, pp. 26–50. DOI: 10/ghg5vj.

Altieri, Domenico, Enrico Tubaldi, Marco De Angelis, Edoardo Patelli, and Andrea Dall'Asta (2018). "Reliability-Based Optimal Design of Nonlinear Viscous Dampers for the Seismic Protection of Structural Systems". In: *Bulletin of Earthquake Engineering* 16.2, pp. 963–982. DOI: 10/gcwszk.

Andrianov, G et al. (2007). "Open TURNS, an Open Source Initiative to Treat Uncertainties, Risks' N Statistics in a Structured Industrial Approach". In: *Proceedings of the ESREL'2007 Safety and Reliability Conference, Stavenger: Norway*. *OpenTURNS*. URL: http://www.openturns.org/.

Angelikopoulos, Panagiotis, Costas Papadimitriou, and Petros Koumoutsakos (2015). "X-TMCMC: Adaptive Kriging for Bayesian Inverse Modeling". In: *Computer Methods in Applied Mechanics and Engineering* 289, pp. 409–428. DOI: 10/f67379.

Astroza, Rodrigo, Hamed Ebrahimian, and Joel P Conte (2017). "Batch and Recursive Bayesian Estimation Methods for Nonlinear Structural System Identification". In: *Risk and Reliability Analysis: Theory and Applications*. Springer, pp. 341–364.

Au, S.K and J.L Beck (2001). "Estimation of Small Failure Probabilities in High Dimensions by Subset Simulation". In: *Probabilistic Engineering Mechanics* 16.4, pp. 263–277. DOI: 10/b7z8hq.

Au, S.K and J.L Beck (2003a). "Importance Sampling in High Dimensions". In: *Structural Safety* 25.2, pp. 139–163. DOI: 10/fshd2x.

Au, S.K and J.L Beck (2003b). "Subset Simulation and Its Applications to Seismic Risk Based on Dynamic Analysis". In: *Journal of Engineering Mechanics, ASCE* 129.8, pp. 901–917. DOI: 10/b3bfsm.

Baker, J.W and C.A Cornell (2005). "A Vector-Valued Ground Motion Intensity Measure Consisting of Spectral Acceleration and Epsilon". In: *Earthquake Engineering and Structural Dynamics* 34.10, pp. 1193–1217. DOI: 10/dq5rbd.

Baker, Jack W and C Allin Cornell (2008). "Uncertainty Propagation in Probabilistic Seismic Loss Estimation". In: *Structural Safety* 30.3, pp. 236–252. DOI: 10/fsp7xk.

Balesdent, Mathieu, Jerome Morio, and Julien Marzat (2013). "Kriging-Based Adaptive Importance Sampling Algorithms for Rare Event Estimation". In: *Structural Safety* 44, pp. 1–10. DOI: 10/ghg5vw.

Bansal, Sahil and Sai Hung Cheung (2018). "A Subset Simulation Based Approach with Modified Conditional Sampling and Estimator for Loss Exceedance Curve Computation". In: *Reliability Engineering & System Safety* 177, pp. 94–107. DOI: 10/gdv3n3.

Barbato, Michele, Francesco Petrini, Vipin U Unnikrishnan, and Marcello Ciampoli (2013). "Performance-Based Hurricane Engineering (PBHE) Framework". In: *Structural Safety* 45, pp. 24–35. DOI: 10/ghghns.

Beck, J.L and A Taflanidis (2013). "Prior and Posterior Robust Stochastic Predictions for Dynamical Systems Using Probability Logic". In: *Journal of Uncertainty Quantification* 3.4, pp. 271–288. DOI: 10/ghg5vk.

Beck, James L. (2010). "Bayesian System Identification Based on Probability Logic". In: *Structural Control and Health Monitoring* 17.7, pp. 825–847. DOI: 10/b63sfn.

Bect, Julien, Ling Li, and Emmanuel Vazquez (2017). "Bayesian Subset Simulation". In: *SIAM/ASA Journal on Uncertainty Quantification* 5.1, pp. 762–786. DOI: 10/gc4fgw.

Beer, Michael, Scott Ferson, and Vladik Kreinovich (2013). "Imprecise Probabilities in Engineering Analyses". In: *Mechanical systems and signal processing* 37.1-2, pp. 4–29. DOI: 10/f43mnj.

Benowitz, Brett A and George Deodatis (2015). "Simulation of Wind Velocities on Long Span Structures: A Novel Stochastic Wave Based Model". In: *Journal of wind engineering and industrial aerodynamics* 147, pp. 154–163. DOI: 10/f74qgt.

Bernier, Carl and Jamie E Padgett (2019). "Fragility and Risk Assessment of Aboveground Storage Tanks Subjected to Concurrent Surge, Wave, and Wind Loads". In: *Reliability Engineering & System Safety* 191, p. 106571. DOI: 10/ghg5vm.

Betz, Wolfgang, Iason Papaioannou, and Daniel Straub (2016). "Transitional Markov Chain Monte Carlo: Observations and Improvements". In: *Journal of Engineering Mechanics* 142.5, p. 04016016. DOI: 10/f8jwpb.

Beyer, Hans-Georg and Bernhard Sendhoff (2007). "Robust Optimization–a Comprehensive Survey". In: *Computer methods in applied mechanics and engineering* 196.33-34, pp. 3190–3218. DOI: 10/bzsqnz.

Bichon, Barron J., Michael S. Eldred, Sankaran Mahadevan, and John M. McFarland (2013). "Efficient Global Surrogate Modeling for Reliability-Based Design Optimization". In: *Journal of Mechanical Design* 135.1, p. 011009. DOI: 10/ghg5vn.

Bijelić, Nenad, Ting Lin, and Greg G Deierlein (2018). "Validation of the SCEC Broadband Platform Simulations for Tall Building Risk Assessments Considering Spectral Shape and Duration of the Ground Motion". In: *Earthquake Engineering & Structural Dynamics* 47.11, pp. 2233–2251. DOI: 10/gd3c32.

Bobby, Sarah, Arthriya Suksuwan, Seymour MJ Spence, and Ahsan Kareem (2017). "Reliability-Based Topology Optimization of Uncertain Building Systems Subject to Stochastic Excitation". In: *Structural Safety* 66, pp. 1–16. DOI: 10/f959tt.

Bourinet, J-M (2016). "Rare-Event Probability Estimation with Adaptive Support Vector Regression Surrogates". In: *Reliability Engineering & System Safety* 150, pp. 210–221. DOI: 10/f8gxpt.

Bourinet, JM, C Mattrand, and V Dubourg (2009). "A Review of Recent Features and Improvements Added to FERUM Software". In: *Proc. of the 10th International Conference on Structural Safety and Reliability (ICOSSAR'09)*.

Catanach, Thomas A and James L Beck (2018). *Bayesian Updating and Uncertainty Quantification Using Sequential Tempered MCMC with the Rank-One Modified Metropolis Algorithm*. arXiv: 1804.08738.

Cha, Eun Jeong and Bruce R. Ellingwood (2012). "Risk-Averse Decision-Making for Civil Infrastructure Exposed to Low-Probability, High-Consequence Events". In: *Reliability Engineering & System Safety* 104, pp. 27–35. DOI: 10/f34kjz.

Chatzi, Eleni N and Andrew W Smyth (2009). "The Unscented Kalman Filter and Particle Filter Methods for Nonlinear Structural System Identification with Non-collocated Heterogeneous Sensing". In: *Structural Control and Health Monitoring: The Official Journal of the International Association for Structural Control and Monitoring and of the European Association for the Control of Structures* 16.1, pp. 99–123.

Ching, Jianye and Yi-Chu Chen (2007). "Transitional Markov Chain Monte Carlo Method for Bayesian Model Updating, Model Class Selection, and Model Averaging". In: *Journal of Engineering Mechanics* 133.7, pp. 816–832. DOI: 10/dp2kns.

Chun, Junho, Junho Song, and Glaucio H Paulino (2019). "System-Reliability-Based Design and Topology Optimization of Structures under Constraints on First-Passage Probability". In: *Structural Safety* 76, pp. 81–94. DOI: 10/gg3s3b.

Ciampoli, M, F Petrini, and G Augusti (2011). "Performance-Based Wind Engineering: Towards a General Procedure". In: *Structural Safety* 33.6, pp. 367–378. DOI: 10/cbk2zp.

Clement, WALTER, DEFAUX Gilles, IOOSS Bertrand, and MOUTOUSSAMY Vincent (2018). *Methods in Structural Reliaiblity, https://rdrr.io/github/clemlaflemme/mistral/f/*.

De Baar, Jouke, Stephen Roberts, Richard Dwight, and Benoit Mallol (2015). "Uncertainty Quantification for a Sailing Yacht Hull, Using Multi-Fidelity Kriging". In: *Computers & Fluids* 123, pp. 185–201. DOI: 10/ghg5vp.

Deb, A., A. L. Zha, Z. A. Caamaño-Withall, J. P. Conte, and J. I. Restrepo (June 24–26, 2019a). *Towards a Simplified and Rigorous Performance-Based Seismic Design of Ordinary Standard Bridges in California*.

Deb, Angshuman, Alex L Zha, Zachary A Caamaño-Withall, Joel P. Conte, and José I Restrepo (May 26, 2019b). "Parametric Probabilistic Seismic Performance Assessment Framework for Ordinary Standard Bridges". In: 13th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP1. Seoul, South Korea. ISBN: 979-11-967125-0-1. DOI: 10.22725/icasp13.390.

Deodatis, George and M Shinozuka (1988). "Auto-Regressive Model for Nonstationary Stochastic Processes". In: *Journal of engineering mechanics* 114.11, pp. 1995–2012. DOI: 10/bh5c2z.

Ding, Fei and Ahsan Kareem (2018). "A Multi-Fidelity Shape Optimization via Surrogate Modeling for Civil Structures". In: *Journal of Wind Engineering and Industrial Aerodynamics* 178, pp. 49–56. DOI: 10/gdtdx9.

Dos Santos, Ketson RM, Ioannis A Kougioumtzoglou, and André T Beck (2016). "Incremental Dynamic Analysis: A Nonlinear Stochastic Dynamics Perspective". In: *Journal of Engineering Mechanics* 142.10, p. 06016007. DOI: 10/f855jj.

Dubourg, Vincent, Bruno Sudret, and Jean-Marc Bourinet (2011). "Reliability-Based Design Optimization Using Kriging Surrogates and Subset Simulation". In: *Structural and Multidisciplinary Optimization* 44.5, pp. 673–690. DOI: 10/d4zmkq.

Echard, B., N. Gayton, and M. Lemaire (2011). "AK-MCS: An Active Learning Reliability Method Combining Kriging and Monte Carlo Simulation". In: *Structural Safety* 33.2, pp. 145–154. DOI: 10/cp6js4.

Erazo, Kalil and Satish Nagarajaiah (2018). "Bayesian Structural Identification of a Hysteretic Negative Stiffness Earthquake Protection System Using Unscented Kalman Filtering". In: *Structural Control and Health Monitoring* 25.9, e2203. DOI: 10/ghg5vq.

Esposito, Simona, Iunio Iervolino, Anna d'Onofrio, Antonio Santo, Francesco Cavalieri, and Paolo Franchin (2015). "Simulation-based Seismic Risk Assessment of Gas Distribution Networks". In: *Computer-Aided Civil and Infrastructure Engineering* 30.7, pp. 508–523. DOI: 10/ghg5vr.

Fenton, Gordon A and Erik H Vanmarcke (1990). "Simulation of Random Fields via Local Average Subdivision". In: *Journal of Engineering Mechanics* 116.8, pp. 1733–1749. DOI: 10/d2f2zc.

Fischer, Erica C, Amit H Varma, and Anil Agarwal (2019). "Performance-Based Structural Fire Engineering of Steel Building Structures: Design-Basis Compartment Fires". In: *Journal of Structural Engineering* 145.9, p. 04019090. DOI: 10/ghg5vv.

Flint, M et al. (June 28–30, 2016). *Developing a Decision Framework for Multi-Hazard Design of Resilient, Sustainable Buildings*.

Gentile, Roberto and Carmine Galasso (2020). "Gaussian Process Regression for Seismic Fragility Assessment of Building Portfolios". In: *Structural Safety* 87, p. 101980. DOI: 10/ghg5vt.

Geraci, Gianluca, Michael S Eldred, and Gianluca Iaccarino (2017). "A Multifidelity Multilevel Monte Carlo Method for Uncertainty Propagation in Aerospace Applications". In: *19th AIAA Non-Deterministic Approaches Conference*, p. 1951. DOI: 10/ghg5vs.

Ghanem, Roger G and Pol D Spanos (1991). *Stochastic Finite Elements: A Spectral Approach*. Springer.

Ghanem, Roger, David Higdon, and Houman Owhadi (2017). *Handbook of Uncertainty Quantification*. Springer.

Gidaris, I., A.A Taflanidis, and G.P Mavroeidis (Aug. 25–29, 2014). *Surrogate Modeling Implementation for Assessment of Seismic Risk Utilizing Stochastic Ground Motion Modeling*.

Gidaris, Ioannis, Alexandros A. Taflanidis, and George P. Mavroeidis (2015). "Kriging Metamodeling in Seismic Risk Assessment Based on Stochastic Ground Motion Models". In: *Earthquake Engineering & Structural Dynamics* 44.14, pp. 2377–2399. DOI: 10/f7t6v8.

Gidaris, Ioannis, Alexandros A Taflanidis, and George P Mavroeidis (2017). "Multiobjective Design of Supplemental Seismic Protective Devices Utilizing Lifecycle Performance Criteria". In: *Journal of Structural Engineering* 144.3, p. 04017225. DOI: 10/gcwhvg.

Giovanis, Dimitris G, Iason Papaioannou, Daniel Straub, and Vissarion Papadopoulos (2017). "Bayesian Updating with Subset Simulation Using Artificial Neural Networks". In: *Computer Methods in Applied Mechanics and Engineering* 319, pp. 124–145. DOI: 10/f98vp5.

Gorissen, Dirk, Ivo Couckuyt, Piet Demeester, Tom Dhaene, and Karel Crombecq (2010). "A Surrogate Modeling and Adaptive Sampling Toolbox for Computer Based Design". In: *Journal of Machine Learning Research* 11 (Jul), pp. 2051–2055.

Goulet, C.A, C.B Haselton, J Mitrani-Reiser, J.L Beck, G Deierlein, K.A. Porter, and J.P Stewart (2007). "Evaluation of the Seismic Performance of Code-Conforming Reinforced-Concrete Frame Building-From Seismic Hazard to Collapse Safety and Economic Losses". In: *Earthquake Engineering and Structural Dynamics* 36.13, pp. 1973–1997. DOI: 10/dpjv8g.

Greco, Rita, Andrea Lucchini, and Giuseppe Carlo Marano (2015). "Robust Design of Tuned Mass Dampers Installed on Multi-Degree-of-Freedom Structures Subjected to Seismic Action". In: *Engineering Optimization* 47.8, pp. 1009–1030. DOI: 10/ghg5v2.

Gu, Quan, Joel P Conte, Ahmed Elgamal, and Zhaohui Yang (2009). "Finite Element Response Sensitivity Analysis of Multi-Yield-Surface J2 Plasticity Model by Direct Differentiation Method". In: *Computer methods in applied mechanics and engineering* 198.30-32, pp. 2272–2285. DOI: 10/c6x942.

Haukaas, T and M Mahsuli (2012). *Reliability-Based Design Optimization with Uncertain Cost*.

Haukaas, Terje and Armen Der Kiureghian (2007). "Methods and Object-Oriented Software for FE Reliability and Sensitivity Analysis with Application to a Bridge Structure". In: *Journal of Computing in Civil Engineering* 21.3, pp. 151–163. DOI: 10/c647c2.

Hu, Zhen and Sankaran Mahadevan (2019). "Probability Models for Data-Driven Global Sensitivity Analysis". In: *Reliability Engineering & System Safety* 187, pp. 40–57. DOI: 10/ghg5vx.

Huang, MF, Qiang Li, Chun Man Chan, WJ Lou, Kenny CS Kwok, and Gang Li (2015). "Performance-Based Design Optimization of Tall Concrete Framed Structures Subject to Wind Excitations". In: *Journal of Wind Engineering and Industrial Aerodynamics* 139, pp. 70–81. DOI: 10/f65b4g.

Jayaram, Nirmal and Jack W Baker (2010). "Efficient Sampling and Data Reduction Techniques for Probabilistic Seismic Lifeline Risk Assessment". In: *Earthquake Engineering & Structural Dynamics* 39.10, pp. 1109–1131.

Jia, G, A Taflanidis, and J.L Beck (June 15–18, 2014). *Adaptive Stochastic Sampling Using Kernel Density Approximations*.

Jia, Gaofeng and Paolo Gardoni (2018). "State-Dependent Stochastic Models: A General Stochastic Framework for Modeling Deteriorating Engineering Systems Considering Multiple Deterioration Processes and Their Interactions". In: *Structural Safety* 72, pp. 99–110. DOI: 10/gc8cxv.

Jia, Gaofeng and Alexandros A. Taflanidis (2013). "Kriging Metamodeling for Approximation of High-Dimensional Wave and Surge Responses in Real-Time Storm/Hurricane Risk Assessment". In: *Computer Methods in Applied Mechanics and Engineering* 261-262, pp. 24–38. DOI: 10/gbdcg4.

Jia, Gaofeng, Alexandros A Taflanidis, and James L Beck (2017). "A New Adaptive Rejection Sampling Method Using Kernel Density Approximations and Its Application to Subset Simulation". In: *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* 3.2, p. D4015001. DOI: 10/gg3svm.

Kennedy, Marc C and Anthony O'Hagan (2001). "Bayesian Calibration of Computer Models". In: *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 63.3, pp. 425–464. DOI: 10/b3q4t2.

Kleijnen, J.P.C (2008). *Design and Analysis of Simulation Experiments*. Vol. 20. Springer.

Koduru, SD and T Haukaas (2010). "Feasibility of FORM in Finite Element Reliability Analysis". In: *Structural Safety* 32.2, pp. 145–153. DOI: 10/fwr2zx.

Kohrangi, Mohsen, Dimitrios Vamvatsikos, and Paolo Bazzurro (2016). "Implications of Intensity Measure Selection for Seismic Loss Assessment of 3-D Buildings". In: *Earthquake Spectra* 32.4, pp. 2167–2189. DOI: 10/f9dhkx.

Kontoroupi, Thaleia and Andrew W Smyth (2017). "Online Bayesian Model Assessment Using Nonlinear Filters". In: *Structural Control and Health Monitoring* 24.3, e1880. DOI: 10/ghg5vz.

Kyprioti, Aikaterini P, Jize Zhang, and Alexandros A Taflanidis (2020). "Adaptive Design of Experiments for Global Kriging Metamodeling through Cross-Validation Information". In: *Structural and Multidisciplinary Optimization*, pp. 1–23. DOI: 10.1007/s00158-020-02543-1.

Le, Viet and Luca Caracoglia (2020). "A Neural Network Surrogate Model for the Performance Assessment of a Vertical Structure Subjected to Non-Stationary, Tornadic Wind Loads". In: *Computers & Structures* 231, p. 106208. DOI: 10/ggkjq5.

Li, Chenzhao and Sankaran Mahadevan (2016). "An Efficient Modularized Sample-Based Method to Estimate the First-Order Sobol' Index". In: *Reliability Engineering & System Safety* 153, pp. 110–121. DOI: 10/f8tfn5.

Li, Dian-Qing, Zhi-Yong Yang, Zi-Jun Cao, Siu-Kui Au, and Kok-Kwang Phoon (2017). "System Reliability Analysis of Slope Stability Using Generalized Subset Simulation". In: *Applied Mathematical Modelling* 46, pp. 650–664. DOI: 10/gbj7d7.

Li, Jie and Jianbing Chen (2009). *Stochastic Dynamics of Structures*. John Wiley & Sons.

Li, Jing, Jinglai Li, and Dongbin Xiu (2011). "An Efficient Surrogate-Based Method for Computing Rare Failure Probability". In: *Journal of Computational Physics* 230.24, pp. 8683–8697. DOI: 10/bcm82r.

Li, Yong and Joel P Conte (2018). "Probabilistic Performance-based Optimum Design of Seismic Isolation for a California High-speed Rail Prototype Bridge". In: *Earthquake Engineering & Structural Dynamics* 47.2, pp. 497–514. DOI: 10/gcwpv5.

Li, Yousun and Ahsan Kareem (1991). "Simulation of Multivariate Nonstationary Random Processes by FFT". In: *Journal of Engineering Mechanics* 117.5, pp. 1037–1058. DOI: 10/brj239.

Liu, Haitao, Yew-Soon Ong, and Jianfei Cai (2018). "A Survey of Adaptive Sampling for Global Metamodeling in Support of Simulation-Based Complex Engineering Design". In: *Structural and Multidisciplinary Optimization* 57.1, pp. 393–416. DOI: 10/gcs48t.

Lophaven, Søren Nymand, Hans Bruun Nielsen, and Jacob Søndergaard (2002). *DACE - A Matlab Kriging Toolbox, Version 2.0*. Technical University of Denmark. *DACE*. URL: http://www.omicron.dk/dace.html.

Mantoglou, Aristotelis and John L Wilson (1982). "The Turning Bands Method for Simulation of Random Fields Using Line Generation by a Spectral Method". In: *Water Resources Research* 18.5, pp. 1379–1394. DOI: 10/fp2r83.

Marelli, Stefano and Bruno Sudret (2014). "UQLab: A Framework for Uncertainty Quantification in Matlab". In: *Vulnerability, Uncertainty, and Risk: Quantification, Mitigation, and Management*, pp. 2554–2563. *UQLab*. URL: https://www.uqlab.com/.

McGuire, Robin K. (2004). *Seismic Hazard and Risk Analysis*. Earthquake engineering research institute.

Medina, J.C and A Taflanidis (2014). "Adaptive Importance Sampling for Optimization under Uncertainty Problems". In: *Computer Methods in Applied Mechanics and Engineering* 279, pp. 133–162. DOI: 10/f6jg3f.

Mehmani, Ali, Souma Chowdhury, Christoph Meinrenken, and Achille Messac (2018). "Concurrent Surrogate Model Selection (COSMOS): Optimizing Model Type, Kernel Function, and Hyper-Parameters". In: *Structural and Multidisciplinary Optimization* 57.3, pp. 1093–1114. DOI: 10/gdcztj.

Murphy, Kevin P (2012). "Machine Learning: A Probabilistic Perspective (Adaptive Computation and Machine Learning Series)". In: *MIT Press* 621485037, p. 15.

Muto, Matthew and James L. Beck (2008). "Bayesian Updating and Model Class Selection for Hysteretic Structural Models Using Stochastic Simulation". In: *Journal of Vibration and Control* 14.1-2, pp. 7–34. DOI: 10/dp5x3c.

Oh, Chang Kook and James L Beck (2018). "A Bayesian Learning Method for Structural Damage Assessment of Phase I IASC-ASCE Benchmark Problem". In: *KSCE Journal of Civil Engineering* 22.3, pp. 987–992. DOI: 10/ghg5v3.

Olivier, Audrey, Dimitrios Giovanis, BS Aakash, Mohit Chauhan, Lohit Vandanapu, and Michael D Shields (2020). "UQpy: A General Purpose Python Package and Development Environment for Uncertainty Quantification". In: *Journal of Computational Science* 47, p. 101204. DOI: 10/ghg5rh. *UQpy*. SURG, Jan. 28, 2021. URL: https://github.com/SURGroup/UQpy (visited on 01/31/2021).

Olivier, Audrey and Andrew W Smyth (2017). "Particle Filtering and Marginalization for Parameter Identification in Structural Systems". In: *Structural Control and Health Monitoring* 24.3, e1874. DOI: 10/ghg5v4.

Papadimitriou, Dimitrios, Dionysios Panagiotopoulos, and Zissimos Mourelatos (2018). "Reliability Based Design Optimization Using First, Second and Quasi-Second Order Saddlepoint Approximations". In: *2018 AIAA Non-Deterministic Approaches Conference*, p. 2172. DOI: 10/ghg5wf.

Papaioannou, Iason, Karl Breitung, and Daniel Straub (2018). "Reliability Sensitivity Estimation with Sequential Importance Sampling". In: *Structural Safety* 75, pp. 24–34. DOI: 10/gd5j3g.

Patelli, Edoardo, Matteo Broggi, Silva Tolo, and Jonathan Sadeghi (2017). "Cossan Software: A Multidisciplinary and Collaborative Software for Uncertainty Quantification". In: *Proceedings of the 2nd ECCOMAS Thematic Conference on Uncertainty Quantification in Computational Sciences and Engineering, UNCECOMP*. DOI: 10/ch3f. *OpenCOSSAN*. URL: http://www.cossan.co.uk/software/open-cossan-engine.php.

Peherstorfer, Benjamin, Karen Willcox, and Max Gunzburger (2018). "Survey of Multifidelity Methods in Uncertainty Propagation, Inference, and Optimization". In: *SIAM Review* 60.3, pp. 550–591. DOI: 10/gd3sm5.

Picheny, V., D. Ginsbourger, O. Roustant, R. T. Haftka, and N. H. Kim (2010). "Adaptive Designs of Experiments for Accurate Approximation of a Target Region". In: *Journal of Mechanical Design* 132.7, p. 071008. DOI: 10/fnqnh2.

Porter, K.A., J.L Beck, and R.V Shaikhutdinov (2002). "Sensitivity of Building Loss Estimates to Major Uncertain Variables". In: *Earthquake Spectra* 18.4, pp. 719–743. DOI: 10/cpmhfj.

Quiroz, Matias, Minh-Ngoc Tran, Mattias Villani, and Robert Kohn (2018). "Speeding up MCMC by Delayed Acceptance and Data Subsampling". In: *Journal of Computational and Graphical Statistics* 27.1, pp. 12–22. DOI: 10/gb2hr5.

Rahman, Sharif (2016). "The F-Sensitivity Index". In: *SIAM/ASA Journal on Uncertainty Quantification* 4.1, pp. 130–162. DOI: 10/ghg5v5.

Ramancha, M. K., R. Astroza, J. P. Conte, J. I. Restrepo, and M. D Todd (Feb. 10–13, 2021a). *Bayesian Nonlinear Finite Element Model Updating of a Full-Scale Bridge Column Using Sequential Monte Carlo*.

Ramancha, M. K., R. Astroza, R. Madarshahian, and J. P Conte (2021b). "Bayesian Updating and Identifiability Assessment of Nonlinear Finite Element Model". In: *Mechanical Systems and Signal Processing*.

Ramancha, Mukesh Kumar, Ramin Madarshahian, Rodrigo Astroza, and Joel P Conte (2020). *Non-Unique Estimates in Material Parameter Identification of Nonlinear FE Models Governed by Multiaxial Material Models Using Unscented Kalman Filtering*. Proceedings of the Society for Experimental Mechanics Series: Model Validation and Uncertainty Quantification, Volume 3. Springer.

Resio, D.T. et al. (2007). *White Paper on Estimating Hurricane Inundation Probabilities*.

Riggs, HR, Ian N Robertson, Kwok Fai Cheung, Geno Pawlak, Yin Lu Young, and Solomon CS Yim (2008). "Experimental Simulation of Tsunami Hazards to Buildings and Bridges". In: *Dalam Proceedings of 2008 NSF Engineering Research and Innovation Conference, Knoxville, Tennessee*.

Saltelli, Andrea (2002). "Making Best Use of Model Evaluations to Compute Sensitivity Indices". In: *Computer physics communications* 145.2, pp. 280–297. DOI: 10/c2th6s.

Schuëller, G.I, H.J Pradlwater, and P.S Koutsourelakis (2004). "A Critical Appraisal of Reliability Estimation Procedures for High Dimensions". In: *Probabilistic Engineering Mechanics* 19.4, pp. 463–474. DOI: 10/bgcq6z.

Shields, MD, G Deodatis, and P Bocchini (2011). "A Simple and Efficient Methodology to Approximate a General Non-Gaussian Stationary Stochastic Process by a Translation Process". In: *Probabilistic Engineering Mechanics* 26.4, pp. 511–519. DOI: 10/cc5vkg.

Shin, H. and M. P. Singh (2014). "Minimum Failure Cost-Based Energy Dissipation System Designs for Buildings in Three Seismic Regions Part II: Application to Viscous Dampers". In: *Engineering Structures*, DOI: 10.1016/j.engstruct.2014.05.012.

Shinozuka, Masanobu and George Deodatis (1991). "Simulation of Stochastic Processes by Spectral Representation". In: *Applied Mechanics Reviews*. DOI: 10/d5tbj2.

Smith, Marra A and Luca Caracoglia (2011). "A Monte Carlo Based Method for the Dynamic "Fragility Analysis" of Tall Buildings under Turbulent Wind Loading". In: *Engineering Structures* 33.2, pp. 410–420. DOI: 10/cfrw5m.

Smith, Ralph C (2013). *Uncertainty Quantification: Theory, Implementation, and Applications*. Vol. 12. Siam.

Sobol, Il'ya Meerovich (1990). "On Sensitivity Estimation for Nonlinear Mathematical Models". In: *Matematicheskoe Modelirovanie* 2.1, pp. 112–118.

Spall, J.C (2003). *Introduction to Stochastic Search and Optimization*. New York: Wiley-Interscience.

Spanos, P.T (1983). "ARMA Algorithms for Ocean Wave Modeling". In: *Journal of Energy Resources Technology*. DOI: 10/cxzpsb.

Spence, Seymour MJ and Massimiliano Gioffrè (2012). "Large Scale Reliability-Based Design Optimization of Wind Excited Tall Buildings". In: *Probabilistic Engineering Mechanics* 28, pp. 206–215. DOI: 10/bp4h6r.

Stern, Raphael E, Junho Song, and Daniel B Work (2017). "Accelerated Monte Carlo System Reliability Analysis through Machine-Learning-Based Surrogate Models of Network Connectivity". In: *Reliability Engineering & System Safety* 164, pp. 1–9. DOI: 10/ghg5v7.

Su, Lei, Hua-Ping Wan, You Dong, Dan M Frangopol, and Xian-Zhang Ling (2018). "Efficient Uncertainty Quantification of Wharf Structures under Seismic Scenarios Using Gaussian Process Surrogate Model". In: *Journal of Earthquake Engineering*, pp. 1–22. DOI: 10/ghg5v6.

Sudret, Bruno (2008). "Global Sensitivity Analysis Using Polynomial Chaos Expansions". In: *Reliability engineering & system safety* 93.7, pp. 964–979. DOI: 10/bjjp5r.

Suksuwan, Arthriya and Seymour MJ Spence (2018). "Optimization of Uncertain Structures Subject to Stochastic Wind Loads under System-Level First Excursion Constraints: A Data-Driven Approach". In: *Computers & Structures* 210, pp. 58–68. DOI: 10/gfm6kq.

Taflanidis, A. A and G Jia (2011). "A Simulation-Based Framework for Risk Assessment and Probabilistic Sensitivity Analysis of Base-Isolated Structures". In: *Earthquake Engineering & Structural Dynamics* 40, pp. 1629–1651. DOI: 10/b6m7d6.

Tripathy, Rohit and Ilias Bilionis (2018). *Deep UQ: Learning Deep Neural Network Surrogate Models for High Dimensional Uncertainty Quantification*. arXiv: 1802.00850.

Vamvatsikos, Dimitrios (2013). "Derivation of New SAC/FEMA Performance Evaluation Solutions with Second-order Hazard Approximation". In: *Earthquake Engineering & Structural Dynamics* 42.8, pp. 1171–1188. DOI: 10/f4x6bj.

Vamvatsikos, Dimitrios (2014). "Seismic Performance Uncertainty Estimation via IDA with Progressive Accelerogram-Wise Latin Hypercube Sampling". In: *Journal of Structural Engineering* 140.8, A4014015. DOI: 10/f6kgn2.

Vetter, C and A.A Taflanidis (2012). "Global Sensitivity Analysis for Stochastic Ground Motion Modeling in Seismic-Risk Assessment". In: *Soil Dynamics and Earthquake Engineering* 38, pp. 128–143. DOI: 10/ghg5v8.

Vlachos, Christos, Konstantinos G Papakonstantinou, and George Deodatis (2018). "Predictive Model for Site Specific Simulation of Ground Motions Based on Earthquake Scenarios". In: *Earthquake Engineering & Structural Dynamics* 47.1, pp. 195–218. DOI: 10/gcp9h3.

Wang, Lijuan, Megan McCullough, and Ahsan Kareem (2014). "Modeling and Simulation of Nonstationary Processes Utilizing Wavelet and Hilbert Transforms". In: *Journal of Engineering Mechanics* 140.2, pp. 345–360. DOI: 10/f5r3fb.

Wang, Zeyu and Abdollah Shafieezadeh (May 26–30, 2019). "Reliability-Based Bayesian Updating Using Machine Learning". In: 13th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP1. Seoul, South Korea. ISBN: 979-11-967125-0-1. DOI: 10.22725/icasp13.368.

Wang, Zhiyi, Irmela Zentner, and Enrico Zio (2018). "A Bayesian Framework for Estimating Fragility Curves Based on Seismic Damage Data and Numerical Simulations by Adaptive Neural Networks". In: *Nuclear Engineering and Design* 338, pp. 232–246. DOI: 10/ghg5v9.

Wang, Ziqi and Armen Der Kiureghian (2016). "Tail-Equivalent Linearization of Inelastic Multisupport Structures Subjected to Spatially Varying Stochastic Ground Motion". In: *Journal of Engineering Mechanics* 142.8, p. 04016053. DOI: 10/f82cj7.

Wang, Ziqi and Junho Song (2016). "Cross-Entropy-Based Adaptive Importance Sampling Using von Mises-Fisher Mixture for High Dimensional Reliability Analysis". In: *Structural Safety* 59, pp. 42–52. DOI: 10/f8fbhc.

Wei, Zhao, Tao Tao, Ding ZhuoShu, and Enrico Zio (2013). "A Dynamic Particle Filter-Support Vector Regression Method for Reliability Prediction". In: *Reliability Engineering & System Safety* 119, pp. 109–116. DOI: 10/f49wsg.

Whittaker, Andrew, RO Hamburger, and M Mahoney (2003). "Performance-Based Engineering of Buildings and Infrastructure for Extreme Loadings". In: *Proceedings, AISC-SINY Symposium on Resisting Blast and Progressive Collapse, American Institute of Steel Construction, New York*.

Zeldin, BA and PD Spanos (1996). "Random Field Representation and Synthesis Using Wavelet Bases". In: *Journal of Applied Mechanics*. DOI: 10/d5wjq4.

Zhang, Jize and Alexandros A Taflanidis (2018). "Adaptive Kriging Stochastic Sampling and Density Approximation and Its Application to Rare-Event Estimation". In: *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* 4.3, p. 04018021. DOI: 10/ghg5wb.

Zhang, Jize and Alexandros A Taflanidis (2019). "Accelerating MCMC via Kriging-Based Adaptive Independent Proposals and Delayed Rejection". In: *Computer Methods in Applied Mechanics and Engineering* 355, pp. 1124–1147. DOI: 10/ghg5wc.

Zhang, Ruiyang, Yang Liu, and Hao Sun (2020). "Physics-Guided Convolutional Neural Network (PhyCNN) for Data-Driven Seismic Response Modeling". In: *Engineering Structures* 215, p. 110704. DOI: 10/ghdgrc.

Zhou, Qi, Xinyu Shao, Ping Jiang, Zhongmei Gao, Hui Zhou, and Leshi Shu (2016b). "An Active Learning Variable-Fidelity Metamodelling Approach Based on Ensemble of Metamodels and Objective-Oriented Sequential Sampling". In: *Journal of Engineering Design* 27.4-6, pp. 205–231. DOI: 10/ghg5wd.

Zhu, Mu, Yang Yang, James K Guest, and Michael D Shields (2017b). "Topology Optimization for Linear Stationary Stochastic Dynamics: Applications to Frame Structures". In: *Structural Safety* 67, pp. 116–131. DOI: 10/gbkpz6.

Cross-Cutting: Artificial Intelligence and Machine Learning

Abbot, J. and J. Marohasy (2014). "Input Selection and Optimisation for Monthly Rainfall Forecasting in Queensland, Australia, Using Artificial Neural Networks". In: *Atmospheric Research* 138, pp. 166–178. DOI: 10/f5vqvq.

Alimoradi, A. and J.L. Beck (2015). "Machine-Learning Methods for Earthquake Ground Motion Analysis and Simulation". In: *Journal of Engineering Mechanics* 141.4, p. 04014147. DOI: 10/f65qjb.

Aquino, W. and J.C. Brigham (2006). "Self Learning Finite Elements for Inverse Estimation of Thermal Constitutive Models". In: *International Journal of Heat and Mass Transfer* 49, pp. 2466–2478. DOI: 10/bpc3jx.

Ataei, N. and J.E. Padgett (2015). "Fragility Surrogate Models for Coastal Bridges in Hurricane Prone Zones". In: *Engineering Structures* 103, pp. 203–213. DOI: 10/f7vs9d.

Bai, Y., B. Adriano, E. Mas, and S. Koshimura (2017). "Machine Learning Based Building Damage Mapping from the ALOS-2/PALSAR-2 SAR Imagery: Case Study of 2016 Kumamoto Earthquake". In: *Journal of Disaster Research* 12 (sp), pp. 646–655. DOI: 10/ghgv67.

Baru, C. (2017). "Open Knowledge Network: Recap & Some Related Work at NSF". In: *Open Knowledge Network – Enabling the Community to Build the Network, National Institute of Health*. URL: https://www.nitrd.gov/nitrdgroups/images/c/ca/OKN_ChaitanBaru.pdf).

Bennett, J., L. Creary, R. Englemore, and R. Melosh (1978). *SACON: A Knowledge-Based Consultant for Structural Analysis*. Technical report STAN-CS-78-699, Stanford University.

Bishop, C.M. (1995). *Neural Networks for Pattern Recognition*. Oxford University Press.

Blundell, C., J. Cornebise, K. Kavukcuoglu, and D. Wierstra (2015). "Weight Uncertainty in Neural Network". In: *Proceedings of the 32nd International Conference on Machine Learning, Proceedings of Machine Learning Research*. PMLR, Lille, France.

Bonatti, P.A., S. Decker, A. Polleres, and V. Presutti (2018). "Knowledge Graphs: New Directions for Knowledge Representation on the Semantic Web". In: *Dagstuhl Reports* 8.9, pp. 29–111.

Cha, Y.J., W. Choi, and O. Buyukozturk (2017). "Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks". In: *Computer Aided Civil and Infrastructure Engineering* 32.5, pp. 361–378. DOI: 10/f928ww.

Chen, G., Q. Xiong, P.J. Morris, E.G. Paterson, A. Sergeev, and Y.-C. Wang (2014). "OpenFOAM for Computational Fluid Dynamics". In: *Notices of the American Mathematical Society* 61.4, pp. 354–363. DOI: 10/gg98np.

Chen, K., W. Lu, F. Xue, P. Tang, and L.H. Li (2018). "Automatic Building Information Model Reconstruction in High-Density Urban Areas: Augmenting Multi-Source Data with Architectural Knowledge". In: *Automation in Construction* 93, pp. 22–34.

Cohn, L.F. and R.A. Harris (1992). *Knowledge-Based Expert Systems in Transportation, Synthesis of Highway Practice 183*. Transportation Research Board.

Cooner, A.J., Y. Shao, and J.B. Campbell (2016). "Detection of Urban Damage Using Remote Sensing and Machine Learning Algorithms: Revisiting the 2010 Haiti Earthquake". In: *Remote Sensing* 8.10, p. 868. DOI: 10/f89z8f.

Council, Applied Technology (Jan. 2015). *Rapid Visual Screening of Buildings for Potential Seismic Hazards: A Handbook*. Third. P-154. FEMA. URL: https://www.fema.gov/media-library-data/1426210695633-d9a280e72b32872161efab26a602283b/FEMAP-154_508.pdf.

Council, National Science and Technology and Technology Council (2016a). *Preparing the Future of Artificial Intelligence*. NSTC, p. 58. URL: https://obamawhitehouse.archives.gov/sites/default/files/whitehouse_files/microsites/ostp/NSTC/preparing_for_the_future_of_ai.pdf.

Darabi, H., B. Choubin, O. Rahmati, A.T. Haghighi, B. Pradhan, and B. Kløve (2019). "Urban Flood Risk Mapping Using the GARP and QUEST Models: A Comparative Study of Machine Learning Techniques". In: *Journal of Hydrology* 569, pp. 142–154. DOI: 10/ggqm9r.

DARPA (2016). *Explainable Artificial Intelligence (XAI)*. DARPA-BAA-16-53. Broad Agency Announcement.

Day, Martyn (Nov. 22, 2019). *Bentley on Digital Twins*. AEC Magazine. URL: https://www.aecmag.com/component/content/article/59-features/1910-bentley-on-digital-twins.

Deng, J., W. Dong, R. Socher, L.-J. Li, K. Li, and F.-F. Li (2009). "ImageNet: A Large-Scale Hierarchical Image Database". In: *IEEE Computer Vision and Pattern Recognition (CVPR. ImageNet*. URL: http://www.image-net.org/.

Dou, J., T. Oguchi, Y.S. Hayakawa, S. Uchiyama, H. Saito, and U. Paudel (2014). "GIS-Based Landslide Susceptibility Mapping Using a Certainty Factor Model and Its Validation in the Chuetsu Area, Central Japan". In: *Landslide Science for a Safer Geoenvironment*. Springer, pp. 419–424.

Dym, C.L. and R.E. Levitt (1991). *Knowledge-Based Systems in Engineering*. NY: McGraw Hill.

Eriksson, D.M. (2018). "Scalable Kernel Methods and Their Use in Black-Box Optimization". PhD thesis, Cornell University.

Federal Emergency Management Agency (2011a). *Hazus–MH 2.1: Earthquake Technical Manual*. Washington, D.C.: FEMA, p. 718.

Ferguson, M., R. Ak, Y.-T.T. Lee, and K.H. Law (2018). "Detection and Segmentation of Manufacturing Defects with Convolutional Neural Networks and Transfer Learning". In: *Smart and Sustainable Manufacturing Systems* 2.1, pp. 137–164. DOI: 10/ghgv69.

Future, Market Research (2019). *Machine Learning Market Growth, Trends, Forecast and Industry Analysis*. MRFR/ICT/1855-CR. Market Research Future, p. 166. URL: https://www.marketresearchfuture.com/reports/machine-learning-market-2494 (visited on 01/19/2021).

Gao, Y. and K.M. Mosalam (2018a). "Deep Transfer Learning for Image-Based Structural Damage Recognition". In: *Computer-Aided Civil and Infrastructure Engineering* 33.9, pp. 748–768. DOI: 10/gd292k.

Gao, Y. and Khalid M. Mosalam (2018b). *Structural ImageNet and PEER Hub ImageNet Challenge*. PEER HUB IMAGENET. URL: https://apps.peer.berkeley.edu/phi-net/.

Garrett Jr, J.H. and I.F.C. Smith (1996). "AI Applications in Structural/Construction Engineering". In: *IEEE Expert* 11.3, pp. 20–22. DOI: 10/dr966t.

Gebrehiwot, A., L. Hashemi-Beni, G. Thompson, P. Kordjamshidi, and T.E. Langan (2019). "Deep Convolutional Neural Network for Flood Extent Mapping Using Unmanned Aerial Vehicles Data". In: *Sensors* 19.7, p. 1486. DOI: 10/ghgv68.

Ghaboussi, J. and J.H. Garrett Jr (1991). "Knowledge-Based Modeling of Material Behavior with Neural Networks". In: *Journal of Engineering Mechanics* 117.1, pp. 132–153. DOI: 10/frq7pb.

Ghaboussi, J., D.A. Pecknold, M. Zhang, and R.M. Haj-Ali (1998). "Autoprogressive Training of Neural Network Constitutive Models". In: *International Journal for Numerical Methods in Engineering* 42, pp. 105–126. DOI: 10/dq4wgs.

Ghorbanzadeh, O., T. Blaschke, K. Gholamnia, S.R. Meena, D. Tiede, and J. Aryal (2019). "Evaluation of Different Machine Learning Methods and Deep-Learning Convolutional Neural Networks for Landslide Detection". In: *Remote Sensing* 11.2, p. 196. DOI: 10/ggbgkk.

Gidaris, Ioannis, Alexandros A. Taflanidis, and George P. Mavroeidis (2015). "Kriging Metamodeling in Seismic Risk Assessment Based on Stochastic Ground Motion Models". In: *Earthquake Engineering & Structural Dynamics* 44.14, pp. 2377–2399. DOI: 10/f7t6v8.

Gizaw, M.S. and T.Y. Gan (2016). "Regional Flood Frequency Analysis Using Support Vector Regression under Historical and Future Climate". In: *Journal of Hydrology* 538, pp. 387–398. DOI: 10/f8r9bw.

Goetz, J.N., A. Brenning, H. Petschko, and P. Leopold (2015). "Evaluating Machine Learning and Statistical Prediction Techniques for Landslide Susceptibility Modeling". In: *Computers & Geosciences* 81, pp. 1–11. DOI: 10/f7hcgp.

Gokkaya, Beliz U., Jack W. Baker, and Greg G. Deierlein (2016). "Quantifying the Impacts of Modeling Uncertainties on the Seismic Drift Demands and Collapse Risk of Buildings with Implications on Seismic Design Checks". In: *Earthquake Engineering & Structural Dynamics* 45.10, pp. 1661–1683. ISSN: 1096-9845. DOI: 10/f9dzzw.

Hamilton, W.L., R. Ying, and J. Leskovec (2017). "Representation Learning on Graphs: Methods and Applications". In: *IEEE Data Engineering Bulletin*.

Hayes-Roth, F., D.A. Waterman, and D.B. Lenat (1983). *Building Expert Systems*. Addison-Wesley.

He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun (2016). "Deep Residual Learning for Image Recognition". In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 770–778. URL: https://arxiv.org/abs/1512.03385.

Hofmann, T., B. Scholkopf, and A.J. Smola (2008). "Kernel Methods in Machine Learning". In: *The Annals of Statistics* 36.3, pp. 1171–1220. DOI: 10/dzvvjn.

ISO (May 2016). *Building Information Modeling—Information Delivery Manual—Part 1: Methodology and Format*. ISO 29481-1:2016. Geneva, Switzerland: ISO.

Jain, D., G. Luth, K.H. Law, and H. Krawinkler (1991a). "A Formal Approach to Automating Conceptual Structural Design, Part I - Methodology". In: *Engineering with Computers* 7, pp. 79–89.

Jain, D., G. Luth, K.H. Law, and H. Krawinkler (1991b). "A Formal Approach to Automating Conceptual Structural Design, Part II - Application to Floor Framing Generation". In: *Engineering with Computers* 7, pp. 91–107. DOI: 10/dt39s7.

Jeong, S., M. Ferguson, R. Hou, J.P. Lynch, H. Sohn, and K.H. Law (2019). "Sensor Data Reconstruction Using Bidirectional Recurrent Neural Network with Application to Bridge Monitoring". In: *Advanced Engineering Informatics* 42.10991.

Jia, G., A. Taflanidis, N.C. Nadal-Caraballo, J. Melby, A. Kennedy, and J. Smith (2016). "Surrogate Modeling for Peak and Time Dependent Storm Surge Prediction over an Extended Coastal Region Using an Existing Database of Synthetic Storms". In: *Natural Hazards* 81, pp. 909–938. DOI: 10/f79r78.

Jia, X., J. Willard, A. Karpatne, J.S. Read, J.A. Zwart, M. Steinbach, and V. Kumar (2020). *Physics-Guided Machine Learning for Scientific Discovery: An Application in Simulating Lake Temperature Profiles*. arXiv: 2001.11086v2.

Joshi, A.J., F. Porikli, and N. Papanikolopulos (2009). "Multi-Class Active Learning for Image Classification". In: *IEEE Conference on Computer Vision and Pattern Recognition*. Miami, FL, USA, pp. 2372–2379.

Kabir, H.M.D., A. Khosravi, M.A. Hosen, and S. Nahavandi (2018). "Neural Network-Based Uncertainty Quantification: A Survey of Methodologies and Applications". In: *IEEE Access, IEEE* 6, pp. 36218–36234. DOI: 10/ghgv7b.

Kafle, K. and C. Kanan (2017). "Visual Question Answering: Datasets, Algorithms, and Future Challenges". In: *Computer Vision and Image Understanding* 163, pp. 3–20. DOI: 10/gcs5zs.

Kartam, N., I. Flood, and J.H. Garrett Jr. (1997). *Artificial Neural Networks for Civil Engineers: Fundamentals and Applications*. American Society of Civil Engineers.

Kersbergen, D. (2018). "Automated Building Damage Classification Using Remotely Sensed Data: Case Study: Hurricane Damage on St". In: *Maarten, Master Thesis, Architecture and the Built Environment*. Delft University of Technology.

Kerschen, G., P. De Boe, J. Golinval, and K. Worden (2005). "Sensor Validation Using Principal Component Analysis". In: *Smart Materials and Structures* 14.1, pp. 36–42. DOI: 10/fsks97.

Kim, S., Y. Matsumi, S. Pan, and H. Mase (2016). "A Real-Time Forecast Model Using Artificial Neural Network for after-Runner Storm Surges on the Tottori Coast, Japan". In: *Ocean Engineering* 122, pp. 44–53. DOI: 10/f82dnp.

Koller, D. and N. Friedman (2009). *Probabilistic Graph Models: Principles and Techniques*. MIT Press.

Kostem, C.N. and M.L. Maher, eds. (1986). *Expert Systems in Civil Engineering*. American Society of Civil Engineers.

Kratzert, F., M. Herrnegger, D. Klotz, S. Hochreiter, and G. Klambauer (2019). "NeuralHydrology – Interpreting LSTMs in Hydrology". In: *Explanable AI: Interpreting, Explaining and Visualizing Deep Learning*. Ed. by Samek, Vedaldi Montavon, and Muller Hansen. Vol. 11700. Springer.

Kumar, A. et al. (2018). "Using Machine Learning to Assess the Risk of and Rrevent Water Main Breaks". In: *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pp. 472–480. DOI: 10/ghgv7f.

Kumar, B. and B. Raphael (1997). "CADREM: A Case-Based System for Conceptual Structural Design". In: *Engineering with Computers* 13.3, pp. 153–164. DOI: 10/bhjwf2.

Le, X.-H., H.V. Ho, G. Lee, and S. Jung (2019). "Application of Long Short-Term Memory (LSTM) Neural Network for Flood Forecasting". In: *Water* 11.7. DOI: 10/ggj67m.

LeCun, Y., Y. Bengio, and G. Hinton (2015). "Deep Learning". In: *Nature* 521, pp. 436–444. DOI: 10/bmqp.

Lehner, H. and L. Dorffner (2020). "Digital geoTwin Vienna: Towards a Digital Twin City as Geodata Hub". In: *Journal of Photogrammetry, Remote Sensing and Geoinformation Science* 88, pp. 63–75. DOI: 10/ggt5jt.

Lenjani, A., C.M. Yeum, S.J. Dyke, and I. Bilionis (2020). "Automated Building Image Extraction from 360o Panoramas for Postdisaster Evaluation". In: *Computer Aided Civil and Infrastructure Engineering* 35.3, pp. 241–257. DOI: 10/ghgv7g.

Li, Y., S. Martinis, and M. Wieland (2019b). "Urban Flood Mapping with an Active Self-Learning Convolutional Neural Network Based on TerraSAR-X Intensity and Interferometric Coherence". In: *ISPRS Journal of Photogrammetry and Remote Sensing* 152, pp. 178–191. DOI: 10/ghgv7c.

Li, Y., S. Ye, and I. Bartoli (2018a). "Semisupervised Classification of Hurricane Damage from Postevent Aerial Imagery Using Deep Learning". In: *Journal of Applied Remote* Sensing,12 (4, p. 045008.

Li, Z., M.-A. Meier, E. Hauksson, Z. Zhan, and J. Andrews (2018b). "Machine Learning Seismic Wave Discrimination: Application to Earthquake Early Warning". In: *Geophysical Research Letters* 45.10, pp. 4773–4779. DOI: 10/gdk3jd.

Lin, T.Y. et al. (2014). "Microsoft COCO: Common Objects in Context". In: *Computer Vision – ECCV 2014. ECCV 2014. Lecture Notes in Computer Science*. Ed. by Fleet D., Pajdla T., Schiele B., and Tuytelaars T. Vol. 8693. Cham: Springer. DOI: 10.1007/978-3-319-10602-1_48.

Lin, X.V., R. Socher, and C. Xiong (2018). "Multi-Hop Knowledge Graph Reasoning with Reward Shaping". In: *Conference on Empirical Methods in Natural Language Processing*. DOI: 10/ggvxk2. arXiv: 1808.10568v2.

Ling, J., R. Jones, and J. Templeton (2016a). "Machine Learning Strategies for Systems with Invariance Properties". In: *Journal of Computational Physics* 318, pp. 22–35. DOI: 10/f8p643.

Lu, X., D. Gu, Z. Xu, Y. Xiong, and Y. Tian (2020). "CIM-Powered Multi-Hazard Simulation Framework Covering Both Individual Buildings and Urban Areas". In: *Sustainability* 12.12, p. 5059. DOI: 10/ghgv7d.

Luo, H. and S.G. Paal (2018). "Machine Learning-Based Backbone Curve Model of Reinforced Concrete Columns Subjected to Cyclic Loading Reversal". In: *Journal of Computing in Civil Engineering* 32.5. DOI: 10/gdw843.

Maninis, K.-K., J. Pont-Tuset, P. Arbelaez, and L. Van Gool (2017). "Convolutional Oriented Boundaries: From Image Segmentation to High-Level Tasks". In: *IEEE Trans. Pattern Anal. Mach. Intell* 40.4, pp. 819–833. DOI: 10/gc8cfj.

Martinović, A., J. Knopp, H. Riemenschneider, and L. Van Gool (2015). "3D All the Way: Semantic Segmentation of Urban Scenes from Start to End in 3D". In: *IEEE Conference on Computer Vision and Pattern Recognition (CVPR*. Boston, MA, pp. 4456–4465. DOI: 10/ggvr3k.

McDermott, P. and C. Wikle (2019). "Bayesian Recurrent Neural Network Models for Forecasting and Quantifying Uncertainty in Spatial-Temporal Data". In: *Entropy* 21.2, p. 184. DOI: 10/ghgv7h.

McKenna, F. (2011). "OpenSees: A Framework for Earthquake Engineering Simulation". In: *Computing in Science & Engineering* 13.4, pp. 58–66. DOI: 10/cd3djt.

Mignan, A. (2019). *Forecasting Aftershocks: Back to Square One after a Deep Learning Anticlimax*. URL: http://doi.org/10.32858/temblor.053.

Mosavi, A., P. Ozturk, and K.W. Chau (2018). "Flood Prediction Using Machine Learning Models". In: *Water* 10.11, p. 1536. DOI: 10.3390/w10111536.

Mousavi, S.M. and G.C. Beroza (2020). "A Machine Learning Approach for Earthquake Magnitude Estimation". In: *Geophysical Research Letters* 47, p. 2019 085976. DOI: 10/ghgv7j.

Nakka, K.K. and M. Salzmann (2018). "Deep Attentional Structured Representation Learning for Visual Recognition". In: *British Machine Vision Conference (BMVC*.

National Science and Technology Council (2016b). *The National Artificial Intelligence Research and Development Strategic Plan*. NSTC. URL: https://www.nitrd.gov/PUBS/national_ai_rd_strategic_plan.pdf.

National Science and Technology Council (2019). *The National Artificial Intelligence Research and Development Strategic Plan, 2019 Update*. NSTC, p. 50. URL: https://www.whitehouse.gov/wp-content/uploads/2019/06/National-AI-Research-and-Development-Strategic-Plan-2019-Update-June-2019.pdf.

NIC (2017). *Data for the Public Good*. London, UK: National Infrastructure Commission. URL: https://nic.org.uk/app/uploads/Data-for-the-Public-Good-NIC-Report.pdf.

Noy, N.F. et al. (2009). "BioPortal: Ontologies and Integrated Data Resources at the Click of a Mouse". In: *Nucleic Acids Research* 37:W170-W173.

Olea, R.A. (2012). *Geostatistics for Engineers and Earth Scientists*. Springer.

Padgett, J., S. Yu, C. Dawson, D. Stanzione, and E. Rathje (2020). *Workshop on Artificial Intelligence in Natural Hazards Engineering*. Texas Advanced Computing Center, University of Texas at Austin, February.

Palmer, R.N. (1987). "Special Issue on Expert Systems". In: *Journal of Computing in Civil Engineering, American Society of Civil Engineers* 1.4.

Park, J. and K.H. Law (2016). "Bayesian Ascent: A Data-Driven Optimization Scheme for Real-Time Control with Application to Wind Farm Power Maximization". In: *IEEE Transactions on Control Systems Technology* 24.5, pp. 1655–1668. DOI: 10/f8znqk.

Park, Junyoung and Jinkyoo Park (2019). "Physics-Induced Graph Neural Network: An Application to Wind-Farm Power Estimation". In: *Energy* 187.115883. DOI: 10.1016/j.energy.2019.115883.

Paulheim, H. (2016). "Knowledge Graph Refinement: A Survey of Approaches and Evaluation Methods". In: *Semantic Web* 8, pp. 489–508. DOI: 10/gc9zzx.

Perrault, R. et al. (2019). *The AI Index 2019 Annual Report*. AI Index Steering Committee, Human-Centered AI Institute, Stanford University.

Pham, B.T., B. Pradhan, D.T. Bui, I. Prakash, and M.B. Dholakia (2016). "A Comparative Study of Different Machine Learning Methods for Landslide Susceptibility Assessment: A Case Study of Uttarakhand Area (India". In: *Environmental Modeling & Software* 84, pp. 240–250. DOI: 10/gfts5s.

Raissi, M., P. Perdikaris, and G.E. Karniadakis (2019). "Physics-Informed Neural Networks: A Deep Learning Framework for Solving Forward and Inverse Problems Involving Nonlinear Partial Differential Equations". In: *Journal of Computational Physics* 378, pp. 686–707. DOI: 10/gfzbvx.

Rasmussen, CE. and C.K.I. Williams (2006). *Gaussian Processes for Machine Learning*. MIT Press.

Rathje, E. et al. (2017). "DesignSafe: A New Cyberinfrastructure for Natural Hazards Engineering". In: *ASCE Natural Hazards Review*. DOI: 10/ghghnv.

Reinanda, R., E. Meij, and M. Rijke (2020). "Knowledge Graphs: An Information Retrieval Perspective". In: *Foundations and Trends® in Information Retrieval* 14.4, pp. 1–158. DOI: 10/ghc8jg.

Resch, B., F. Usländer, and C. Havas (2018). "Combining Machine-Learning Topic Models and Spatiotemporal Analysis of Social Media Data for Disaster Footprint and Damage Assessment". In: *Cartography and Geographic Information Science* 45.4, pp. 362–376.

Rudin, C. and J. Radin (2019). "Why Are We Using Black Box Models in AI When We Don't Need to? A Lesson from an Explainable AI Competition". In: *Harvard Data Science Review*. DOI: 10/ggkpn8.

Sacks, R., C. Eastman, G. Lee, and P. Teicholz (2018). *BIM Handbook: A Guide to Building Information Modeling for Owners*. 3rd. Designers, Engineers, Contractors, and Facility Managers, Wiley.

Salazar, J.E. (2015). "Predicting Wind Induced Damage to Residential Structures: A Machine Learning Approach". PhD thesis, Rice University.

Salehia, H. and R. Burguernoa (2018). "Emerging Artificial Intelligence Methods in Structural Engineering". In: *Engineering Structures* 171, pp. 170–189. DOI: 10/gd9dnw.

Samek, W., G. Montavon, A. Vedaldi, L.K. Hansen, and K.-R. Muller, eds. (2019). *Explainable AI: Interpreting*. Explaining and Visualizing Deep Learning, Springer.

Santin, G. and B. Haasdonk (2019). *Kernel Methods for Surrogate Modeling*. URL: https://arxiv.org/abs/1907.10556.

Schrotter, G. and C. Hürzeler (2020). "The Digital Twin of the City of Zurich for Urban Planning". In: *Journal of Photogrammetry, Remote Sensing and Geoinformation Science* 88, pp. 99–112. DOI: 10/ggvkr3.

Seo, Sungyong and Yan Liu (2019). *Differentiable Physics-Informed Graph Networks*. arXiv: 1902.02950v2. URL: https://arxiv.org/abs/1902.02950.

Simon, H.A. (1973). "The Structure of Ill-Structured Problems". In: *Artificial Intelligence* 4, pp. 181–201. DOI: 10/bt6p4t.

Sriram, D., M.L. Maher, and S.J. Fenves (1985). "Knowledge-Based Expert Systems in Structural Design". In: *Computers & Structures* 20.1-3, pp. 1–9. DOI: 10/dnztx7.

Sriram, R.D. (1997). *Intelligent Systems for Engineering: A Knowledge-Based Approach*. Springer Verlag.

Stevens, R., C.A. Goble, and S. Bechhofer (2000). "Ontology-Based Knowledge Representation for Bio-Informatics". In: *Briefings in Bioinformatics* 1.4, pp. 398–414. DOI: 10/bch8cz.

Straub, D. and A. Der Kiureghian (2010). "Bayesian Network Enhanced with Structural Reliability Methods: Methodology". In: *Journal of Engineering Mechanics, ASCE* 136.10, pp. 1248–1258.

Subramanian, D., J. Salazar, L. Duenas-Osorio, and R. Stein (2013). "Constructing and Validating Geographically Refined HAZUS-MH4 Hurricane Wind Risk Models: A Machine Learning Approach". In: *Advances in Hurricane Engineering: Learning from Our Past*, pp. 1056–1066.

Szegedy, C., S. Ioffe, V. Vanhoucke, and A.A. Alemi (2017). "Inception-v4, Inception-Resnet and the Impact of Residual Connections on Learning". In: *Proceedings of the 31st AAAI Conference on Artificial Intelligence*, pp. 4278–4284.

Szegedy, C., V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna (2016). "Rethinking the Inception Architecture for Computer Vision". In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2828–2826.

Thomas, J., K.W. Bowyer, and A. Kareem (2011). "Towards a Robust Automated Hurricane Damage Assessment from High Resolution Images". In: *13th International Conference on Wind Engineering*, pp. 10–15.

Van Melle, W., E.H. Shortliffe, and B.G. Buchanan (1984). "EMYCIN: A Knowledge Engineer's Tool for Constructing Rule-Based Expert Systems". In: *Rule-Based Expert Systems: The MYCIN Experiments of the Stanford Heuristic Programming Project*. Ed. by Buchanan and Shortliffe. Addison Wesley.

Wang, Chaofeng (Sept. 28, 2019). *SURF*. DOI: 10.5281/zenodo.3463676. Qian Yu, Chaofeng Wang, Barbaros Cetiner, Stella X. Yu, Frank Mckenna, Ertugrul Taciroglu, and Kincho H. Law. *Building Information Modeling and Classification by Visual Learning At A City Scale*. Oct. 14, 2019. DOI: 10/ghmgmv. arXiv: 1910.06391 [cs].

Wang, K., W.L. Ellsworth, G.C. Beroza, G. Williams, M. Zhang, D. Schroeder, and J. Rubinstein (2019b). "Seismology with Dark Data: Image-Based Processing of Analog Records Using Machine Learning for the Rangely Earthquake Control Experiment". In: *Seismological Research Letters* 90 (2A), pp. 553–562. DOI: 10/gg3x4w.

Wang, Y., Z. Fang, H. Hong, and L. Peng (2020b). "Flood Susceptibility Mapping Using Convolutional Neural Network Frameworks". In: *Journal of Hydrology* 582, p. 124482. DOI: 10/ghgv7k.

Whetzel, P.L., N.F. Noy, N.H. Shah, P.R. Alexander, C. Nyylas, T. Tudorache, and M.A. Musen (2011). "BioPortal: Enhanced Functionality via New Web Services from the National Center for Biomedical Ontology to Access and Use Ontologies in Software Applications". In: *Nucleic Acids Research* 39. *BioPortal*. URL: http://bioportal.bioontology.org/.

Wilkinson, M.D. et al. (2016). "The FAIR Guiding Principles for Scientific Data Management and Stewardship". In: *Scientific Data* 3.160018. DOI: 10/bdd4. pmid: 26978244.

Willard, J., X. Jia, S. Xu, M. Steinbach, and V. Kumar (2020). *Integrating Physics-Based Modeling with Machine Learning: A Survey*. arXiv: 2003.04919v4.

Winkler, D., M. Haltmeier, M. Kleidorfer, W. Rauch, and F. Tscheikner-Gratl (2018). "Pipe Failure Modeling for Water Distribution Networks Using Boosted Decision Trees". In: *Structure and Infrastructure Engineering* 14.10, pp. 1402–1411.

Wirtz, D., N. Karajan, and B. Haasdonk (2012). "Surrogate Modeling of Multiscale Models Using Kernel Methods". In: *International Journal on Numerical Methods in Engineering* 101.1, pp. 1–28.

Wong, V.W.H., M. Ferguson, Law K.H., and Y.-T.T. Lee (2019). "An Assistive Learning Workflow on Annotating Images for Object Detection". In: *IEEE International Conference on Big Data (IEEE BigData 2019*. Los Angeles, CA. DOI: 10/ghgv7m.

Wu, Z., S. Pan, F. Chen, G. Long, and P.S. Yu (2020). "A Comprehensive Survey on Graph Neural Networks". In: *IEEE Transactions on Neural Networks and Learning Systems*. DOI: 10.1109/tnnls.2020.2978386.

Xie, Y., M.E. Sichani, J.E. Padgett, and R. DesRoches (2020). "The Promise of Implementing Machine Learning in Earthquake Engineering: A State-of-the-Art Review". In: *Earthquake Spectra*. DOI: 10/ghgv66.

Xu, K., J. Ba, R. Kiros, K. Cho, A.Salakhutdinov Courville, Zemel R., R., and Y. Bengio (2015). "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention". In: *International Conference on Machine Learning (ICML*. Vol. 37, pp. 2048–2057.

Xu, Y.L., L. Hu, and A. Kareem (2014). "Conditional Simulation of Non-Stationary Fluctuating Wind Speeds for Long-Span Bridges". In: *Journal of Engineering Mechanics, ASCE* 140.1, pp. 61–73. DOI: 10/f5kxf2.

Yao, X., L.G. Tham, and F.C. Dai (2008). "Landslide Susceptibility Mapping Based on Support Vector Machine: A Case Study on Natural Slopes of Hong Kong, China". In: *Geomorphology* 101.4, pp. 572–582.

Yeum, C.M., J. Choi, and S.J. Dyke (2019). "Automated Region-of-Interest Localization and Classification for Visual Assessment of Civil Infrastructure". In: *Structural Health Monitoring* 18.3, pp. 675–689.

Yu, Q., C. Wang, B. Cetiner, S. Yu, F. McKenna, E. Taciroglu, and K.H. Law (2019). "Building Information Modeling and Classification by Visual Learning at a City Scale". In: *Workshop on Artificial Intelligence for Humanitarian Assistance and Disaster Response, Neural Information Processing Systems*. Vancouver, Canada.

Yu, Q., C. Wang, F. McKenna, S.X. Yu, E. Taciroglu, B. Cetiner, and K.H. Law (2020). "Large-Scale Rapid Visual Screening of Soft-Story Buildings from Street View Images Using Deep Learning Classification". In: *Earthquake Engineering and Engineering Vibration (to appear*.

Yu, S. and C. Baker (2016). *Image Captioning with Multiple Perspective and FrameNet for Earthquake Damage Assessment*. Berkeley, CA: International Computer Science Institute.

Yu, Z., C. Feng, M.-Y. Liu, and S. Ramalingam (2017). "Casenet: Deep Category-Aware Semantic Edge Detection". In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. DOI: 10/gg8nsv.

Zhang, D., L. Lu, L. Guo, and G. Emkarniadakis (2019a). "Quantifying Total Uncertainty in Physics-Informed Neural Networks for Solving Forward and Inverse Stochastic Problems". In: *Journal of Computational Physics* 397.108850.

Zhou, B., A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba (June 2016a). "Learning Deep Features for Discriminative Localization". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 2921–2929. DOI: 10/gf2j8c.

Digital Resources

Introduction

[1] *ADCIRC* (2020). URL: https://adcirc.org/ (visited on 10/24/2020). R.A. Luettich, J.J. Westerink, and N.W. Scheffner. *ADCIRC: An Advanced Three-Dimensional Circulation Model for Shelves, Coasts, and Estuaries*. Dredging research program technical report DRP-92-6. Vicksburg, MS: U.S Army Engineers Waterways Experiment Station, 1992.

[2] *EE-UQ* (2020). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/EE-UQ-Documentation (visited on 12/08/2020).

[3] *GEOCLAW* (n.d.). Version 5.7.x. URL: http://www.clawpack.org/geoclaw.

[4] *HydroUQ* (2020). NHERI-SimCenter. URL: https://github.com/NHERI-SimCenter/HydroUQ (visited on 12/08/2020).

[5] OpenFOAM (2018). *OpenFOAM*. URL: https://openfoam.org.

[6] *OpenSees* (2020). URL: https://opensees.berkeley.edu/.

[7] *quoFEM* (Nov. 2020). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/quoFEM-Documentation (visited on 12/08/2020).

[8] *R2DTool* (n.d.). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/R2D-Documentation/.

[9] *SURF* (2020). *SURF*. NHERI-SimCenter. DOI: 10.5281/zenodo.3463676. Chaofeng Wang. *SURF*. Sept. 28, 2019. DOI: 10.5281/zenodo.3463676. Qian Yu, Chaofeng Wang, Barbaros Cetiner, Stella X. Yu, Frank Mckenna, Ertugrul Taciroglu, and Kincho H. Law. *Building Information Modeling and Classification by Visual Learning At A City Scale*. Oct. 14, 2019. DOI: 10/ghmgmv. arXiv: 1910.06391 [cs].

[10] Wang, C., Q. Yu, F. McKenna, B. Cetiner, S.X. Yu, E. Taciroglu, and K.H. Law (2020a). *BRAILS*. NHERI-SimCenter. URL: https://nheri-simcenter.github.io/BRAILS-Documentation/.

[11] *WE-UQ* (Sept. 8, 2020). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/WE-UQ-Documentation/ (visited on 12/08/2020).

[12] Zsarnoczay, A. and P. Kourehpaz (2020). *PELICUN*. Version 2.1.1. NHERI-SimCenter. URL: https://nheri-simcenter.github.io/pelicun/ (visited on 11/26/2020).

[13] Zsarnóczay, A., F. McKenna, C Wang, W. Elhaddad, and M. Gardner (2020). *PBE*. NHERI-SimCenter. URL: https://simcenter.designsafe-ci.org/research-tools/pbe-application/ (visited on 11/26/2020).

Hazards: Earthquake - Ground Shaking

[14] *AWP-ODC* (n.d.). URL: http://hpgeoc.github.io/awp-odc-os/. Y. Cui et al. "Scalable Earthquake Simulation on Petascale Supercomputers". In: *Proceedings of the 2010 ACM/IEEE International Conference for High Performance Computing, Networking, Storage and Analysis*. New Orleans, LA, 2010. DOI: 10/bbvk5x.

[15] *CyberShake* (n.d.). URL: https://scec.usc.edu/scecpedia/CyberShake. Robert Graves et al. "CyberShake: A Physics-Based Seismic Hazard Model for Southern California". In: *Pure and Applied Geophysics* 168.3, pp. 367–381. ISSN: 1420-9136. DOI: 10/bxxbmm.

[2] *EE-UQ* (2020). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/EE-UQ-Documentation (visited on 12/08/2020).

[16] *EvW* (n.d.). NHERI-SimCenter. URL: https://simcenter.designsafe-ci.org/learning-tools/evw-application/.

[17] FEMA (2018c). *Hazus 4.2*. Version 4.2. Washington D.C: FEMA Mitigation Division.

[18] *HAZ* (2017). URL: https://github.com/abrahamson/HAZ (visited on 11/25/2020).

[19] *MDOF* (n.d.). NHERI-SimCenter. URL: https://simcenter.designsafe-ci.org/learning-tools/multiple-degrees-of-freedom/.

[20] *NSHMP-Haz* (n.d.). URL: https://github.com/usgs/nshmp-haz/wiki.

[21] *OpenQuake* (n.d.). URL: https://www.globalquakemodel.org/openquake. M. Pagani et al. "OpenQuake Engine: An Open Hazard (and Risk) Software for the Global Earthquake Model". In: *Seismological Research Letters* 85.3, pp. 692–702. DOI: 10/ghghnx.

[6] *OpenSees* (2020). URL: https://opensees.berkeley.edu/.

[22] *OpenSHA* (n.d.). URL: https://opensha.org/. E.H. Field, T.H. Jordan, and C.A. Cornell. "OpenSHA: A Developing Community-Modeling Environment for Seismic Hazard Analysis". In: *Seismological Research Letters* 74.4, pp. 406–419. DOI: 10/ccn2qb.

[23] Petersson, N. Anders and Bjorn Sjogreen (n.d.). *SW4*. Version 2.01. Zenodo. DOI: 10.5281/zenodo.1063644. *SW4*. *Geodynamics/SW4*. Nov. 20, 2017. DOI: 10.5281/zenodo.1063644.

[24] *PGT* (n.d.). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/PileGroupTool/.

[25] *R-CRISIS* (n.d.). URL: http://www.r-crisis.com/. M. Ordaz, F. Martinelli, A. Aguilar, C. Meletti, and V. D'Amico. *R-CRISIS. Program and Platform for Computing Seismic Hazard.*

[8] *R2DTool* (n.d.). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/R2D-Documentation/.

[26] *S3HARK* (n.d.). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/s3hark-Documentation/.

[27] *Smelt* (n.d.). NHERI-SimCenter. URL: https://github.com/NHERI-SimCenter/smelt.

[28] *TFT* (n.d.). NHERI SimCenter. URL: https://nheri-simcenter.github.io/TFT-Documentation/.

[29] *The Broadband Platform* (May 30, 2019). Version 19.4. URL: https://strike.scec.org/scecpedia/Broadband_Platform. P.J. Maechling, F. Silva, S. Callaghan, and T.H. Jordan. "SCEC Broadband Platform: System Architecture and Software Implementation". In: *Seismological Research Letters* 86.1. DOI: 10/ghgjmf.

[13] Zsarnóczay, A., F. McKenna, C Wang, W. Elhaddad, and M. Gardner (2020). *PBE*. NHERI-SimCenter. URL: https://simcenter.designsafe-ci.org/research-tools/pbe-application/ (visited on 11/26/2020).

Hazards: Earthquake - Surface Fault Rupture

[30] *ABAQUS* (n.d.). URL: www.simulia.com.

[31] *FLAC* (n.d.). URL: https://www.itascacg.com/software/FLAC.

[32] *LAMMPS* (Dec. 2020). Sandia. URL: https://github.com/lammps (visited on 12/07/2020).

[33] *LIGGGHTS-PUBLIC* (2012). DCS Computing GmbH. URL: https://www.cfdem.com/ (visited on 11/26/2020).

[34] *LMGC90* (n.d.). URL: http://mimetics-engineering.fr/index.php/en/lmgc90-2/.

[35] *LS-DYNA* (n.d.). URL: http://www.lstc.com/.

[6] *OpenSees* (2020). URL: https://opensees.berkeley.edu/.

[36] *PFC* (n.d.). URL: https://www.itascainternational.com/software/pfc.

[37] *PLAXIS* (n.d.). URL: https://www.bentley.com/en/products/brands/plaxis.

[7] *quoFEM* (Nov. 2020). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/quoFEM-Documentation (visited on 12/08/2020).

[38] *YADE* (n.d.). URL: https://yade-dem.org/doc/. V. Šmilauer, E. Catalano, B. Chareyre, S. Dorofeenko, J. Duriez, A. Gladky, and J. Kozicki. *Yade Documentation - 2nd Edition*. The Yade Project, 2015.

Hazards: Earthquake - Soil Liquefaction

[39] *Cliq* (n.d.). URL: https://geologismiki.gr/products/cliq/.

[31] *FLAC* (n.d.). URL: https://www.itascacg.com/software/FLAC.

[40] *LiqIT* (n.d.).

[41] *Liquefy-Pro* (n.d.). URL: https://civiltech.com/liquefypro/.

[42] *NovoLIQ* (n.d.). URL: https://novotechsoftware.com/geotechnical-software/soil-liquefaction-software/.

[6] *OpenSees* (2020). URL: https://opensees.berkeley.edu/.

[37] *PLAXIS* (n.d.). URL: https://www.bentley.com/en/products/brands/plaxis.

Hazards: Earthquake - Slope Stability and Landslides

[30] *ABAQUS* (n.d.). URL: www.simulia.com.

[31] *FLAC* (n.d.). URL: https://www.itascacg.com/software/FLAC.

[35] *LS-DYNA* (n.d.). URL: http://www.lstc.com/.

[6] *OpenSees* (2020). URL: https://opensees.berkeley.edu/.

[37] *PLAXIS* (n.d.). URL: https://www.bentley.com/en/products/brands/plaxis.

[7] *quoFEM* (Nov. 2020). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/quoFEM-Documentation (visited on 12/08/2020).

[43] *SLAMMER* (n.d.). URL: https://www.usgs.gov/software/slammer-seismic-landslide-movement-modeled-using-earthquake-records. Randall W Jibson, Ellen M Rathje, Matthew W Jibson, and Yong W Lee. *SLAMMER: Seismic Landslide Movement Modeled Using Earthquake Records*. US Geological Survey, 2013.

Hazards: Tropical Cyclone - Wind

[16] *EvW* (n.d.). NHERI-SimCenter. URL: https://simcenter.designsafe-ci.org/learning-tools/evw-application/.

[19] *MDOF* (n.d.). NHERI-SimCenter. URL: https://simcenter.designsafe-ci.org/learning-tools/multiple-degrees-of-freedom/.

[27] *Smelt* (n.d.). NHERI-SimCenter. URL: https://github.com/NHERI-SimCenter/smelt.

Hazards: Tropical Cyclone - Storm Surge

[1] *ADCIRC* (2020). URL: https://adcirc.org/ (visited on 10/24/2020). R.A. Luettich, J.J. Westerink, and N.W. Scheffner. *ADCIRC: An Advanced Three-Dimensional Circulation Model for Shelves, Coasts, and Estuaries*. Dredging research program technical report DRP-92-6. Vicksburg, MS: U.S Army Engineers Waterways Experiment Station, 1992.

[44] *CFD Notebooks* (n.d.). NHERI SimCenter. URL: https://github.com/NHERI-SimCenter/CFD-Notebooks.

[45] *Clawpack* (2020). URL: https://www.clawpack.org/. Randall LeVeque and Kyle Mandli. *Clawpack Source Code*. 2020. URL: https://osf.io/kmw6h/ (visited on 01/28/2021).

[46] Deltares Systems (2011). *Delft3D*. URL: https://oss.deltares.nl/web/delft3d (visited on 10/24/2020).

[47] *FVCOM* (n.d.). URL: http://fvcom.smast.umassd.edu/fvcom/. C.S. Chen, H.D. Liu, and R.C. Beardsley. "An Unstructured Grid, Finite-Volume, Three-Dimensional, Primitive Equations Ocean Model: Application to Coastal Ocean and Estuaries". In: *Journal of Atmospheric and Oceanic Technology* 20.1, pp. 159–186. DOI: 10/fw62c8.

[3] *GEOCLAW* (n.d.). Version 5.7.x. URL: http://www.clawpack.org/geoclaw.

[4] *HydroUQ* (2020). NHERI-SimCenter. URL: https://github.com/NHERI-SimCenter/HydroUQ (visited on 12/08/2020).

[5] OpenFOAM (2018). *OpenFOAM*. URL: https://openfoam.org.

[48] *SLOSH* (n.d.). *SLOSH: Sea, Lake, and Overland Surges from Hurricanes*. URL: https://www.nhc.noaa.gov/surge/slosh.php. Chester P. Jelesnianski, Jye Chen, and Wilson A. Shaffer. *SLOSH: Sea, Lake and Overland Surges from Hurricanes*. NWS 48. NOAA, Apr. 1992, Silver Spring, MD. URL: https://www.hsdl.org/?view&did=779560.

Hazards: Tsunami - Inundation

[1] *ADCIRC* (2020). URL: https://adcirc.org/ (visited on 10/24/2020). R.A. Luettich, J.J. Westerink, and N.W. Scheffner. *ADCIRC: An Advanced Three-Dimensional Circulation Model for Shelves, Coasts, and Estuaries*. Dredging research program technical report DRP-92-6. Vicksburg, MS: U.S Army Engineers Waterways Experiment Station, 1992.

[44] *CFD Notebooks* (n.d.). NHERI SimCenter. URL: https://github.com/NHERI-SimCenter/CFD-Notebooks.

[3] *GEOCLAW* (n.d.). Version 5.7.x. URL: http://www.clawpack.org/geoclaw.

[4] *HydroUQ* (2020). NHERI-SimCenter. URL: https://github.com/NHERI-SimCenter/HydroUQ (visited on 12/08/2020).

[5] OpenFOAM (2018). *OpenFOAM*. URL: https://openfoam.org.

[49] *Tsunami-HySEA* (n.d.). EDANYA group. URL: https://edanya.uma.es/hysea/index.php/models/tsunami-hysea.

Response: Structural Systems

[50] *BFM* (n.d.). NHERI-SimCenter. URL: https://simcenter.designsafe-ci.org/learning-tools/braced-frame-modeling/.

[2] *EE-UQ* (2020). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/EE-UQ-Documentation (visited on 12/08/2020).

[16] *EvW* (n.d.). NHERI-SimCenter. URL: https://simcenter.designsafe-ci.org/learning-tools/evw-application/.

[51] *FEAP* (n.d.). URL: http://feap.berkeley.edu/.

[52] *FEAPpv* (n.d.). URL: http://projects.ce.berkeley.edu/feap/feappv/.

[35] *LS-DYNA* (n.d.). URL: http://www.lstc.com/.

[19] *MDOF* (n.d.). NHERI-SimCenter. URL: https://simcenter.designsafe-ci.org/learning-tools/multiple-degrees-of-freedom/.

[5] OpenFOAM (2018). *OpenFOAM*. URL: https://openfoam.org.

[6] *OpenSees* (2020). URL: https://opensees.berkeley.edu/.

[7] *quoFEM* (Nov. 2020). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/quoFEM-Documentation (visited on 12/08/2020).

[8] *R2DTool* (n.d.). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/R2D-Documentation/.

[27] *Smelt* (n.d.). NHERI-SimCenter. URL: https://github.com/NHERI-SimCenter/smelt.

[53] Wang, C. and F. McKenna (2020). *SWIM*. NHERI-SimCenter. URL: https://github.com/NHERI-SimCenter/SWIM.

[11] *WE-UQ* (Sept. 8, 2020). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/WE-UQ-Documentation/ (visited on 12/08/2020).

Response: Geotechnical Systems

[30] *ABAQUS* (n.d.). URL: www.simulia.com.

[54] *Anura3D* (n.d.). URL: http://www.mpm-dredge.eu/.

[55] *CB-Geo-MPM* (Oct. 2020). URL: https://www.cb-geo.com/research/mpm/.

[56] *Claymore* (n.d.). Philadelphia, PA. URL: https://github.com/penn-graphics-research/claymore. Xinlei Wang et al. "A Massively Parallel and Scalable Multi-GPU Material Point Method". In: *ACM Transactions on Graphics* 39.4, 30:30:1–30:30:15. ISSN: 0730-0301. DOI: 10/gg9638.

[57] *DeepSoil* (n.d.). URL: http://deepsoil.cee.illinois.edu/. Y.M.A Hashash, M.I. Musgrove, J.A. Harmon, O. Ilhan, G. Xing, D.R. Groholski, C.A. Phillips, and D. Park. *DEEPSOIL 7.0, User Manual*. Urbana, IL: University of Illinois at Urbana-Champaign, 2020.

[2] *EE-UQ* (2020). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/EE-UQ-Documentation (visited on 12/08/2020).

[51] *FEAP* (n.d.). URL: http://feap.berkeley.edu/.

[31] *FLAC* (n.d.). URL: https://www.itascacg.com/software/FLAC.

[33] *LIGGGHTS-PUBLIC* (2012). DCS Computing GmbH. URL: https://www.cfdem.com/ (visited on 11/26/2020).

[35] *LS-DYNA* (n.d.). URL: http://www.lstc.com/.

[6] *OpenSees* (2020). URL: https://opensees.berkeley.edu/.

[36] *PFC* (n.d.). URL: https://www.itascainternational.com/software/pfc.

[24] *PGT* (n.d.). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/PileGroupTool/.

[37] *PLAXIS* (n.d.). URL: https://www.bentley.com/en/products/brands/plaxis.

[58] *ProShake* (n.d.). URL: http://www.proshake.com/.

[7] *quoFEM* (Nov. 2020). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/quoFEM-Documentation (visited on 12/08/2020).

[59] *Real-ESSI* (n.d.). URL: http://real-essi.us/.

[26] *S3HARK* (n.d.). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/s3hark-Documentation/.

[60] *Strata* (n.d.). URL: https://github.com/arkottke/strata. Albert R. Kottke and Ellen M. Rathje. *Technical Manual for Strata*. 2008/10. Berkeley, CA: Pacific Earthquake Engineering Research Center, University of California, Berkeley, 2008.

[28] *TFT* (n.d.). NHERI SimCenter. URL: https://nheri-simcenter.github.io/TFT-Documentation/.

[61] *Uintah* (2020). URL: http://uintah.utah.edu/.

[13] Zsarnóczay, A., F. McKenna, C Wang, W. Elhaddad, and M. Gardner (2020). *PBE*. NHERI-SimCenter. URL: https://simcenter.designsafe-ci.org/research-tools/pbe-application/ (visited on 11/26/2020).

Response: Computational Fluid Dynamics - Wind

[62] ANSYS (2018). *ANSYS Fluent*. URL: https://www.ansys.com/products/fluids/ansys-fluent.

[44] *CFD Notebooks* (n.d.). NHERI SimCenter. URL: https://github.com/NHERI-SimCenter/CFD-Notebooks.

[63] Mackenzie-Helnwein, P., J. Wan, and F. McKenna (2020). *Turbulent Inflow Tool*. Version 1.1.0. NHERI-SimCenter. URL: https://nheri-simcenter.github.io/TinF-Documentation/.

[5] OpenFOAM (2018). *OpenFOAM*. URL: https://openfoam.org.

[11] *WE-UQ* (Sept. 8, 2020). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/WE-UQ-Documentation/ (visited on 12/08/2020).

Response: Computational Fluid Dynamics - Water

[1] *ADCIRC* (2020). URL: https://adcirc.org/ (visited on 10/24/2020). R.A. Luettich, J.J. Westerink, and N.W. Scheffner. *ADCIRC: An Advanced Three-Dimensional Circulation Model for Shelves, Coasts, and Estuaries*. Dredging research program technical report DRP-92-6. Vicksburg, MS: U.S Army Engineers Waterways Experiment Station, 1992.

[62] ANSYS (2018). *ANSYS Fluent*. URL: https://www.ansys.com/products/fluids/ansys-fluent.

[44] *CFD Notebooks* (n.d.). NHERI SimCenter. URL: https://github.com/NHERI-SimCenter/CFD-Notebooks.

[64] *COMSOL* (2018). URL: https://www.comsol.com.

[3] *GEOCLAW* (n.d.). Version 5.7.x. URL: http://www.clawpack.org/geoclaw.

[65] H.E.L.Y.X. (2018). *H.E.L.Y.X.* URL: https://engys.com/products/helyx.

[4] *HydroUQ* (2020). NHERI-SimCenter. URL: https://github.com/NHERI-SimCenter/HydroUQ (visited on 12/08/2020).

[66] IHFOAM (2018). *IHFOAM*. URL: https://ihfoam.ihcantabria.com/.

[67] olaFlow (2018). *olaFlow: CFD for Waves Software*. URL: olaflow.github.io. Pablo Higuera. “Application of Computational Fluid Dynamics to Wave Action on Structures”. University of Cantabria, 2015.

[5] OpenFOAM (2018). *OpenFOAM*. URL: https://openfoam.org.

[68] S.T.A.R.-C.C.M.+ (2018). *S.T.A.R.-C.C.M.+*. URL: https://mdx.plm.automation.siemens.com/star-ccm-plus.

[69] *SU2* (2020). URL: https://su2code.github.io/.

Performance: Buildings

[70] *CAPRA* (n.d.). URL: https://ecapra.org/. Mabel C. Marulanda, Martha L. Carreño, Omar D. Cardona, Mario G. Ordaz, and Alex H. Barbat. “Probabilistic Earthquake Risk Assessment Using CAPRA: Application to the City of Barcelona, Spain”. In: *Natural Hazards* 69.1, pp. 59–84. ISSN: 1573-0840. DOI: 10/f5dn54.

[17] FEMA (2018c). *Hazus 4.2*. Version 4.2. Washington D.C: FEMA Mitigation Division.

[71] *MAEViz* (n.d.). URL: http://mae.cee.illinois.edu/software/software_maeviz.html.

[21] *OpenQuake* (n.d.). URL: https://www.globalquakemodel.org/openquake. M. Pagani et al. "OpenQuake Engine: An Open Hazard (and Risk) Software for the Global Earthquake Model". In: *Seismological Research Letters* 85.3, pp. 692–702. DOI: 10/ghghnx.

[72] *OpenSLAT* (Mar. 13, 2019). URL: https://github.com/openslat/SLAT (visited on 11/26/2020).

[73] *PACT* (n.d.). URL: https://femap58.atcouncil.org/pact. Applied Technology Council. *Implementation Guide*. Second. Vol. 2. Seismic Performance Assessment of Buildings P-58-2. Federal Emergency Management Agency, Dec. 2018. URL: https://www.fema.gov/media-library-data/1557508320921-d67f745e88e04e54a1f40f8e94835042/FEMA_P-58-1-SE_Volume1_Methodology.pdf.

[8] *R2DTool* (n.d.). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/R2D-Documentation/.

[74] *SP3* (n.d.). Haselton Baker Risk Group. URL: https://www.hbrisk.com/.

[12] Zsarnoczay, A. and P. Kourehpaz (2020). *PELICUN*. Version 2.1.1. NHERI-SimCenter. URL: https://nheri-simcenter.github.io/pelicun/ (visited on 11/26/2020).

[13] Zsarnóczay, A., F. McKenna, C Wang, W. Elhaddad, and M. Gardner (2020). *PBE*. NHERI-SimCenter. URL: https://simcenter.designsafe-ci.org/research-tools/pbe-application/ (visited on 11/26/2020).

Performance: Transportation Networks

[17] FEMA (2018c). *Hazus 4.2*. Version 4.2. Washington D.C: FEMA Mitigation Division.

[21] *OpenQuake* (n.d.). URL: https://www.globalquakemodel.org/openquake. M. Pagani et al. "OpenQuake Engine: An Open Hazard (and Risk) Software for the Global Earthquake Model". In: *Seismological Research Letters* 85.3, pp. 692–702. DOI: 10/ghghnx.

[12] Zsarnoczay, A. and P. Kourehpaz (2020). *PELICUN*. Version 2.1.1. NHERI-SimCenter. URL: https://nheri-simcenter.github.io/pelicun/ (visited on 11/26/2020).

Performance: Water, Sewer, and Gas Pipelines

[75] *EPANET* (n.d.). URL: https://www.epa.gov/water-research/epanet. L.A. Rossman. *EPANET 2 Users Manual, U.S.* Cincinnati, OH: Environmental Protection Agency, 2000.

[76] *GIRAFFE* (n.d.). Y. Wang and T.D. O'Rourke. *Seismic Performance Evaluation of Water Supply Systems*. MCEER technical report 08-0015. Buffalo, NY: MCEER, 2008.

[77] *WNTR* (n.d.). URL: https://wntr.readthedocs.io/en/stable/. K.A. Klise, D. Moriarty, M.L. Bynum, R. Murray, J. Burkhardt, and T.M. Haxton. “Water Network Tool for Resilience (WNTR) User Manual, U.S”. In: *Environmental Protection Agency*, pp. 600–17 264.

[12] Zsarnoczay, A. and P. Kourehpaz (2020). *PELICUN*. Version 2.1.1. NHERI-SimCenter. URL: https://nheri-simcenter.github.io/pelicun/ (visited on 11/26/2020).

Performance: Electrical Transmission Substations and Lines

[17] FEMA (2018c). *Hazus 4.2*. Version 4.2. Washington D.C: FEMA Mitigation Division.

[78] *MatPower* (n.d.). URL: https://matpower.org/. R. D. Zimmerman, C. E. Murillo-Sánchez, and R. J. Thomas. “MATPOWER: Steady-State Operations, Planning, and Analysis Tools for Power Systems Research and Education”. In: *IEEE Transactions on Power Systems* 26.1, pp. 12–19. ISSN: 1558-0679. DOI: 10/b94mfs.

[79] *OpenDSS* (n.d.). URL: https://sourceforge.net/p/electricdss/wiki/Home/.

Recovery: Communities

[80] *DESaster* (2018). URL: https://github.com/milessb/DESaster. Scott Miles. *DESaster, A Discrete Event Disaster Recovery Simulation, Currently Focused on Housing, Built on Top of the Simpy Discrete Event Simulation Python Library.* 2020. URL: https://github.com/milessb/DESaster.

[81] *IN-CORE* (n.d.). URL: http://resilience.colostate.edu/in_core.shtml.

Recovery: Housing

[80] *DESaster* (2018). URL: https://github.com/milessb/DESaster. Scott Miles. *DESaster, A Discrete Event Disaster Recovery Simulation, Currently Focused on Housing, Built on Top of the Simpy Discrete Event Simulation Python Library.* 2020. URL: https://github.com/milessb/DESaster.

Cross-Cutting: Uncertainty Quantification

[82] *COSSAN-X* (n.d.). URL: http://www.cossan.co.uk/software/cossan-x.php. Edoardo Patelli, Matteo Broggi, Silva Tolo, and Jonathan Sadeghi. “Cossan Software: A Multidisciplinary and Collaborative Software for Uncertainty Quantification”. In: *Proceedings of the 2nd ECCOMAS Thematic Conference on Uncertainty Quantification in Computational Sciences and Engineering, UNCECOMP*. 2017. DOI: 10/ch3f.

OpenCOSSAN. URL: http://www.cossan.co.uk/software/open-cossan-engine.php.

[83] *Dakota* (n.d.). Sandia. URL: https://dakota.sandia.gov/. Brian M Adams, WJ Bohnhoff, KR Dalbey, JP Eddy, MS Eldred, DM Gay, K Haskell, Patricia D Hough, and Laura P Swiler. *DAKOTA, a Multilevel Parallel Object-Oriented Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis: Version 5.0 User's Manual*. Tech. Rep. SAND2010-2183. Sandia National Laboratories, 2009.

[84] Labbe, Roger (Nov. 24, 2020). *FilterPy*. URL: https://github.com/rlabbe/filterpy (visited on 11/25/2020).

[85] *MIT Uncertainty Quantification Library* (n.d.). URL: http://muq.mit.edu/.

[86] *OpenCOSSAN* (n.d.). URL: http://www.cossan.co.uk/software/open-cossan-engine.php. Edoardo Patelli, Matteo Broggi, Silva Tolo, and Jonathan Sadeghi. "Cossan Software: A Multidisciplinary and Collaborative Software for Uncertainty Quantification". In: *Proceedings of the 2nd ECCOMAS Thematic Conference on Uncertainty Quantification in Computational Sciences and Engineering, UNCECOMP*. 2017. DOI: 10/ch3f.

[7] *quoFEM* (Nov. 2020). NHERI-SimCenter. URL: https://nheri-simcenter.github.io/quoFEM-Documentation (visited on 12/08/2020).

[87] *SMT* (Jan. 30, 2021). *Surrogate Modeling Toolbox*. smt. URL: https://github.com/SMTorg/smt (visited on 01/31/2021). Mohamed Amine Bouhlel, John T. Hwang, Nathalie Bartoli, Rémi Lafage, Joseph Morlier, and Joaquim R. R. A. Martins. "A Python Surrogate Modeling Framework with Derivatives". In: *Advances in Engineering Software* 135, p. 102662. ISSN: 0965-9978. DOI: 10/gghbp7.

[88] *UQ-Pyl* (2015). Beijing, China. URL: http://www.uq-pyl.com/. Chen Wang, Qingyun Duan, Charles H. Tong, Zhenhua Di, and Wei Gong. "A GUI Platform for Uncertainty Quantification of Complex Dynamical Models". In: *Environmental Modelling & Software* 76, pp. 1–12. ISSN: 1364-8152. DOI: 10/ghk8tg.

[89] *UQLab* (n.d.). URL: https://www.uqlab.com/. Stefano Marelli and Bruno Sudret. "UQLab: A Framework for Uncertainty Quantification in Matlab". In: *Vulnerability, Uncertainty, and Risk: Quantification, Mitigation, and Management*. 2014, pp. 2554–2563.

[90] *UQpy* (Jan. 28, 2021). SURG. URL: https://github.com/SURGroup/UQpy (visited on 01/31/2021). Audrey Olivier, Dimitrios Giovanis, BS Aakash, Mohit Chauhan, Lohit Vandanapu, and Michael D Shields. "UQpy: A General Purpose Python Package and Development Environment for Uncertainty Quantification". In: *Journal of Computational Science* 47, p. 101204. DOI: 10/ghg5rh.

Cross-Cutting: Artificial Intelligence and Machine Learning

[91] *CAFFE* (2013). Berkeley Vision and Learning Center. URL: https://caffe.berkeleyvision.org/ (visited on 11/25/2020). Yangqing Jia, Evan Shelhamer,

Jeff Donahue, Sergey Karayev, Jonathan Long, Ross Girshick, Sergio Guadarrama, and Trevor Darrell. “Caffe: Convolutional Architecture for Fast Feature Embedding”. In: *MM á14É Proceedings of the 22nd ACM International Conference on Multimedia*. June 20, 2014. URL: https://doi-org.stanford.idm.oclc.org/10.1145/2647868.2654889 (visited on 11/25/2020).

[92] *CNTK* (2015). Microsoft. URL: https://docs.microsoft.com/en-us/cognitive-toolkit/ (visited on 11/25/2020).

[93] *Keras* (2015). Keras. URL: https://keras.io/ (visited on 11/26/2020).

[94] *PyTorch* (n.d.). URL: https://pytorch.org/.

[95] *Scikit-Learn* (n.d.). URL: https://scikit-learn.org.

[96] *TensorFlow* (2020). tensorflow. URL: https://www.tensorflow.org/ (visited on 11/25/2020). Martín Abadi et al. *TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems*. Mar. 14, 2016. URL: https://arxiv.org/abs/1603.04467v2 (visited on 11/25/2020).

[97] *Theano* (2011). Theano. URL: https://github.com/Theano/Theano (visited on 11/26/2020).

[98] Wang, C., C. Jiang, S.Y. Yu, F. McKenna, and K.H. Law (2019a). *NHERI-SimCenter/BIM2SAM.AI*. URL: https://doi.org/10.5281/zenodo.3509957..

[53] Wang, C. and F. McKenna (2020). *SWIM*. NHERI-SimCenter. URL: https://github.com/NHERI-SimCenter/SWIM.