



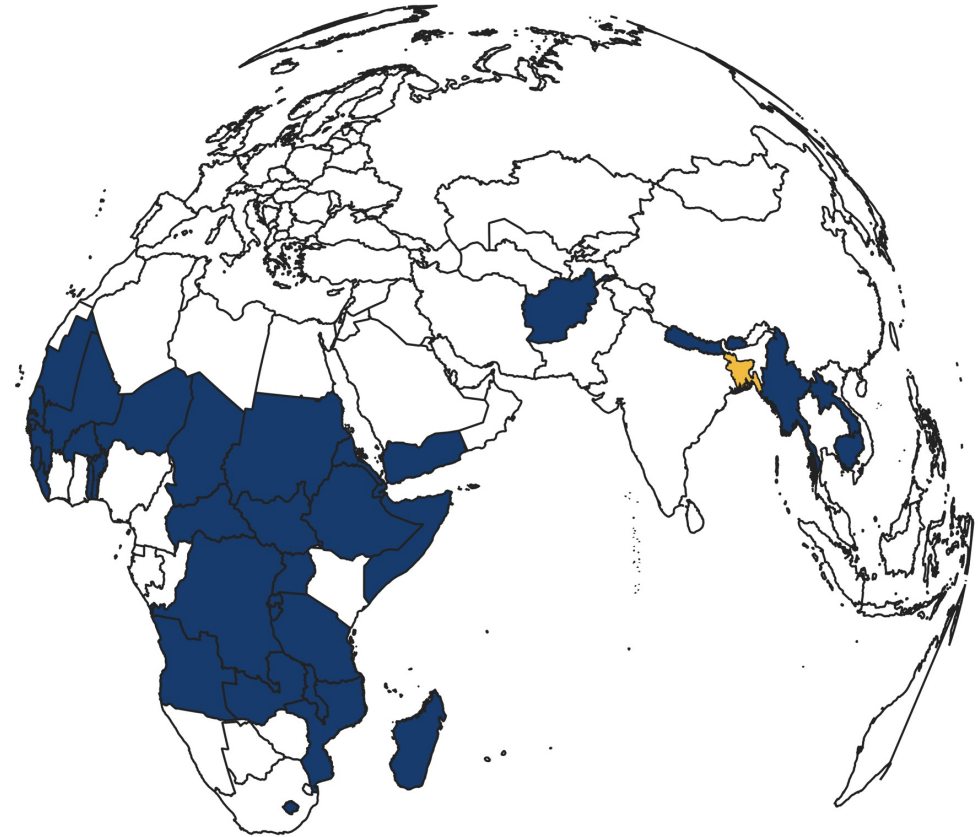
Global Mapping of Exposure and Physical Vulnerability Dynamics in Least Developed Countries using Remote Sensing & Machine Learning

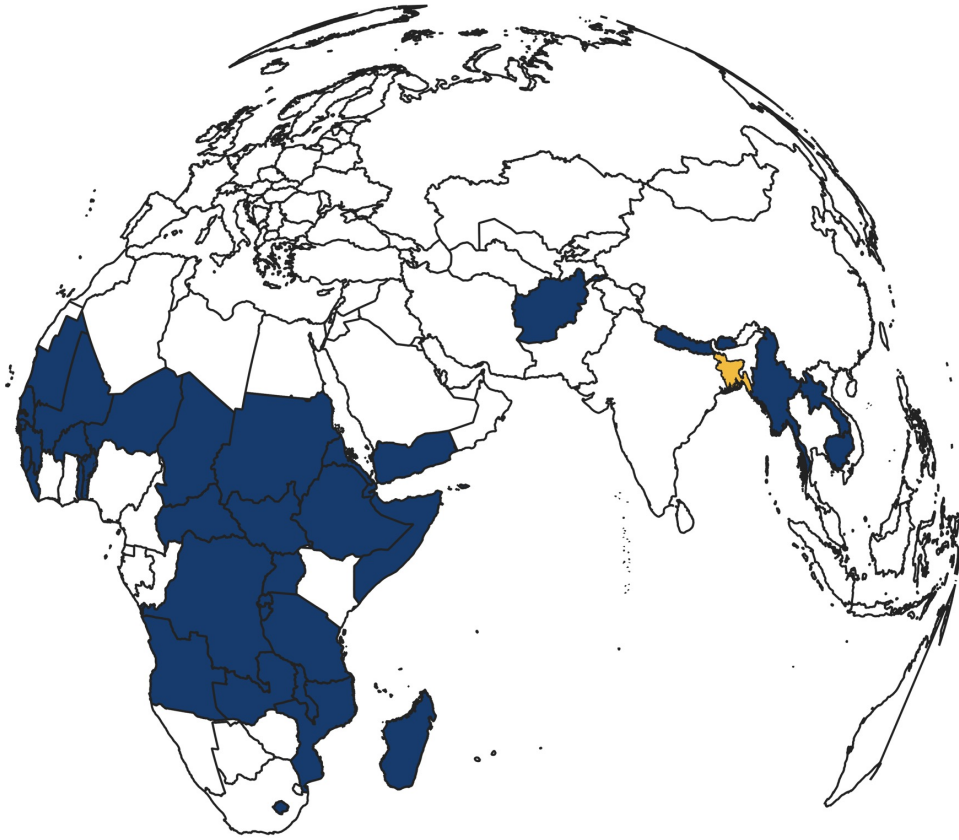
Joshua Dimasaka^{1,2,3}, Christian Geiß^{4,5}, Emily So^{1,3}

¹University of Cambridge ²UKRI CDT AI for Environmental Risks

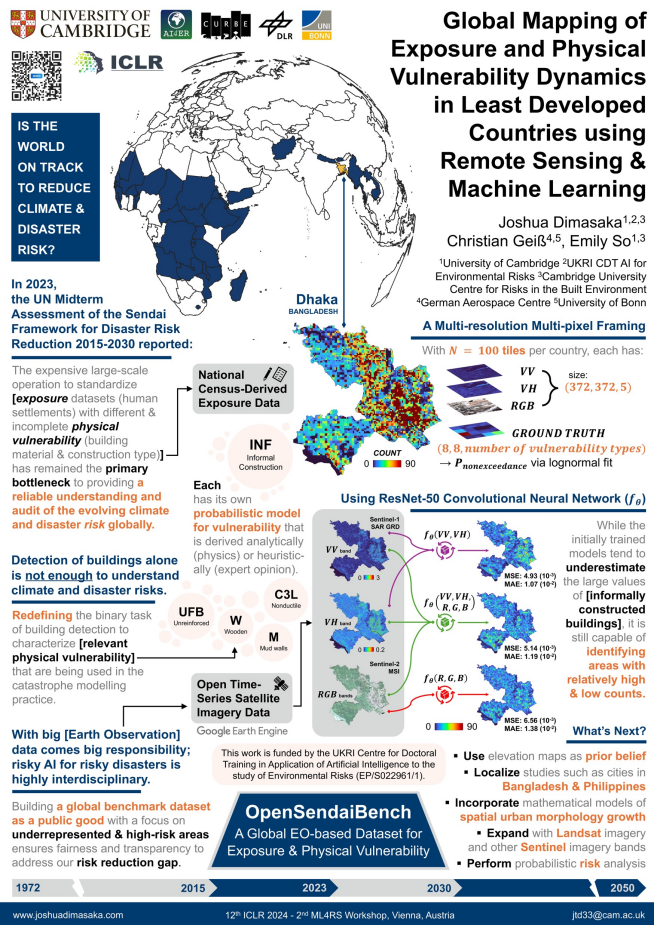
³Cambridge University Centre for Risks in the Built Environment

⁴German Aerospace Centre ⁵University of Bonn





**IS THE
WORLD
ON TRACK
TO REDUCE
CLIMATE &
DISASTER
RISK?**



In 2023, the UN Midterm Assessment of the Sendai Framework for Disaster Risk Reduction 2015-2030 reported:

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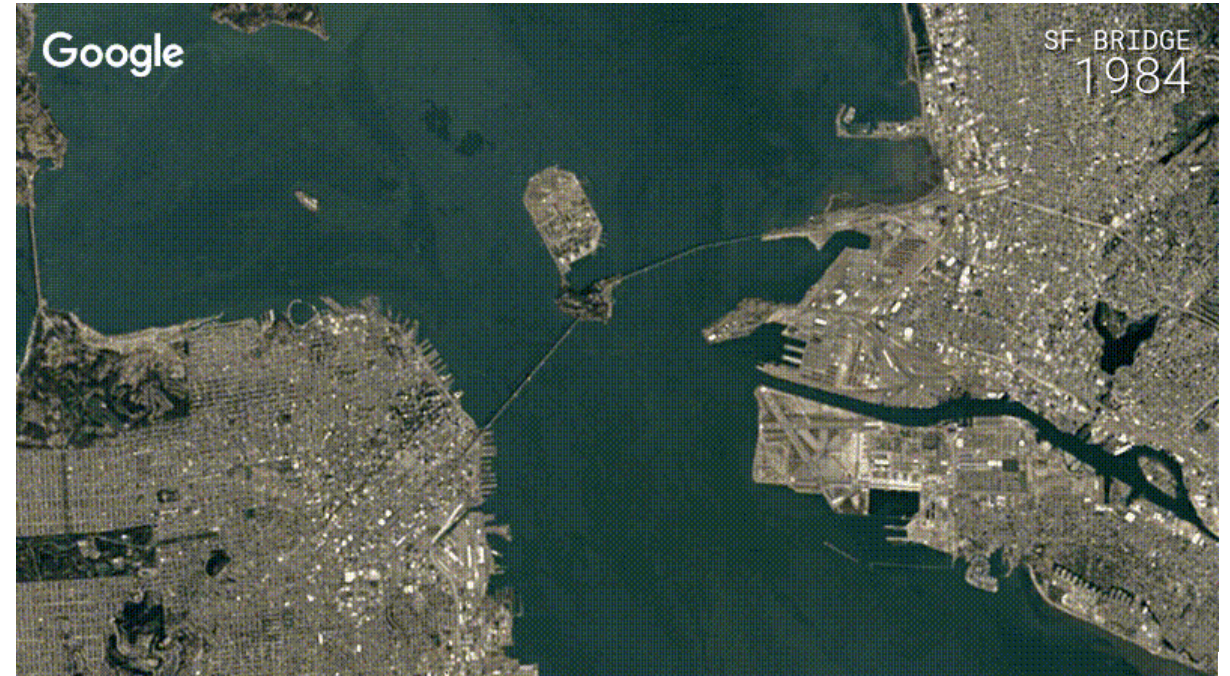
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climate and disaster risks.**

Redefining the binary task
of building detection to
characterize **[relevant
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that are being used in the
catastrophe modelling
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**With big [Earth Observation]
data comes big responsibility;
risky AI for risky disasters is
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Building **a global benchmark dataset
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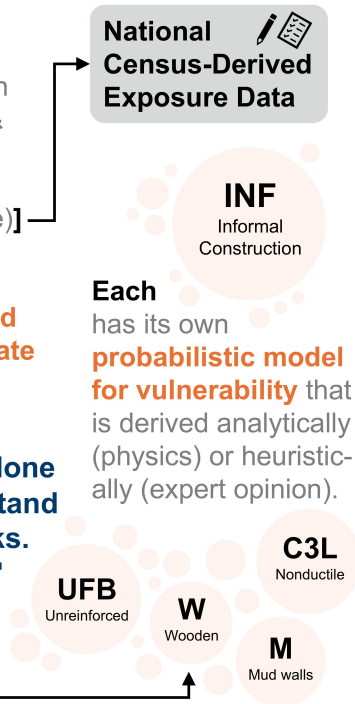
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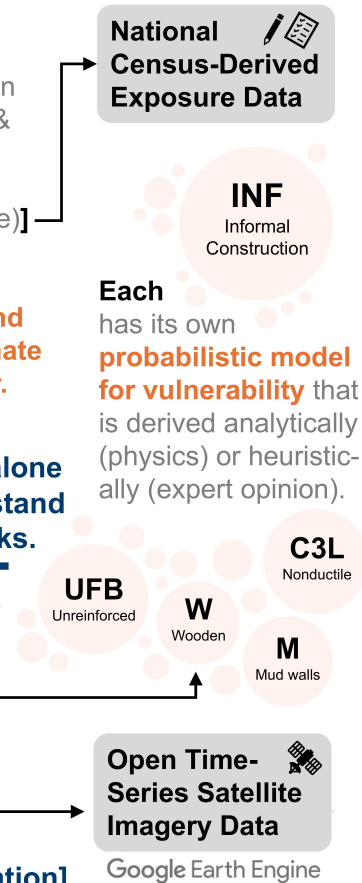
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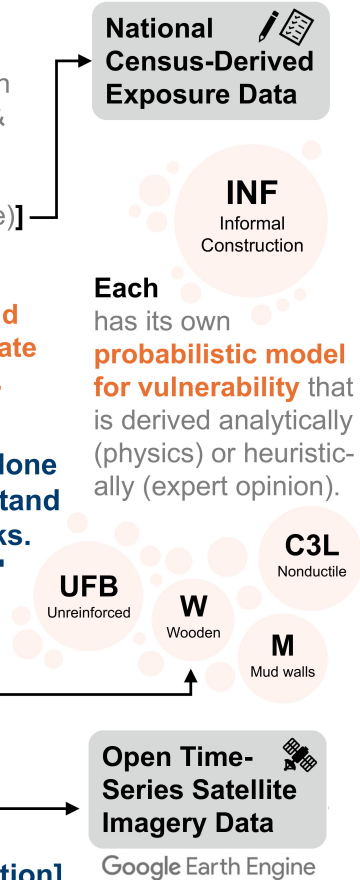
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zenodo

The Cambridge Disaster Risk Quantification Auditing Project

Published 2024 | Version 1.0.0

OpenSendaiBench: A Benchmark Dataset of Building Exposure and Vulnerability Dynamics for EO-based Auditing of Global Disaster Risk

Dimasaka, Joshua^{1,2,3}; Geiß, Christian^{4,5}; So, Emily^{1,3}

This Zenodo repository is the official global dataset for the research poster "Global Mapping of Exposure and Physical Vulnerability Dynamics in Least Developed Countries using Remote Sensing and Machine Learning" at 2nd Machine Learning for Remote Sensing Workshop, 12th International Conference on Learning Representations (ICLR) in Vienna, Austria, on 11th of May 2024. The GitHub repository of Python codes can be accessed here: github.com/riskaudit/OpenSendaiBench. The following technical info is from the four-page paper of this research poster. If you have any inquiries or would like to access any related materials, please feel free to visit my website (joshuadimasaka.com) or our project website (riskaudit.github.io), follow our project's GitHub repository (github.com/riskaudit), or send an email to jtd33@cam.ac.uk.

Technical info (English)

1. National Census-Derived Exposure Data

We rasterized every country-wide point dataset of building counts from the METEOR project with a defined physical vulnerability type at a spatial resolution of 15 arcseconds or approximately 500 meters at the equator (Huyck et al., 2019). We then implemented a rigorous probability-based approach in extracting 100 square tiles for each country. In sampling these 100 square tiles per country, we considered the number of physical vulnerability types that are present in every pixel to ensure that every label including those unlabeled pixels is represented.

2. Time-Series Satellite Imagery

With the previously extracted geographical extents, we obtained the following pre-processed time-series satellite imagery via Google Earth Engine (Gorelick et al., 2017).

2.1. Sentinel-1 SAR GRD

At 10-m spatial resolution, we used the annual mean of the Ground Range Detected (GRD) scenes that are acquired from the dual-polarization C-band Synthetic Aperture Radar (SAR) instrument at 5.405GHz of Sentinel-1 satellite (Copernicus Sentinel data, 2024a). As a result, covering the years from 2015 to 2023, we extracted nine annual mean of the two bands:

- VV (vertical transmit, vertical receive) and
- VH (vertical transmit, horizontal receive) signals.

To avoid data incompleteness across large areal extent, we disregarded filtering by orbital number and satellite direction. We also note that there are countries such as Angola, Comoros, Ethiopia, Kiribati, and Tuvalu with either partially or fully complete VV and VH signals because the orbit of Sentinel-1 satellite does not cover these areas for some time or only a single VV signal is available.

2.2. Sentinel-2 Harmonized MSI

271 VIEWS

495 DOWNLOADS

Versions

Version	Published
Version 1.0.0	2024
Version v1	Feb 7, 2024

Cite all versions? You can cite all versions by using the DOI 10.5281/zenodo.10628877. This DOI represents all versions, and will always resolve to the latest one. Read more.

External resources

Indexed in

OpenAIRE

Communities

The Cambridge Disaster Risk Quantification Auditing Project



OpenSendaiBench

A Global EO-based Dataset for Exposure & Physical Vulnerability

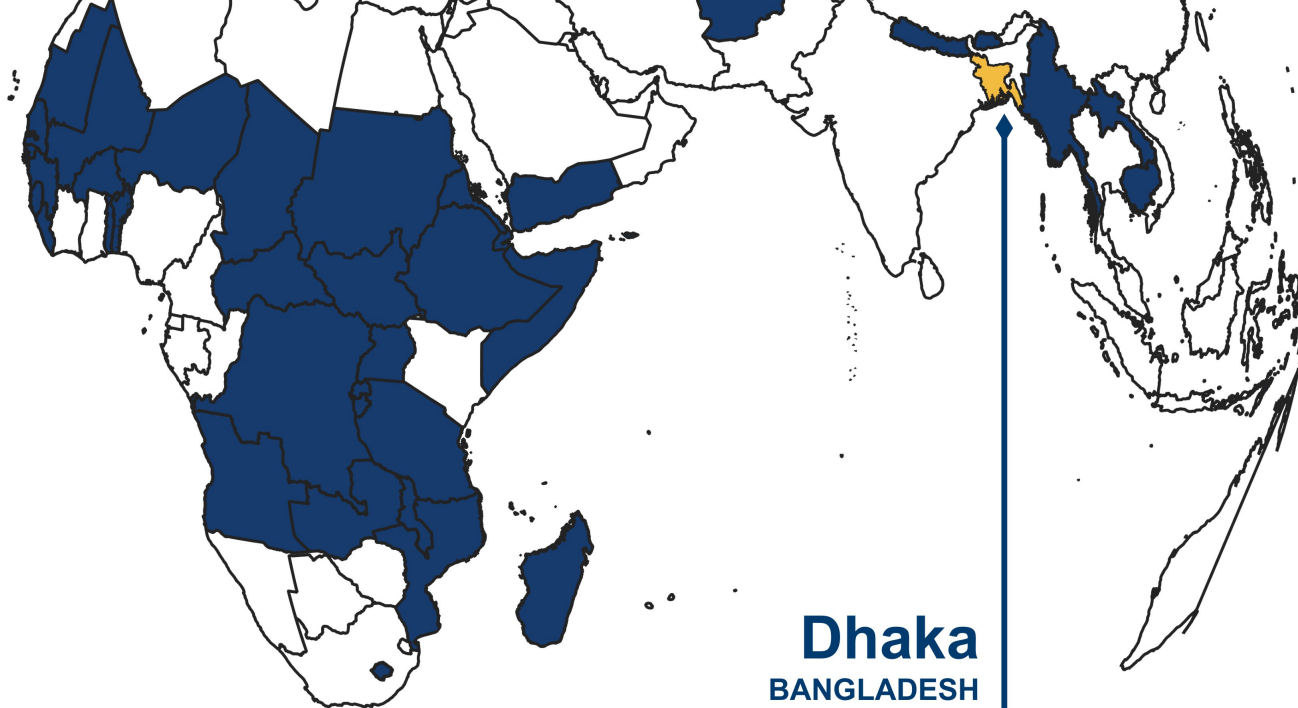
1972

2015

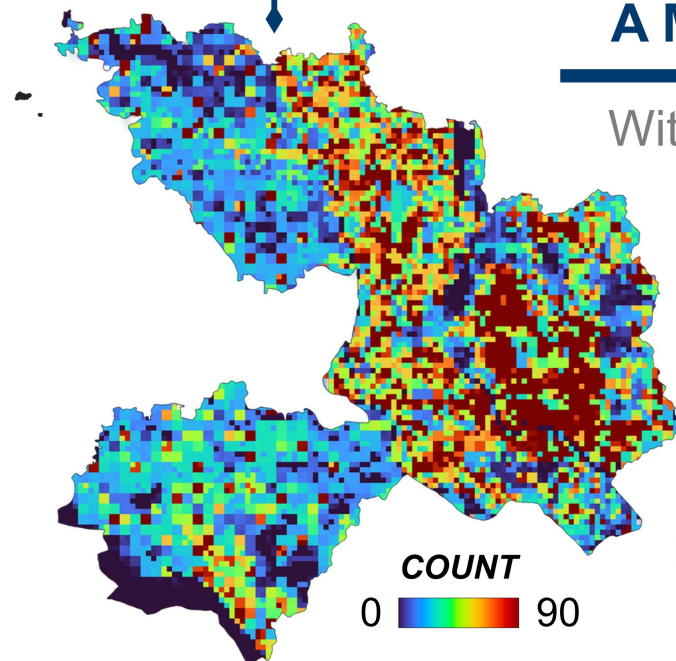
2023

2030

2050

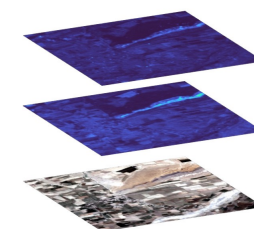


Dhaka
BANGLADESH



A Multi-resolution Multi-pixel Framing

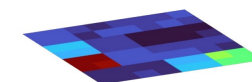
With $N = 100$ tiles per country, each has:



VV
VH
RGB

size:

(372, 372, 5)

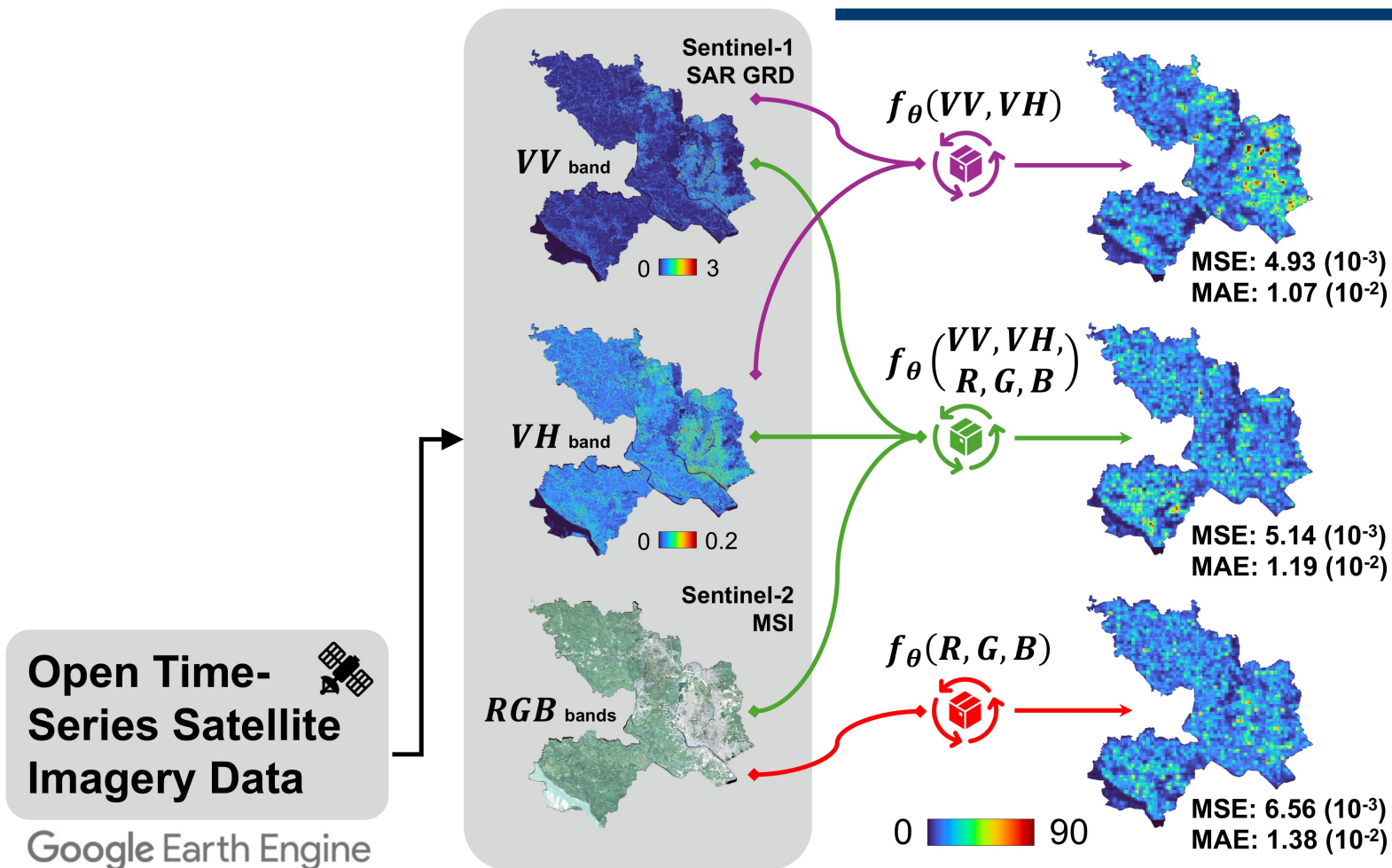


GROUND TRUTH

(8, 8, number of vulnerability types)

→ $P_{nonexceedance}$ via lognormal fit

Using ResNet-50 Convolutional Neural Network (f_θ)



While the initially trained models tend to **underestimate** the large values of [informally constructed buildings], it is still capable of **identifying areas with relatively high & low counts.**

What's Next?

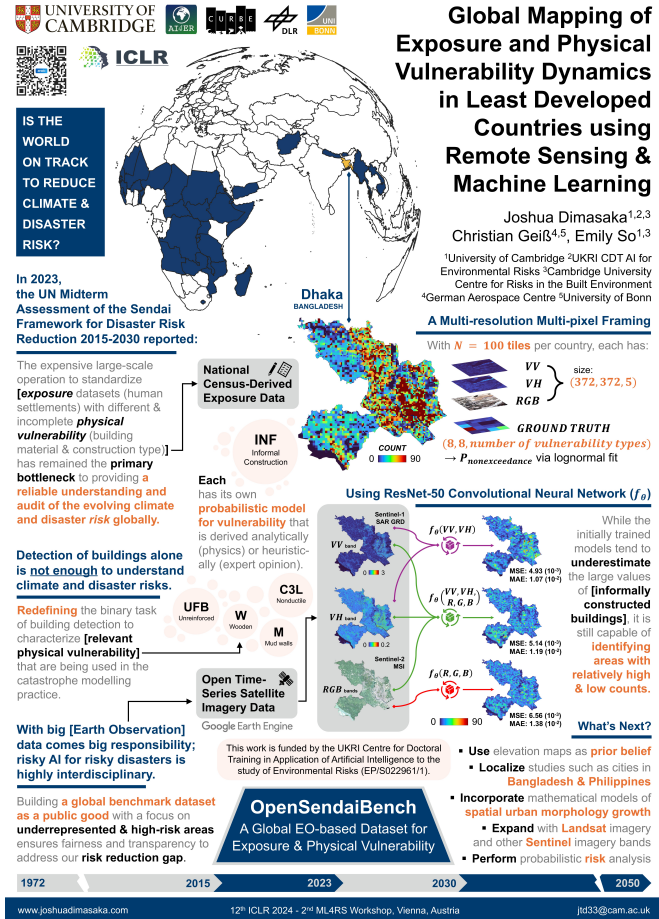
- **Use** elevation maps as **prior belief**
 - **Localize** studies such as cities in **Bangladesh & Philippines**
- **Incorporate** mathematical models of **spatial urban morphology growth**
 - **Expand** with **Landsat** imagery and other **Sentinel** imagery bands
 - **Perform** probabilistic **risk** analysis

The
Alan Turing
Institute



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