

Data-driven resilience assessment for transport infrastructure exposed to multiple hazards

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ABSTRACT: The exposure of critical transport infrastructure to natural hazards and climate change effects has severe consequences on world economies and societies and, thus, safety and resiliency of transport networks are of paramount importance. The currently available frameworks for quantitative risk and resilience-based design and assessment have been mainly developed for bridges exposed to earthquakes. However, there is an absence of well-informed exposure, vulnerability, functionality and recovery models, which are the main components in the quantification of resilience. The present paper proposes an integrated framework for the data-driven resilience assessment of transport infrastructure exposed to multiple hazards by using multiscale monitoring data, such as terrestrial and airborne data, as well as open-access crowd data and environmental measurements. Monitoring and early warnings are expected to produce accurate and rapidly informed quantitative risk and resilience assessments for transport infrastructure and to enhance asset management. Therefore, this framework aims to facilitate stakeholders' decision-making for daily and catastrophic events and to support adaptation and preparedness with preventive and/or retrofitting measures against multiple hazards.

1 INTRODUCTION

The exposure of critical transport infrastructure to natural hazards has severe consequences on world economies and societies. Indicatively, transport infrastructure closures and delays result on an average annual economic loss of £2 billion in the UK, which is expected to \$10 billion by 2040 (Department for Transport 2015). Thus, safety and reliability of road networks are critical for supporting the world economy. For example, the heavy 2007 rainfall in the UK affected the road network, with the cost estimated at £60m, while during the 2009 floods in Cumbria, at least 20 bridges were destroyed or damaged, causing one fatality, £34m of restoration costs and large societal impact. The direct and indirect economic losses due to landslides affecting road networks are of

similar impact (Winter et al. 2016). Common failures of transport infrastructure and traffic disruptions are frequently caused by hydraulic nature hazards, e.g. heavy precipitation, flash floods, scour, debris accumulation and ice, as well as by other geohazards, e.g. earthquakes, landslides, subsidence, shrinking/swelling of soils and debris flows. These effects were proved to be exacerbated due to climate change, which is one of the acknowledged challenges that the infrastructure owners currently face (Dawson et al. 2016). In Europe, 30%–50% of road maintenance cost (up to €13bn p.a.) is due to weather stresses, while 10% of these costs are associated with extreme weather events (Nemry & Demirel 2012). Therefore, transport infrastructure operators are increasingly faced with the challenge of delivering resilient infrastructure by optimising asset miti-

gation measures against natural hazards and climatic changes, based on their resources.

It is widely recognised that Quantitative Risk Analysis (QRA) is important, especially for the resilience and adaptability of critical assets (FHWA 2013, HM Government 2016). QRA estimates the potential economic, functional and social losses in a specific period, determined probabilistically as a function of hazard, exposure and vulnerability including the associated uncertainties. *Hazard* refers to the possible occurrence of natural or human-induced physical events that may have adverse effects on exposed assets. Each hazard is characterized by its location, intensity or magnitude, frequency and probability. *Exposure* refers to the inventory of elements in an area or a network in which hazard events may occur. *Vulnerability* refers to the propensity of exposed elements such as transport infrastructure assets to suffer adverse effects when impacted by hazard events (UNISDR 2009). Nevertheless, recent comprehensive research by Argyroudis et al. (2019) into the available vulnerability models has shown that the literature is fragmented and covers only partially the QRA of bridges exposed to single hazards, e.g. earthquakes (Gidaris et al. 2017).

Furthermore, the resilience-based design and assessment frameworks, which account for the assets' vulnerability and the rapidity of damage recovery (Dong and Frangopol 2016), have been mainly developed for bridges exposed to earthquakes. They are gradually being adopted in practical applications (Chan & Schofer 2015), while are expected to be incorporated in the next generation of provisions and guidelines (Cimellaro et al. 2010, Almufti & Willford 2013). For the quantitative resilience assessment, well-informed recovery models that account for both geotechnical, structural and operational/functionality effects are required, yet, completely missing from the literature or they are limited solely for earthquake hazard (Mitoulis et al. 2019).

More importantly, a vast of monitoring and remote sensing data and evidence, which is available to transport asset owners remains unexploited. This includes terrestrial, e.g. data generated by cameras and mobile activity, instrumented monitoring of bridges and geotechnical assets, and airborne data, e.g. InSAR, hyperspectral imaging, aerial photography, UAV/Drone sensors, as well as open-access crowd data, e.g. Google and/or Waze traffic data, weather and air pollution measurements. Yet, this wealth of information provides reliable means for producing accurate and rapidly informed QRAs and resilience assessments for critical transport assets.

The present paper proposes an integrated framework along with representative examples for the monitoring data-driven risk and resilience assessment of transport infrastructure exposed to multiple hazards by integrating multiscale monitoring systems. Monitoring data is expected to provide reliable

means for producing accurate and rapidly informed and automated quantitative risk and resilience assessments for transport assets. The framework aims to facilitate stakeholders' unbiased decision-making for daily and catastrophic events. A monitoring enhanced asset management is also discussed, including the use of early warning signals to detect critical behaviour of infrastructure assets. In this respect, monitoring driven asset management aims to support adaptation and preparedness with preventive and/or retrofitting measures against multiple hazards for short-term planning or extensions of the transport networks for enhancing resilience in the long-term.

2 MONITORING DATA DRIVEN RESILIENCE ASSESSMENT OF TRANSPORT ASSETS

The proposed framework is illustrated in Figure 1, and it is outlined in the following for representative and common types of transport infrastructure assets. The framework includes the different components of risk and resilience, namely, exposure, hazard, vulnerability, functionality and restoration/reinstatement models. Monitoring and remote sensing data can be used to develop new models and/or improve the accuracy and reduce the uncertainty of the theoretical models and the input for risk and resilience assessments in asset and network level (Figure 1F).

2.1 Exposure of critical assets

Transport infrastructure are exposed to diverse natural and weather-related hazards throughout their lifetime, which may have different effects on the various transport assets (Figure 1A). Argyroudis et al. (2019) summarised the effects of critical geotechnical and hydraulic hazards to transport infrastructure assets. For example, road pavements can sustain inundation, cracking or washout when exposed to floods, and ground failures, such as settlement, heaving or lateral spreading. The effects of floods on bridges include scour, hydraulic forces on piers/abutments/deck, aggravated by debris accumulation and ground movements, which can be aggravated due to climate change effects. In case of seismic hazard, structural elements of bridges can experience different damage modes, while geotechnical assets, e.g. backfill, can sustain settlement, heave, or slump failures. Walls retaining slopes or embankments may be exposed to precipitation, scouring, ground and landslides/debris flows.

Exposure and inventory data of transport networks are key components of reliable disaster risk assessment, commonly obtained from available databases, census data or by in-situ surveys. Monitoring systems and new technologies can enable accurate and low-cost evaluation of infrastructure

exposure or improvement of inventories, and hence, they can reduce the relevant uncertainties. For existing or older infrastructure for which the available databases are limited or not existing, remote sensing can provide fast and low-cost retrieval of exposure data with sufficient accuracy. In this context, LiDAR systems have been used to obtain information for road surface geometry (e.g. lane width, number of lanes) and its environment (e.g. road markings, pavement cracks, street signs, vegetation) (Guan et al. 2016). Exposure datasets and network models can be retrieved through Open Street Maps, Google maps and high-resolution imagery (Gil 2015, Wang et al. 2016).

2.2 Hazards and intensity measures

The intensity measures (IM), describe the severity and characteristics of the hazard and are used to correlate the response of each asset with the hazard. Common IM are the peak ground acceleration (PGA) for ground shaking, permanent ground deformation (PGD) for ground failure, and peak flow discharge or velocity or water depth for floods. The IM are usually defined based on available hazard data and maps provided by national agencies or platforms, e.g. for floods (Alfieri et al. 2014) or earthquakes (ESHM13, Woessner et al. 2015) or with site-specific hazard analysis (Figure 1B). The hazard maps or models correlate the IM with the annual exceedance probabilities of the hazard for different return periods, e.g. 5, 50, 100, 500, 1000 years. Based on the available hazard data, asset-specific hazard actions can be defined by utilising closed-form solutions. The IM should be adjusted by providing a range of projections, to account for exacerbation of hazard effects under climate change (Forzieri et al. 2016). Continuous monitoring of hazards provides new data for more reliable hazard models, or site-specific hazard analysis. For example, gauge stations in river bridges provide hydrologic data and flow records, which can be used to estimate the flood actions on bridge components (Archer & Fowler 2018, Dysarz et al. 2019).

2.3 Vulnerability and functionality models

The quantification of risk is commonly based on fragility functions, which describe the probability of exceeding certain damage states (minor, moderate, extensive, complete). They are defined based on probabilistic correlations between engineering demand parameters (EDPs) and IMs, on the basis of representative failure modes of the infrastructure assets, which may include combinations of structural and geotechnical failures (Figure 1D). The fragility functions can be developed based on numerical modelling, statistical data from past damages, expert elicitations or combination of the above (Yuan et al.

2019, Argyroudis et al. 2019). They are usually provided for representative typologies of the assets based on critical vulnerability parameters, e.g. for bridges: type of pier and abutment, deck, number of spans, lengths and foundation type. In some cases, asset-specific fragility models are developed (Stefanidou & Kappos 2019). Long-term monitoring data, such as vibration data recorded with accelerometers on a bridge, can be used to track changes in the structural system, due to changes in natural frequencies, i.e. degradation of element structural stiffness due to ageing. Moreover, accelerometers and LVDTs can be used to monitor the deflection of the deck, concrete cracks, stiffness reduction and expansion joint movements. These measurements can provide data for the safety and risk assessment of the structure, as well as for the time-dependent fragility analysis of the asset. This information can be used to update the numerical model of the structure, and consequently, to update the estimated fragility functions, considering the change in asset parameters (e.g. Torbol et al. 2013, Cheng et al. 2019), due to ageing effects or accumulation of damage (dashed curves in Figure 1D).

Functionality loss models quantify the induced, i.e. non-structural related, effects of hazards on the mobility, i.e. vehicle speed as shown in Figure 1C (e.g. Lam et al. 2018). Traffic cameras and drones can be used to identify the traffic conditions, including the closure or partial obstruction due to: (i) inundation, snow, ice or debris accumulation on the pavement, (ii) rockfall, ice or debris on the road surface at bridge decks, (iii) debris or water flow and accumulation on the road/embankment surface or tunnel portals originating from the slope. These data can be used to correlate the functionality of the road with a hazard intensity measure, for example the standing water depth (Pregolato et al. 2017).

2.4 Restoration models for transport infrastructure

The reinstatement (for induced non-structural damage) and restoration (for structural damage) functions, correlate the level of the restored functionality with time after the commencement of repair works, i.e. rapidity of recovery (Figure 1E). They are commonly developed based on expert elicitation approaches or completely missing from the literature (Mitoulis et al. 2019), considering the type and extent of damage, the available resources, the local practices and the associated uncertainties. Traffic data provides valuable evidence for the recovery process after a disruption and can be used to improve or develop new reinstatement and/or restoration models. These models can be updated with the use of satellite or UAV/Drone images, taken in different periods after the disruption and during the recovery of the damaged asset, to quantify the process of traffic recovery and/or the process of the restoration

works (dashed functions in Figure 1E). Traffic data and drivers' characteristics and behaviours after a disaster can be detected and analysed using UAV and surveillance cameras (Salvo et al. 2017, Kim et al. 2019).

3 MONITORING DATA DRIVEN RESILIENCE ASSESSMENT OF TRANSPORT NETWORKS

The resilience analysis in a network level considers the post-disaster evolution of the origin-destination (OD) matrix, as this is dependent on the damaged assets with partial or full closures. Damage and functionality level are identified based on the models described in 2.3 for the given exposure (2.1) and hazard intensities (2.2). Traffic analyses are employed based on dynamic adaptation of the OD matrices, prior to and after the hazard event, considering the gradual repair and opening of the assets and the network functionality recovery on the basis of the restoration/reinstatement functions described in 2.4. The critical components of the network are defined based on their impact on the cost and downtime during the restoration of the network functionality, considering the resilience objectives set by the stakeholder. Traffic information extracted from Call Detail Record (CDR) crowd data, e.g. Google and/or Waze, or weather and air pollution measurements can provide input for the quantification of indirect losses and consequences, such as traffic delays, business interruption and environmental impacts after the occurrence of a disaster (Kaiser et al. 2017).

The resilience assessment of the network and its evolution with time is illustrated in Figure 2 measured by the functionality of the network for an extreme hazard event, e.g. a flash flood, a debris flow or an earthquake. Practically, the network resilience is a function of the resilience and functionality of its assets, e.g. bridge, tunnel, embankment, road pavement, and is dependent on the capacity of the structural components, e.g. foundations, deck, piers. The black solid line represents a transport network without monitoring (NM), where inspections are only performed in certain periods of time. The red line corresponds to the improved resilience models based on the monitoring (M) of infrastructure as described in the previous section. The functionality of the network starts from 1.0, i.e. the designed performance, while different periods at the life-cycle of the infrastructure are shown in the figure, i.e. 1: *normal function* (with monitoring M1 or without monitoring NM1); during this period is possible to observe a drop in the functionality due to degradation of the infrastructure. 2: *mitigation measures* (M2, NM2) after the occurrence of an extreme event, which causes an abrupt loss of the network functionality. 3: *normal function/adaptation* (M4, NM4), and potentially life extension.

These periods are usually different and do not necessarily coincide when monitoring is applied. Monitoring influences the abovementioned periods as follows: (a) a more reliable evaluation of the functionality loss due to degradation or increased traffic demands can be achieved if monitoring is applied in period 1 (normal functionality), (b) the post-damage response time and the lag time in decision making can be reduced when monitoring data are available, for defining the extent of damage and the impact on the network (period 2), (c) the recovery will be faster ($t_{rec}^M < t_{rec}^{NM}$) due to more expedient and better understanding of the infrastructure condition (period 2), (d) the reliability of the loss and resilience assessment models is increased, by lowering the uncertainty (in all periods), and particularly in the post-disaster period when information is limited and of low quality when monitoring is not available, (e) a timely decision making and application of mitigation or adaptation measures can be enabled (period 4), well before the infrastructure reaches its critical functionality $f_{critical}$, and hence allowing continuous and expedient adaptation to the new demands ($t_{adapt}^{Mi} < t_{adapt}^{NMi}$). For item (c), it is noticed that a monitored infrastructure is more likely to gain its initial functionality, whereas an infrastructure that is not monitored is unlikely to accurately reach the same level of functionality, after mitigation measures are applied. Moreover, monitoring systems can provide timely early warnings after the time of the initiation of the infrastructure deterioration, due to the accumulation of damage or after the loss of capacity of the infrastructure following an extreme event. The use of early warning techniques is further discussed in the next section.

4 MONITORING ENHANCED ASSET MANAGEMENT

4.1 Use of airborne data in asset management

Satellite images or UAV/Drone LiDAR data can be enabled for high-resolution measurements of ground and pavement displacements, such as settlements, lateral spreading, heaving and potholes, caused by floods, earthquakes or ground failures (Pan et al. 2018). Remote sensing techniques, including photogrammetric surveys, Light Detection and Ranging (LiDAR) datasets, Interferometric Synthetic Aperture Radar (InSAR), aerial and hyperspectral imagery can facilitate the management of geotechnical assets, such as embankments, cuttings and natural slopes and support the decision-making by the network owners (Wolf et al. 2015, Pritchard et al. 2018). UAV/Drone LiDAR technology can be used to generate 3D images of the assets and identify dis-

placements and possible failures, while multispectral aerial imagery can be applied to assess the slope stability, the debris flow or water flow and their accumulation originating from the slope. For example, Miller et al. (2011) used airborne laser scanning (ALS) and multispectral aerial imagery to determine key slope stability variables. This data was used to parameterize a coupled hydrological–geotechnical model, to simulate slope behaviour of highway or railway earthworks, such as embankments and cuts, under current and future climates. The resulted slope risk mapping provides practical means to infrastructure operators for prioritising site inspections.

Recently, UAVs have been integrated in post-disaster reconnaissance to document structural or geotechnical damage and collect data of system behaviour during and after extreme hazard events such as earthquakes, floods and hurricanes (Zekkos et al. 2016, Greenwood et al. 2019). UAVs have been also integrated in the inspection and monitoring of bridges, to detect deformations and cracking (Gillins et al. 2016).

4.2 Early warning signals of critical behaviour of infrastructure assets

Early warning signals is a part of general tipping point analysis (Livina et al. 2015, Prettyman et al. 2019) that allows one to anticipate, detect and forecast critical trajectories of dynamical systems. Recently the early warning signals were studied in sensor data of bridges (Livina et al. 2014) and in electromagnetic data (Livina et al. 2019). The NPL footbridge was studied with multiple sensors installed along the construction, which underwent various stress and damage experiments (Livina et al. 2014). Those parts susceptible to damage demonstrated early warning signals, along-side the environmental signals with clear seasonal oscillations. Perry et al. (2015) demonstrated early warning signals in laboratory experiments with beams made of reinforced concrete, and early warning signals allowed to distinguish various conditions of the installation. Prettyman et al. (2019) summarised the multivariate approach in analysis of sensor data and their early warning signals in the context of geophysical data. This framework provides techniques for detecting and tracking of development of crucial behaviour in spatially distributed data. The principle of early warning signals is in monitoring (in sliding windows) the changes of memory in time series – by means of lag-1 autocorrelation or longer-term persistence that can be estimated using Detrended Fluctuation Analysis (Livina & Lenton, 2007) or power spectrum (Prettyman et al. 2018). When the autocorrelated memory increases in time series, it indicates approaching critical behaviour in the dynamical system. This approach allows to implement a proactive system for structure health monitoring in

infrastructure assets, where sensor data would be analysed for early warning signals prior to crucial events, such as cracks, failures, and other damages.

5 CONCLUSIONS

This paper introduced a resilience-based assessment and management framework for critical transport infrastructure exposed to natural hazards and climate change effects, enhanced by terrestrial and airborne monitoring systems. Monitoring data and evidence can be used to develop new models, and/or to calibrate, improve, and reduce the uncertainties of available ones for assessing the exposure, hazard, vulnerability, functionality and damage restoration. Hence, a monitoring data-driven resilience-based management of transport infrastructure can be achieved for improved functionality, and adaptation of the network to changing conditions. This can be extended by including early warning signals for the detection of critical behaviour of transport assets. Monitoring-data driven asset management is expected to facilitate stakeholders' unbiased decision-making for daily and catastrophic events, and to support adaptation and preparedness with preventive and/or retrofitting measures against multiple hazards.

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REFERENCES

- Alfieri, L., Salamon, P., Bianchi, A., Neal, J., Bates, P.D., Feyen, L., 2014. Advances in pan-European flood hazard mapping, *Hydrol. Process.* 28 (18): 4928-4937.
- Almufti, I., Willford, M.R. 2013. Resilience-based earthquake design (REDi) rating system, version 1.0. Arup.
- Archer, D.R., Fowler, H.J. 2018. Characterising flash flood response to intense rainfall and impacts using historical information and gauged data in Britain. *Journal of Flood Risk Management* 11: S121-S133.
- Argyroudis, S.A., Mitoulis, S.A., Winter, M.G., Kaynia, A.M. 2019. Fragility of transport assets exposed to multiple hazards: State-of-the-art review toward infrastructural resilience. *Reliab Eng Syst Saf* 191, 106567.
- Chan, R., Schofer, J.L. 2015. Measuring transportation system resilience: response of rail to weather disruptions. *Natural Hazards Review* 17(1).

- Cheng, Y., Zhang, J., Wu, J. 2019. Fragility analysis of a self-anchored suspension bridge based on structural health monitoring data. *Advances in Civil Engineering*: 7467920.
- Cimellaro, G.P., Reinhorn, A.M., Bruneau, M. 2010. Framework for analytical quantification of disaster resilience. *Engineering Structures* 32.
- Dawson, R.J., et al. 2016. UK Climate Change Risk Assessment Evidence Report: Chapter 4, Infrastructure. *Report prepared for the Adaptation Sub-Committee of the Committee on Climate Change*, London.
- Department for Transport 2015. Road investment strategy: for the 2015/16-2019/20 Road Period, UK. ISBN 9781474115780, www.gov.uk/government/publications.
- Dong, Y., Frangopol, D. 2016. Probabilistic multihazard resilience of bridges considering climate change. *Journal of Performance of Constructed Facilities* 30(5): 04016034.
- Dysarz, T., Wicher-Dysarz, J., Sojka, M., Jaskuła, J. 2019. Analysis of extreme flow uncertainty impact on size of flood hazard zones for the Wronki gauge station in the Warta river. *Acta Geophysica* 67(2): 661-676.
- FHWA 2013. Risk-based transportation asset management: building resilience into transportation assets. Report 5: managing external threats through risk-based asset management. US Department of Transportation, Federal Highway Administration, March, Available at: <https://www.fhwa.dot.gov/asset/pubs/hif13018.pdf>
- Forzieri, G., Feyen, L., Russo, S., Voudoukas, M., Alfieri, L., ... & Cid, A. 2016. Multi-hazard assessment in Europe under climate change. *Climatic Change* 137: 105-119.
- Gidaris, I., Padgett, J. E., Barbosa, A. R., Chen, S., Cox, D., Webb, B., Cerato, A. 2017. Multiple-hazard fragility and restoration models of highway bridges for regional risk and resilience assessment in the United States: state-of-the-art review. *J Structural Engineering* 143(3): 04016188.
- Gil, J. 2015. Building a multimodal urban network model using OpenStreetMap data for the analysis of sustainable accessibility. In *OpenStreetMap in GIScience: Experiences, Research, Applications*, pp. 229-251, Springer.
- Gillins, M.N., Gillins, D.T., Parrish, C. 2016. Cost-effective bridge safety inspections using unmanned aircraft systems (UAS). *Proc., Geotechnical and Structural Engineering Congress 2016*, 1931-1940. Reston, VA: ASCE.
- Greenwood, W.W., Lynch, J.P., & Zekkos, D. 2019. Applications of UAVs in civil infrastructure. *Journal of Infrastructure Systems* 25(2): 04019002.
- Guan, H., Li, J., Cao, S., & Yu, Y. 2016. Use of mobile LiDAR in road information inventory: A review. *International Journal of Image and Data Fusion* 7(3): 219-242.
- HM Government. 2016. National flood resilience review <https://www.gov.uk/government/publications/national-flood-resilience-review>
- Kaiser, M.S., Lwin, K.T., Mahmud, M., Hajializadeh, D., Chaipimonplin, T., Sarhan, A., Hossain, M.A. 2017. Advances in crowd analysis for urban applications through urban event detection. *IEEE Transactions on Intelligent Transportation Systems* 19(10): 3092-3112.
- Lam, J.C., Adey, B.T., Heitzler, M., Hackl, J., Gehl, P., van Erp, N., D'Ayala, D., van Gelder, P., Hurni, L. 2018. Stress tests for a road network using fragility functions and functional capacity loss functions. *Reliab Eng Syst Saf* 173.
- Livina, V., Barton, E., Forbes, A. 2014. Tipping point analysis of the NPL footbridge. *J Civil Struct Health Monit* 4:91-98.
- Livina, V., Van Martins, T.M., Forbes, A.B. 2015. Tipping point analysis of atmospheric oxygen concentration, *Chaos* 25, 036403.
- Livina, V., Lewis, A., Wickham, M. 2019. Tipping point analysis of electrical resistance data with early warning signals of failure for predictive maintenance, arXiv:1904.04636
- Miller, PE., Mills, JP., Barr, SL., Birkinshaw, SJ., Hardy, AJ., Parkin, G., Hall, SJ. 2011. A remote sensing approach for landslide hazard assessment on engineered slopes. *IEEE Trans on Geoscience & Remote Sensing* 50(4): 1048-1056.
- Mitoulis, S., Argyroudis, S., Lamb, R. 2019. Risk and resilience of bridgeworks exposed to hydraulic hazards, *Proc. IABSE2019*, New York, 4-6 September.
- Nemry, F., Demirel, H. 2012. Transport and climate change: a focus on road and rail transport infrastructures. *JRC72217*, EUR 25553 EN.
- Pan, Y., Zhang, X., Cervone, G., & Yang, L. 2018. Detection of asphalt pavement potholes and cracks based on the unmanned aerial vehicle multispectral imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 11(10): 3701-3712.
- Perry, M., Livina, V., Niewczas, P. 2015. Tipping point analysis of cracking in reinforced concrete. *Smart Materials and Structures* 25 (1): 015027.
- Pregolato, M., Ford, A., Wilkinson, S.M., Dawson, R.J. 2017. The impact of flooding on road transport: A depth-disruption function. *Transportation research Part D: Transport and Environment* 55: 67-81.
- Prendergast, L.J., Gavin, K. 2014. A review of bridge scour monitoring techniques. *J Rock Mech Geotech Eng* 6(2).
- Prettyman, L.J., Kuna, T., Livina, V. 2018. A novel scaling indicator of early warning signals helps anticipate tropical cyclones, *Europhysics Letters* 121:10002.
- Prettyman, J., Kuna, T., Livina, V. 2019. Generalised early warning signals in multivariate and gridded data with an application to tropical cyclones. *Chaos* 29, 073105.
- Pritchard, O., Bhreasail, A.N., Campbell, G., Carluccio, S., Willis, M., Codd, J. 2018. Practical remote survey applications for improved geotechnical asset management on England's strategic road network. *Proc. 7th Transport Research Arena TRA 2018*, Vienna, Austria.
- Pritchard, O., Ní Bhreasail, A., Campbell, G. 2018. Practical remote survey applications for improved geotechnical asset management on England's strategic road network. *Proc. Transport Research Arena TRA2018*, Vienna, Austria.
- Stefanidou, S.P., Kappos, A.J. 2019. Bridge-specific fragility analysis: when is it really necessary? *Bulletin of Earthquake Engineering* 17(4): 2245-2280.
- Torbol, M., Gomez, H., Feng, M. 2013. Fragility analysis of highway bridges based on long-term monitoring data. *Computer-Aided Civil Infrastructure Eng* 28(3): 178-192.
- Wang, W., Yang, N., Zhang, Y., Wang, F., Cao, T., & Eklund, P. 2016. A review of road extraction from remote sensing images. *Journal of Traffic & Transportation Engineering (English ed)* 3(3): 271-282.
- Winter, M. G., Shearer, B., Palmer, D., Peeling, D., Harmer, C., Sharpe, J. 2016. The economic impact of landslides and floods on the road network. *Procedia Eng* 143: 1425-1434.
- Woessner, J., Danciu, L., Giardini, D., Crowley, H., Cotton, F., Grunthal, G., ... Stucchi, M. 2015. The 2013 European Seismic Hazard Model: Key Components and Results. *Bulletin of Earthquake Engineering* 13(12):3553-3596.
- Wolf, RE., Bouali, EH., Oommen, T., Dobson, R., Vitton, S., Brooks, C., Lautala, P. 2015. Final report: Sustainable Geotechnical Asset Management along the Transportation Infrastructure Environment Using Remote Sensing. Michigan Technological University, USDOT Cooperative Agreement No. RITARS-14-H-MTU.
- Yuan, V., Argyroudis, S., Tubaldi, E., Pregolato, M., Mitoulis, S. 2019. Fragility of bridges exposed to multiple hazards and impact on transport network resilience. *Proc. SE-CED2019 Earthquake risk and engineering towards a resilient world*, Greenwich, September 9-10.
- Zekkos, D., Manousakis, J., Greenwood, W., Lynch, J. 2016. Immediate UAV-enabled infrastructure reconnaissance following recent natural disasters: Case histories from Greece. *Proc. 1st Intern Conf on Natural Hazards and Infrastructure (ICONHIC)*, Chania, Greece, 28-30 June.

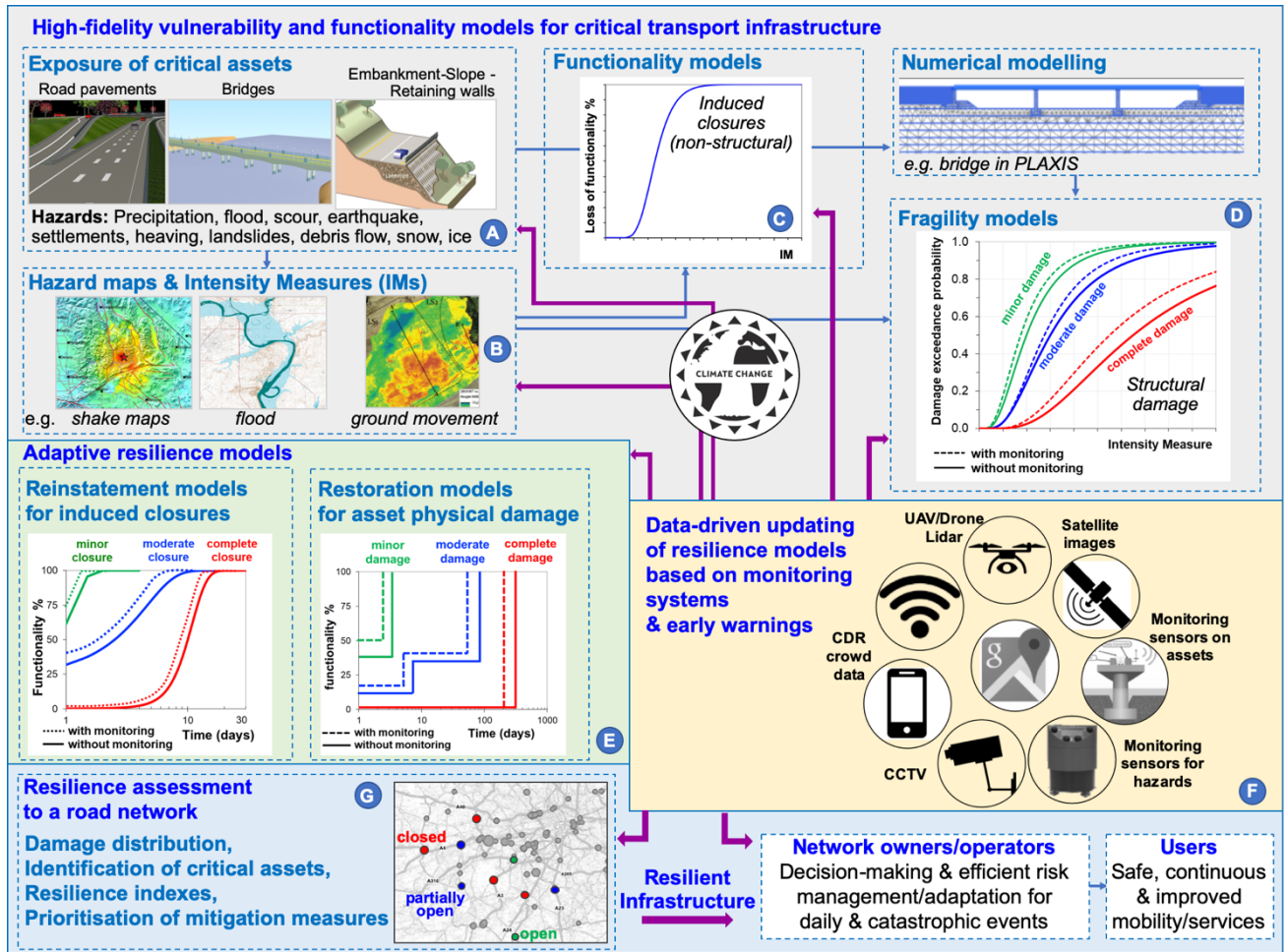


Figure 1. Monitoring data-driven resilience assessment of transport infrastructure exposed to multiple hazards

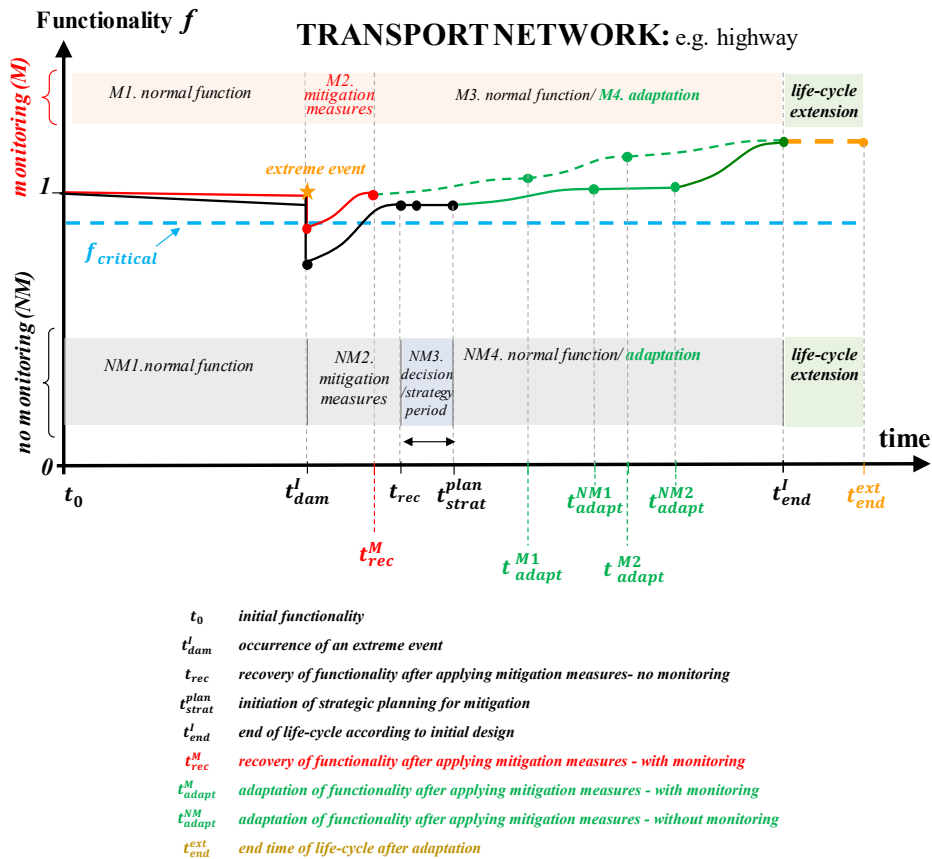


Figure 2. Resilience of transport networks throughout their life-cycle due to natural or human-induced hazards: e.g. seismic event, flush floods, landslide, fire, explosion.