Risk Analysis of Physical Assets:

Addressing the current gaps in modeling hazards and structures/infrastructure

Paolo Gardoni, Ph.D.
Armin Tabandeh, Ph.D.
Neetesh Sharma, Ph.D.
Fabrizio Nocera

MAECENTER
toward a Multi-hazard Approach to Engineering

ILLINOIS

February 21, 2021

Copyright

Contact Information

If you have any questions regarding this document, contact:
Professor Paolo Gardoni
Civil and Environmental Engineering
3118 Newmark Civil Engineering Laboratory, MC-250
205 North Mathews Ave.
Urbana, IL 61801-2352
USA

Tel: (217) 333-5103
Email: gardoni@illinois.edu

For more information on the MAE Center, visit www. http://mae.cee.illinois.edu

Table of Contents

Table of Contents 3
Executive Summary 4
1. Introduction 6
2. Insurance Risk Assessment 10
2.1. Determining the value at risk 10
2.2. Determining the insured losses 12
3. Current Gaps 13
4. Addressing the Current Gaps 15
4.1. Virtual representation of physical assets 15
4.2. Spatiotemporal evolution of hazards 18
4.2.1. Earthquakes 19
4.2.2. Storm surges 21
4.2.3. Wildfires 25
4.3. Time-varying vulnerability of interdependent systems 27
5. Summary and Conclusions 29
Acknowledgments 30
References 31

Executive Summary

This paper focuses on three topics that represent current challenges in risk analysis of physical assets, namely, (1) the development of a systematic approach for creating digital twins of physical assets, (2) the modeling of the spatiotemporal evolution of hazards, and (3) the modeling of the time-varying vulnerability of interdependent physical assets.

Accurate risk analysis requires representative mathematical models of physical assets. These mathematical models create digital twins of reality. Data needed to create the digital twins are typically unstructured and incomplete. Current work lacks a systematic approach for processing and augmenting data to, for example, model assets where data are missing or capturing the physical assets' future developments and conditions (e.g., future expansions of infrastructure and the effects of aging and deterioration). A significant challenge in developing the digital twins is deciding the boundary and resolution of the virtual representation and selecting models for required analyses from multiple candidate models, each of different computational cost and accuracy. We developed a systematic approach for creating the digital twins of physical assets for risk analysis. Our approach considers the constraints in computational resources, quantifies all the relevant sources of uncertainty, and refines the computational models based on their roles in predicting the consequences of various risks.

Risk analysis requires accurate modeling of the spatiotemporal variability of hazards. While seismic hazards have received significant attention in past decades, other hazards such as hurricanes and wildfires, which have recently caused substantial damages and insured losses, have received less attention. Thus, there is a clear need to consider the frequency and severity of these hazards and, when appropriate, expand the methodologies developed for seismic hazards to them. Besides, many parts of the world are likely to face multiple hazards. These hazards may interact with one another, and their combined effects on physical assets can lead to increased vulnerability to future hazards. Accurate hazard modeling requires accounting for the temporal aspects of hazards. For example, climate change is impacting the likelihood of occurrence and the magnitude of weather-related perils. The spatial variability of hazards'

intensity plays a significant role in modeling direct physical damages to physical asset portfolios and capturing indirect losses due to cascading effects. We developed physics-based models for three specific hazards while capturing the spatiotemporal evolution of the hazards' intensity measures. These hazards are earthquake main shock-aftershocks sequences, storm surges, and wildfires. The developed models are transportable globally and can be used for long-term hazard predictions and preparedness. The models can also be updated using real-time data from unfolding events; hence, they can facilitate short-term decision-making processes to optimize the management of resources needed in the immediate aftermath of a natural disaster.

Current modeling, design, maintenance, recovery, financing principles, and regulatory standards usually focus on physical assets in isolation and do not consider hazards' interactions, infrastructure interdependencies, and time-varying vulnerability of physical assets due to aging and deterioration. Aging and deterioration can considerably increase the vulnerability of physical assets like infrastructure and reduce their service lives. These adverse effects also increase the likelihood of prolonged post-disaster recovery and lack of access to infrastructure services. Interdependencies among different physical assets exacerbate the cascading effects. For example, pumping stations in potable water infrastructure may stop functioning due to damages to the supporting electric power infrastructure. Modeling interdependencies of physical assets is critical in predicting direct and indirect incurred losses due to the lack of access to infrastructure services. Failure to capture the combined effects of deterioration and interdependencies leads to significant underestimation of actual incurred losses due to hazards. We developed a rigorous physics-based approach to model the time-varying vulnerability of interdependent physical assets. The developed models provide information about direct damages to physical assets due to multiple hazards, cascading effects of infrastructure's reduction or loss of functionality, and post-disaster recovery of physical assets. The developed models are also customizable to the specific conditions of physical assets. Examples of these conditions include physical assets' age and deterioration level, environmental conditions that affect their deterioration, repair and maintenance history, service demand on infrastructure, and post-disaster recovery resources (e.g., budget, skilled labor, material.)

1. Introduction

Decision-making is often based on information about risks associated with possible courses of action or possible outcomes (Bedford and Cooke 2001; Gardoni and Murphy 2014). Risk analysis requires defining all consequences relevant to the decision-making process and quantifying their probabilities (Gardoni et al. 2016a). Managers of physical assets, administrative policymakers, and insurance companies often must make decisions about significant investments that involve predicting the extent and consequences of damages to physical assets due to multiple hazards with an eye to both the near term and the distant future (Gardoni and LaFave 2016). Events such as earthquakes, hurricanes, or wildfires bring wide-ranging direct and indirect consequences that must be identified and considered in an effective risk analysis. For example, direct consequences may include casualties and damages to physical assets, inventories, and equipment. There are also indirect consequences associated with business interruption, lost tax revenues, lost sales, service interruptions, long-term health impacts, and lower property values in the impacted areas (Gardoni et al. 2016b; Nocera and Gardoni 2019a,b).

Risk analysis of physical assets relies on representative digital twins. A digital twin consists of a virtual representation of the physical assets for a specific analysis. The virtual representation requires collecting and integrating data from multiple sources about relevant geographical and environmental conditions (such as where the assets are located), when and how the assets are used, how essential the assets are, what the interdependencies are, and what the assets' physical and operational states are. The required data depend on the analyses to be performed (e.g., predicting only direct costs has different data requirements than also predicting indirect costs.) The problem is that the collected data are typically unstructured and incomplete. *Current models lack a systematic approach for processing and augmenting data to account for assets where data are missing and fail to capture physical assets' future developments and conditions* (e.g., future expansions of infrastructure and the effects of aging and deterioration). Creating the digital twins also entails deciding the boundaries and resolution of the virtual representation and selecting specific models for the intended analyses from multiple candidate models, each of different fidelity and computational costs (Gardoni and Murphy 2020; Tabandeh et al. 2021a; Nocera and Gardoni 2021a). In addition, the digital twin cannot entirely capture all the relevant aspects of reality. Typically, missing or limited data about physical assets and several sources of uncertainty affect the prediction of consequences. Uncertainty propagation, hence, must be included when creating the digital twins to define the likelihood of different scenarios. *There is a need for a systematic approach for creating such a probabilistic virtual representation of physical assets*.

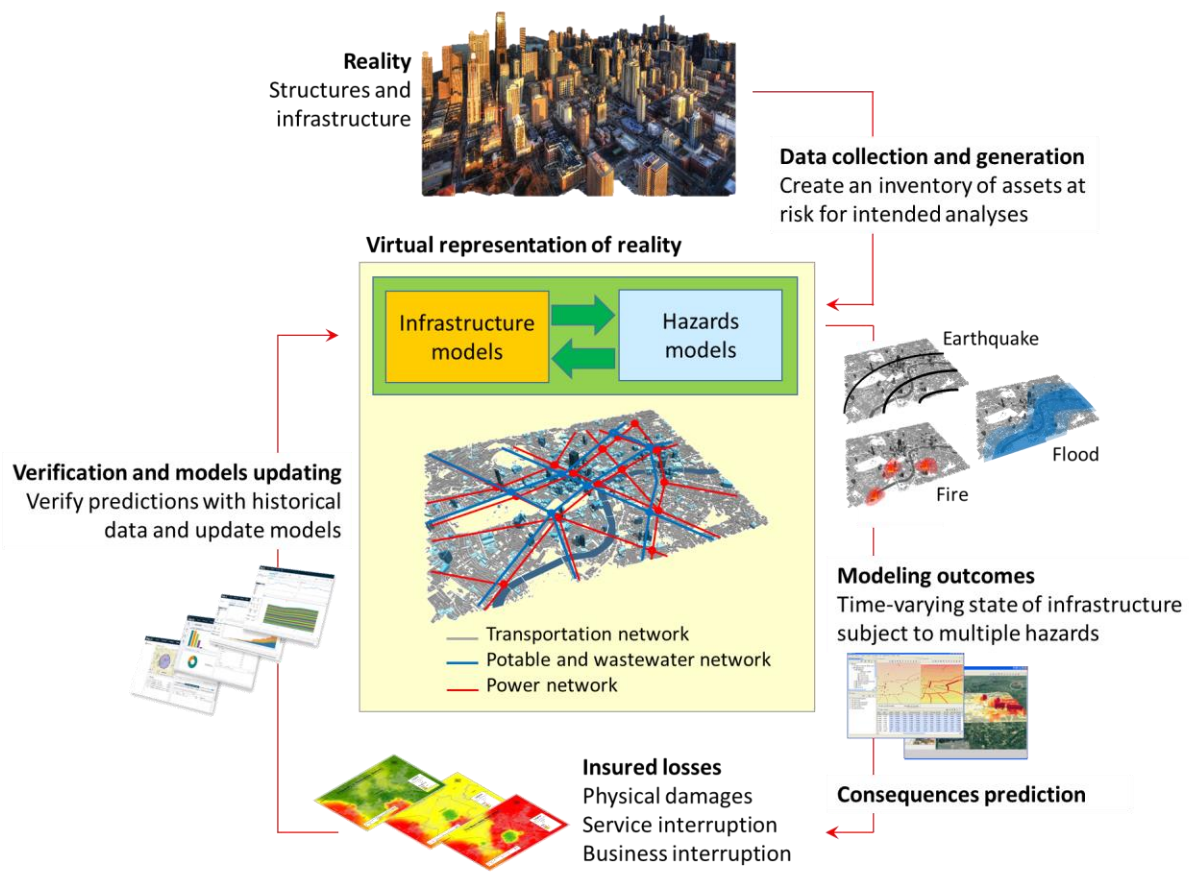
Physical assets can be subject to multiple hazards during their service lives. Significant attention has been paid to the seismic risk of earthquake main shocks. However, earthquake main shocks are typically followed by a sequence of aftershocks occurring shortly after the main shock, well-before any repairs and recovery can be implemented. Damage sustained from a significant main shock makes physical assets more vulnerable and more likely to collapse with a small aftershock (Kumar and Gardoni 2014; Hu et al. 2018). The spectrum of hazards is also expanding; hurricanes and wildfires have been occurring more frequently with significantly increasing losses. Different hazards may interact with one another (Gardoni and LaFave 2016). For example, the likelihood of landslides and flooding increases in regions previously impacted by wildfires (e.g., Kousky et al. 2018; Raymond et al. 2020). Risk analysis of physical assets distributed over a large area (e.g., infrastructure and building portfolios) requires modeling the spatial extent of the hazards' impact. When modeling the temporal and spatial evolutions of hazards, data scarcity poses a significant challenge. Extreme events such as earthquakes, hurricanes, and wildfires are, by definition, rare; hence, accurate modeling of their intensity measures cannot solely rely on recorded data from past events. In addition, climate change is making data from past events less informative. The past is not always a reliable predictor of the future. The current approaches used in catastrophe modeling usually rely on fully physics-driven hazard models (e.g., Grenier et al. 2020). *However, fully physics-driven models are computationally intensive and require many input data that are difficult to obtain and uncertain. In turn, these input data introduce significant uncertainties in model predictions.*

The state of physical assets and their level of interdependencies control the spatial extent of hazard-induced damages and determine the duration of post-disaster disruptions to the services they provide to businesses and communities (Sharma et al. 2020a; Iannacone et al. 2021; Nocera and Gardoni 2021b). The accumulation of damages due to aging and deterioration processes (like corrosion) and past extreme events like earthquakes, hurricanes, or wildfires makes physical assets increasingly vulnerable to future hazards if no or only partial restoration is implemented. The increased vulnerability makes the asset more susceptible to severe damages, prolongs its post-disaster recovery, and increases the chances of extensive reduction or loss of services provided by the asset (Jia et al. 2017; Sharma et al. 2018; Iannacone et al. 2021).

A realistic risk assessment also requires capturing the effects of improvement strategies such as maintenance, repair, retrofit, and recovery activities (Jia et al. 2017; Iannacone et al. 2021). This is key to encouraging organizations and communities to proactively embrace the actions that will make them less vulnerable to risk. As a result, insurance will be more available and affordable in high-hazard areas. In addition to the temporal changes in physical assets, their spatial interdependencies also play a significant role in risk analysis (Guidotti et al. 2016; Sharma et al. 2019, 2020a,b). The collection of different physical assets forms an interdependent system whose components interact with one another and with hazards (Sharma and Gardoni 2019, 2021). For example, electric power transmission lines that traverse heavily forested areas can trigger wildfires. In turn, power outages due to wildfires or preventive power shutoff can significantly affect businesses and other infrastructure that rely on provided services (Nocera and Gardoni 2019a,b). *However, current modeling, design, maintenance, recovery, financing principles, and regulatory standards usually focus on physical assets in isolation and do not consider hazards' interactions and their combined effects on the physical assets' time-varying vulnerability*.

MAE Center's approach to risk analysis of physical assets

Risk analysis starts with data collection and creating a digital twin of reality - a fundamental step that controls all the subsequent analyses. The developed physics-based models for physical assets and different hazards are part of the creation of the digital twin. A significant challenge in modeling the impact of rare events is the scarcity of recorded data. The scale of physical assets, specifically the interdependent infrastructure, also makes it impossible to use experimental data. The MAE Center approach to the data scarcity challenge has two aspects. First, the developed approach has a hierarchical structure that leverages models at levels at which data are more available. Second, at lower levels of the hierarchy, physics-based models are developed that integrate first principles (i.e., rules of physics and mechanics) with the more available data. The developed physics-based approach facilitates updating models incorporating the effects of deterioration, repair, maintenance, and recovery. The digital twins coupled with physics-based models allows us to generate incurred losses maps under different hazard scenarios and at different times during physical assets' service lives. Physics-based models can be updated based on data from historical events. We use such data to verify the developed models and update them to improve their future predictions.



The MAE Center at the University of Illinois at Urbana-Champaign developed a rigorous approach for risk analysis of physical assets subject to multiple hazards. The approach accurately predicts the consequences of damages to physical assets and their spatiotemporal variabilities for risk-informed decisions. This paper focuses on the three general areas that represent current research gaps in the risk analysis of physical assets, namely, the development of a systematic approach to creating digital twins of physical assets, the modeling of the spatiotemporal evolution of hazards, and the modeling of the time-varying vulnerability of interdependent physical assets. The paper presents the significance of these gaps and how the MAE Center approach has addressed them. The rest of the paper is organized into five sections. To provide context, Section 2 gives a brief overview of insurance risk assessment. Section 3 presents the current gaps in the risk analysis of physical assets. Section 4 explains the developed MAE Center approach to address the current gaps. Finally, the last section summarizes the paper.

2. Insurance Risk Assessment

Insuring physical assets subject to natural hazards has traditionally focused on structures and not infrastructure. However, there is a rising concern and motivation for risk-informed infrastructure management (Tonn et al. 2021). Some insurance policies cover the losses incurred by individuals or businesses due to the cascading effects of loss of infrastructure services (NAIC 2020). So, considerations might also be given to insured infrastructure. This section discusses essential requirements for insurance risk analysis that are valid for both structures and infrastructure.

2.1. Determining the value at risk

Determining the value at risk is based on the valuation of the inventory of the assets exposed to the considered hazards. It requires the inventory of the assets, the valuation of the assets, and the hazard exposure footprint.

Some geographical boundaries usually define the extent of exposed inventory for risk analysis. Different stakeholders may be interested in different regions of interest. For example, a government may define the region of interest within certain political or mapped geographic boundaries (such as territories or counties), while a business such as an insurance company may define the region of interest as an area in which it underwrites insurance coverage. Creating an inventory for analysis requires collecting data (sometimes, but not always, publicly available) and generating data by inference from different sources or generating synthetic data (Boakye et al. 2019; Sharma et al. 2020 a,b) to supplement the existing data. Because the inventory and operational details of physical assets can be misused, data collection and use must follow privacy laws and laws governing strategic assets' security. Data availability, types, and structures might vary from place to place, even within the United States.

Once we have defined the region of interest and created the assets' inventory, the next step is to assign a value to each asset. In general, such valuation may differ depending on the type of stakeholder and intended analyses. In the insurance industry, monetary or financial risk measurement is the most common form of valuation (Grenier et al. 2020). Outside the insurance industry, valuation in terms of impact on people's well-being has also been used (Murphy and Gardoni 2006; Gardoni and Murphy 2020). When using a monetary or financial measure, we assign an economic value to each element in the inventory. The value maybe the present value or a replacement cost of the physical asset. Discounting processes such as depreciation and present net worth may also be relevant if the economic value is present value rather than replacement cost (Gardoni et al. 2016b).

The final step is to identify the subset of the inventory exposed to a hazard in specific scenarios. Hazard exposures can be direct or indirect due to cascading effects (e.g., propagation of damages from other assets that are directly damaged, or propagation of disruptions through supply chains.) However, most physical damages are due to direct exposure to hazards. Natural hazards usually feature specific spatiotemporal patterns. The footprint can be from a past event for validation or from a hazard model that creates probable hazard scenarios for future events' predictions.

2.2. Determining the insured losses

Once we have the inventory and value at risk, we can calculate the losses by combining the hazard intensity information at each location with the vulnerability of each asset to the hazard intensity. The inventory must contain additional data for each asset to determine insured losses. Typical data include the physical and geometric attributes that determine the vulnerability of each asset to specific hazards. Examples of such attributes for buildings include year built, construction type, number of stories, and occupation type. If the functionality and cascading impacts on consumers and businesses are also of interest, the inventory must contain information regarding the operational characteristics of the physical assets. Examples of such operational characteristics for potable water infrastructure include the consumption rate and pattern, working pressure and velocity, tanks and pumps hydraulic properties.

Since structures and infrastructure components are part of a system, their damages may propagate with cascading effects across the system. We can account for the propagation of damages by analyzing the operations of structures and infrastructure and modeling the loss or reduction in their functionality. Using the functionality, we can calculate two types of losses, i.e., the loss due to damage propagation and the opportunity cost of unavailable services.

Financial losses may also occur due to liability. The damage to the assets owned by one entity may result in damage to other public or private properties. The magnitude of loss in liability may be more severe and more challenging to predict than the direct damage. For example, Pacific Gas and Electric Company (PG&E) suffered enormous financial loss when found liable for starting wildfires and causing property damage and loss of life. The company was found guilty of causing 84 deaths and agreed to pay $13.5 billion to people who lost their homes and businesses from wildfires during the 2017 and 2018 wildfires, which led to PG&E filing for bankruptcy protection (Brickley 2019; Penn and Eavis 2020). Such losses can be predicted by considering the interdependencies of systems subject to multi-hazard scenarios (Guidotti et al. 2019; Gardoni 2019; Sharma and Gardoni 2021).

Finally, the lack of services may lead to cascading impacts on dependent individual businesses and whole economic sectors. Such losses for individual companies may be insured under additional coverage, such as contingent business interruption insurance (Nocera and Gardoni 2019a,b). For example, the recovery of power may take several days after the hazard occurrence, and a business may lose production capacity due to the lack of power. A business may also lose demand if the consumers relocate or change their consumption patterns due to the hazard impact.

3. Current Gaps

The risk analysis of physical assets presents several challenges and research opportunities. The MAE Center has been working on tackling several of these challenges. This section provides an overview of some of the challenges; the following section presents how the MAE Center has addressed them by improving state-of-the-art risk analysis of physical assets.

Accurate risk analysis relies on an equivalent digital twin of physical assets' reality. There are several challenges in creating the digital twins of physical assets, which are either overlooked in current research or addressed in an ad hoc manner. Significant challenges include 1) dealing with missing, incomplete, and unstructured data about physical assets characteristics and their operating conditions; 2) the definition of digital twins' boundaries to accurately capture direct damages to physical assets, their functionality losses, and indirect losses due to cascading effects, 3) the selection of digital twins' spatial and temporal resolutions for reducing the computational cost while maintaining the desired level of accuracy for intended analyses, and 4) the selection of computational models from multiple candidate models subject to available computational resources and the desired accuracy level.

An additional challenge is developing an accurate hazard model that provides the hazard's intensity at each exposed asset. Depending on the hazard, several types of models can be used for developing hazard intensity maps, such as high-fidelity simulation of the hazard physics or statistical models based on past data and limited simulations of physics-based models. The high-fidelity simulations of the hazard require a large amount of data and computational resources. However, such models can generate accurate hazard maps only if the input data are known with high certainty. On the other hand, statistical models require fewer input data and computational resources at the cost of higher model uncertainty. Another gap in current approaches for risk analysis is the unavailability of spatiotemporal models that can provide high-resolution results in the region of interest with reasonable accuracy and manageable computational cost (Contento et al. 2019a,b, 2020).

The last challenge is related to the time-varying vulnerability of interdependent physical assets. The state of physical assets at the time of the occurrence of a hazard and their level of interdependencies determine the extent of damages to these assets and the following cascading disruptions. Typical vulnerability estimates are time-invariant. However, physical assets deteriorate during their service lives due to routine use, an aggressive operating environment, and past extreme events. Deteriorations are an important concern in risk analysis since they can significantly increase the vulnerability of physical assets. Deteriorations are also highly uncertain and not easily detectable unless extensively developed. By the time the deterioration becomes visible, a substantial portion of the physical asset's service life has already been depleted, and costly repair or replacement would be inevitable for continued operation. In the absence of a proper account of deterioration, the errors in estimating the vulnerability of physical assets (and in turn of their damage and recovery times) can be significant (Choe et al. 2009, Kumar and Gardoni 2012, 2014a,b, Gardoni 2017). The states of physical assets may also vary due to various maintenance, repair, and recovery activities (Kumar et al. 2015; Jia et al. 2017; Jia and Gardoni 2018; Sharma et al. 2020). Interdependencies among physical assets can further amplify already increased vulnerabilities due to cascading effects. Inadequate maintenance and recovery preparedness (possibly due to the lack of information about physical assets' actual state) can result in hazard consequences that go far beyond the expected damages and a slower recovery (Ayyub 2014; Gardoni 2019; Nocera et al. 2019a). A realistic risk analysis of physical assets requires models to predict their time-varying vulnerabilities, hazard-induced damages, and physical and service recovery.

4. Addressing the Current Gaps

4.1. Virtual representation of physical assets

Creating a virtual representation of physical assets begins with collecting and integrating data about structures and infrastructure from multiple sources, such as utility companies, insurers, government organizations, published research, and social media (Boakye et al. 2019; Sharma et al. 2021). The type, amount, and structure of required data depend on the intended analyses and the physical quantities of interest. For example, if the value at risk is of interest, data collection can be limited to the region of interest impacted by relevant hazards and include the number of physical assets of different types and their geolocations. Instead, if infrastructure functionality and cascading effects on people and supported businesses are of interest, data on operational attributes are also needed.

Raw data collected from different sources are typically unstructured and incomplete. As a result, the data need to be processed and synthetically enhanced to create a complete virtual representation of reality (Boakye et al. 2019). We use data mining and big data analytics to process unstructured data and extract structured information for use in the intended analyses. For the treatment of incomplete data, we generate representative data using both novel methodologies and best industry practices. Examples include the generation of synthetic data

Creating the virtual representation requires deciding the boundaries and modeling the resolutions of structures and infrastructure, capturing their interdependencies, and selecting models for specific analyses. For example, the definition of the footprint of infrastructure typically depends on the following four key factors:

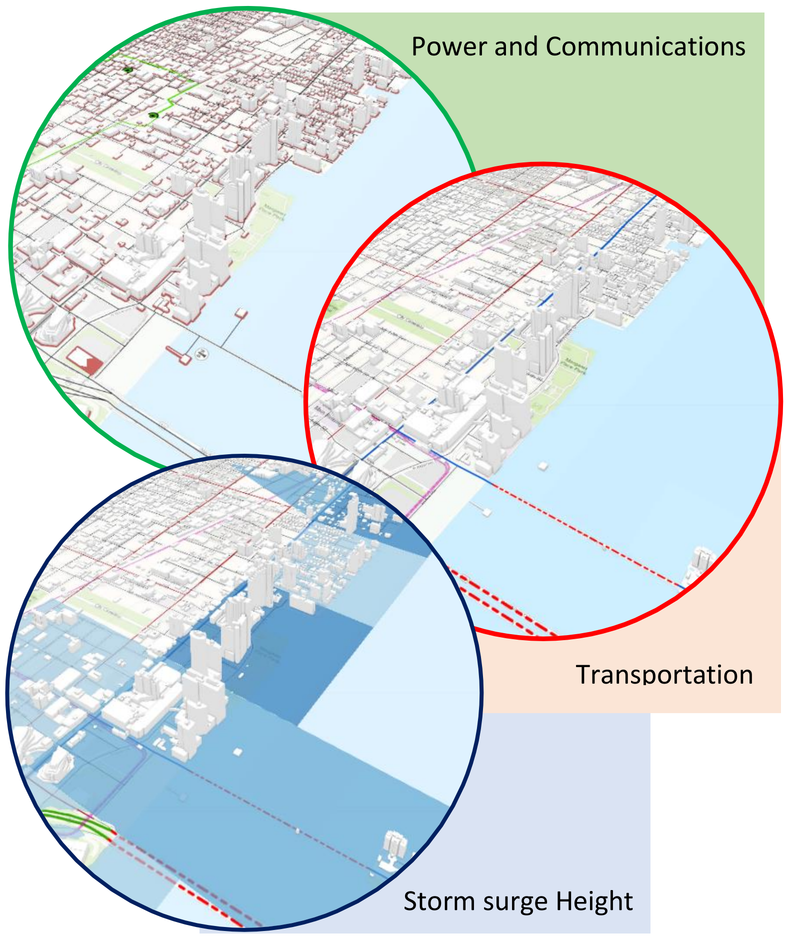
- The type of information of interest (physical damage or functionality analysis);
- The existence of easily recognizable physical boundaries and the possibility to model the boundary conditions;

- The existence and location of strategic elements need to be included, like generation nodes (depending on the purpose of analyses); and
- Modeling of damage propagation among physical assets.

Once the footprints of the structures and infrastructure are defined, we need to define their modeling resolutions. For example, modeling infrastructure at different resolutions affects our ability to capture the spatial variability of hazards' impact on infrastructure. A detailed representation of infrastructure requires a significant amount of input data and high computational costs. In contrast, a simplified representation of infrastructure (i.e., a skeletonized network) requires less detailed input data and has lower computational costs. However, the adoption of a skeletonized network may affect the accuracy

Virtual Representation of Hazards and Infrastructure in Miami-Dade County, FL

In this example, the region of interest is defined by the political boundaries of Miami-Dade County, Florida. We created the digital twin of the power, communications, and transportation in this region of interest. We created the inventory that includes geolocation of physical assets, type of asset, quantity, operational attributes, and monetary value. We considered a storm surge hazard scenario due to a hurricane. We estimated the water height at each location as discussed in Section 4.2. The figure below shows a 3D of the typical details we created over the entire region of interest.



of the results. A skeletonized network may be unable to capture the changes over time and space in the relevant quantity of interests and the cascading effects due to interdependencies among infrastructure (Guidotti et al. 2019).

Infrastructure Value at Risk of Storm Surge in Miami-Dade County, FL

We used the digital twins, the hazard intensity measures for the selected scenario, and the monetary values of each asset to estimate the value at risk of storm surge in the region of interest. The table below shows a subset of the infrastructure inventory that falls within the defined footprints of the storm surge. The rates are typical reconstruction costs and used for illustration purposes only. We calculate the total infrastructure value at risk subject to storm surge to be above 10 billion dollars.

Asset	Unit	Quantity	Rate[1]	Value[2]
Highway and interstate	Lane miles	507	4.00	2,028
Local	Lane miles	4,178	1.50	6,267
Thoroughfare	Lane miles	587	2.00	1,174
Unpaved	Lane miles	129	1.00	129
Bridges	Lane miles	18.5	40.0	740
Tunnels	Lane miles	3	10.0	30
Power transmission	Miles	277	2.00	554
Power distribution	Miles	3,906	0.50	1,953
Power plants	Number	2	500.0	1,000
Power substations	Number	38	2.00	76
Communication antennas and towers	Number	86	0.20	17.2
			Total	13,968.2

[1]The rate is in million $ per unit, for illustration only
[2]The value is in million $

We developed a rigorous approach to select the appropriate modeling resolution of infrastructure (Nocera and Gardoni 2021a). The developed approach addresses the tradeoff between accuracy and simplicity when modeling infrastructure. The developed approach uses information from the topology of the infrastructure model to obtain equivalent networks. The equivalency depends on the modeled infrastructure, type of analysis, and information of interest. For instance, in a connectivity analysis for a transportation system, links in an equivalent network can have an equivalent length representing the total length of the simplified roads. Similarly, considering a flow analysis for a power system, edges in an equivalent network can have equivalent operational attributes, such as electrical resistance and impedance. Furthermore, we developed metrics to estimate the accuracy of equivalent networks. The developed metrics measure the level of agreement between estimates of the quantities of interest computed using different network resolution levels. The information from such a metric is used to inform if a skeletonized network is sufficiently detailed or oversimplified. In the developed approach, the selection of the modeling resolution is iterated until the desired tradeoff among accuracy, simplicity, and computational efficiency is achieved.

4.2. Spatiotemporal evolution of hazards

This section presents physics-based probabilistic models for several hazards. The models address the data scarcity problems in modeling rare events by combining first principles (i.e., rules of physics and mechanics) with data from multiple sources. For short-term predictions, these models can help optimize resource management (both human and economic) in the aftermath of hazards. For long-term predictions, these models can help develop suitable strategies for updating insurance premiums (Contento et al. 2017) and develop financial instruments such as catastrophe bonds (Hofer et al. 2019, 2020).

Hazard models must capture the spatiotemporal variabilities of intensity measures to determine the impacts on physical assets. For a given scenario, the hazards' footprint (defined as the region where physical assets have non-zero failure probability) could be smaller than the footprint of physical assets, yet it should generally contain the source of the hazard. However, the hazard model's footprint (defined as the region over which we need to estimate hazards' intensity measures) needs to be at least as large as the footprint of physical assets. The resolution of the hazard models affects the ability to capture the spatiotemporal variabilities of hazards' intensity measures over physical assets' footprint, which is critical for modeling damages to physical assets distributed over a large area. Considering a seismic scenario as an example: in a region within 30-50 km from the earthquake source (i.e., in the near-field of the seismic source), directivity effects may induce higher values of intensity measures along specific directions, or the shape of the basin and the specific topography may result in amplification effects. These factors limit the accuracy of traditional ground motion prediction equations. Therefore, the use of more accurate models such as three-dimensional physics-based models (e.g., Stupazzini et al. 2019) may be needed to capture these aspects.

4.2.1. Earthquakes

An accurate prediction of earthquake intensity measures is critical to the seismic risk analysis of physical assets. Earthquake main shocks are usually followed by a sequence of aftershocks of relatively significant magnitudes and a high occurrence rate that gradually decays over time (Utsu and Ogata 1995). Therefore, physical assets might be subject to a sequence of shocks, not only a single main shock. The increased vulnerability of physical assets in the aftermath of a main shock further highlights the significance of capturing temporal aspects in seismic risk analysis (Yeo and Cornell 2005; Kumar and Gardoni 2012). The estimates of earthquakes' intensity measures generally depend on the characteristics of seismic sources, the travel paths of seismic waves, and local site conditions. In a sequence, the main shock and its following aftershocks occur spatially and temporally close to each other and, thus, share similar seismic characteristics (Hu et al. 2018). Mathematically, such similarities introduce spatial and temporal statistical dependence among the estimates of earthquake intensity measures (Hu et al. 2018). Therefore, accurate seismic hazard analysis requires modeling the joint probability distribution of earthquake intensity measures in main shock-aftershocks sequences.

The database of recorded earthquake ground motions for main shock-aftershocks sequences is sparse and lacks required variabilities for many regions and assessment scenarios. Therefore, there has been increasing interest in generating synthetic ground motions that integrate results from seismological and geotechnical models with empirical data (Hu et al. 2018). Alternatively, Ground Motion Prediction Equations (GMPEs) provide selected information about earthquake ground motion intensity measures for a given earthquake and can be coupled with hazard functions that define the likelihood of an earthquake of a certain intensity (Kumar and Gardoni 2013). Information from the GMPEs captures specific characteristics of earthquake ground motions that might be relevant to the seismic risk assessment of specific physical assets, such as the peak ground acceleration at a site and the spectral accelerations at different natural periods. Current GMPEs represent a set of univariate probabilistic models that partially capture the spatial statistical dependence of individual intensity measures at different sites. The literature includes supplementary models that capture statistical dependence among 1) different intensity measures at a given site and 2) vectors of intensity measures at different sites. Likewise, we need to generalize current GMPEs to model the temporal evolution of earthquake intensity measures in main shock-aftershocks sequences. This extension generally requires GMPEs for the intensity measures of earthquake aftershocks and modeling the temporal statistical dependence among the intensity measures of 1) each main shock and its aftershocks, and 2) different aftershocks in the same sequence (Hu et al. 2019).

We developed mathematical formulations to generate synthetic ground motions and predict their intensity measures in main shock-aftershock sequences (Hu et al. 2018, 2019). The developed stochastic model for synthetic ground motions captures the spatiotemporal evolution of main shock-aftershock sequences in a two-step process (Hu et al. 2018). The model first generates a scenario that includes realizing the magnitudes, locations, and occurrence times of main shock-aftershock sequences (see Figure 1). For each main shock or aftershock event, the model then generates representative synthetic ground motions for specific seismic characteristics and site conditions. Additionally, we developed a mathematical formulation to model the joint probability distribution of the vector of intensity measures and their evolution over time in main shock-aftershock sequences (Hu et al. 2019). The developed joint probability distribution integrates the developed sub-models for main shocks, aftershocks, and their statistical dependence. For main shocks, we use current GMPEs to estimate the vector of intensity measures, whereas, for aftershocks, we develop a set of new GMPEs. The developed GMPEs for aftershocks capture 1) the nuances in modeling the intensity measures of aftershocks beyond a single correction term in current GMPEs, and 2) the temporal statistical dependence among intensity measures of aftershocks in the same sequence.

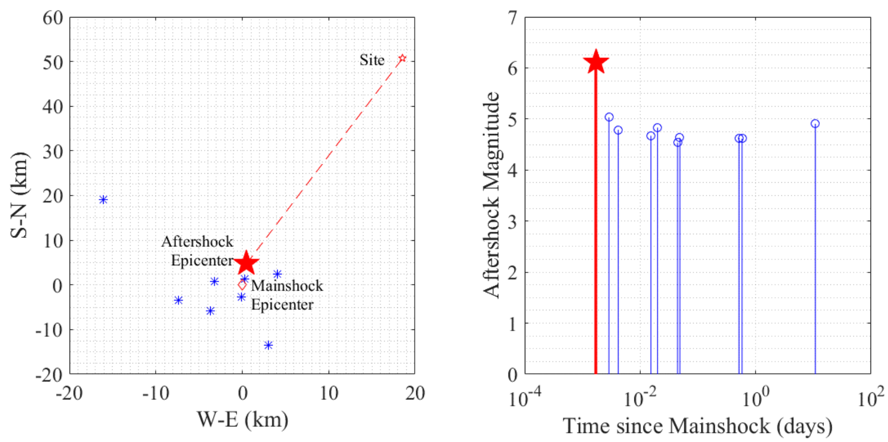


Figure 1: Generated main shock-aftershocks sequences scenario that includes the realized spatial distribution of the shocks (left plot) and their time-varying magnitudes as a function of time elapsed since the occurrence of the main shock (right plot) (Adapted from Hu et al. 2019)

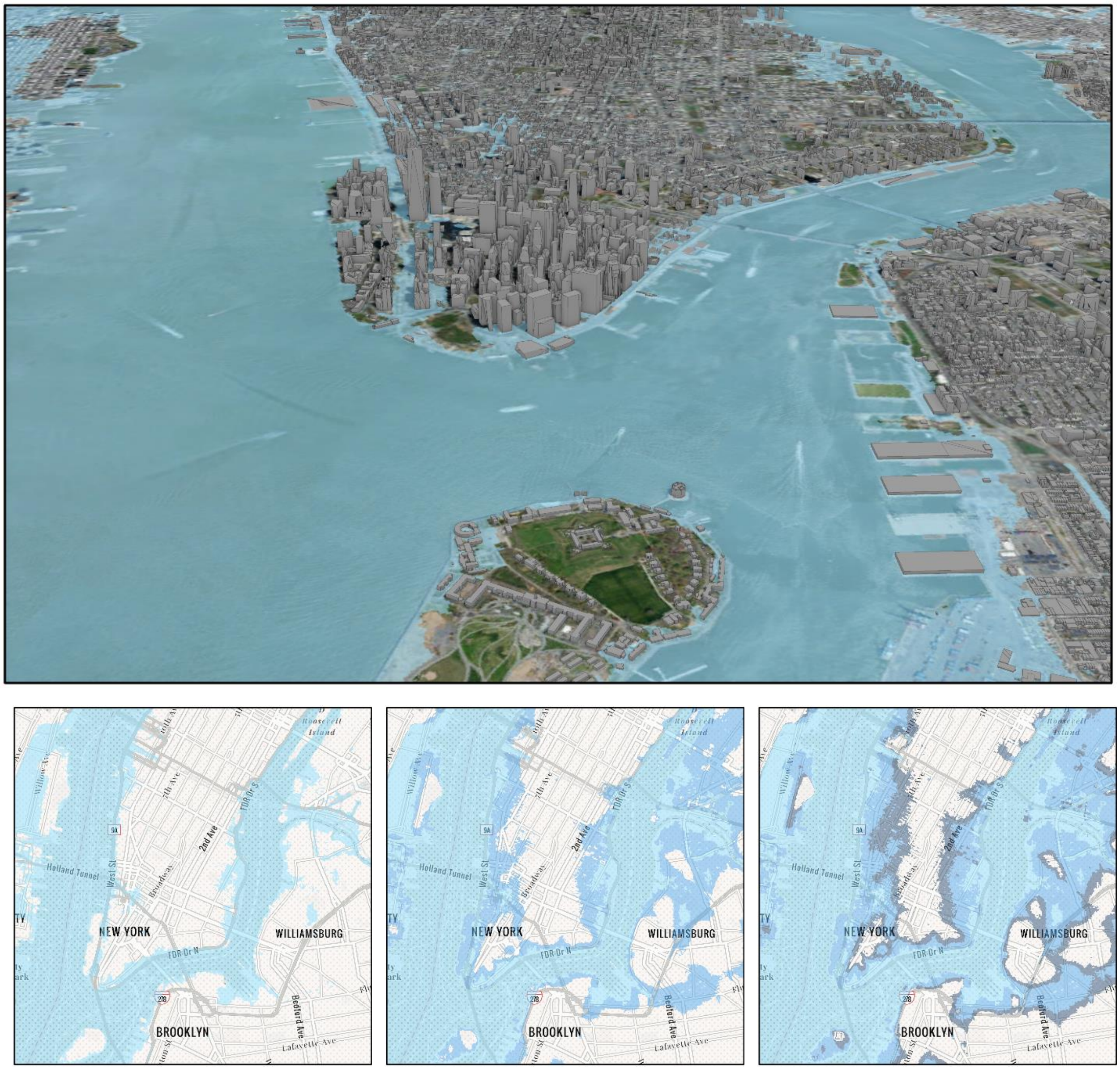
4.2.2. Storm surges

Hurricane hazards pose a severe threat to large portions of the coastal areas of the United States. Among the different aspects of the hurricane hazard, storm surge is responsible for a significant portion of the damage to physical assets and has a profound economic impact. Storm surge is an abnormal rise of water generated by a storm above the astronomical tide. In the last decades, hurricanes such as Ike in 2008 and Katrina in 2005 resulted in devastating damage to physical assets due to storm surges. The damage to physical assets from Ike is estimated at $24.90 billion, while damage to physical assets from Katrina is estimated to be higher than $108 billion. The effects of climate change may increase the frequency and magnitude of extreme weather events like hurricanes (Murphy et al. 2018; Contento et al. 2019b). Likewise, the shifts of population and economic development to hazard-prone coastal areas of the United States and the continuously increasing population density increase the exposure conditions. Consequently, the related damage to physical assets and the related economic losses may further increase in future hazard scenarios (Contento et al. 2017; Murphy et al. 2018).

Storm surge is primarily caused by the hurricane's strong winds and geomorphological characteristics, with a minimal contribution from the low pressure of the storm. The wind circulation around the eye of a hurricane produces a vertical circulation in the ocean. In shallow waters near the coast, the horizontal circulation is disrupted by the ocean bottom; thus, the water rises and goes inland. Due to many factors in play, even a low-intensity hurricane can generate a high surge. For example, Hurricane Ike, a Category 2 hurricane on the Safir-Simpson scale, generated a storm surge of several meters in height.

The models currently available use shallow-water equations to model the hydrodynamics of the storm surge. Examples include the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) model (Jelesnianski et al. 1992) and the Advanced Circulation (ADCIRC) model (Westerink et al. 1994). However, models like SLOSH and ADCIRC are computationally inefficient, and the hardware required to support the computational burden is not commonly available to perform probabilistic analyses. Their computational inefficiency also makes it impossible to develop real-time predictions as hurricanes unfold.

We developed physics-based models to estimate the time evolution of storm surges (Contento et al. 2020). The developed models provide an estimate of the probability of a location being flooded, as well as estimates of the storm surge heights if a location is predicted to be flooded. The developed models capture the fundamental physics of the phenomena, expressing the storm surge's dependence on factors such as wind speed, central pressure, the distance of the hurricane eye to the location, bathymetric slope, and convexity of the coastline. Furthermore, the flexibility of the developed formulation enables using data from both high-fidelity simulations and historical records. The models can be trained with records related to the actual climate and then updated to consider different climate change scenarios. Such models are suitable for probabilistic analyses because the estimates are obtained with a limited computational burden compared to models like SLOSH or ADCIRC. Specifically, the developed models can be used for both long-term and short-term predictions. For the long-term predictions, the models predict storm surge for a given climate change scenario. For the short-term predictions, the models can be used to provide real-time estimates of storm surge as the hurricane unfolds. Figure 3 shows a schematic description of the obtained results from such real-time predictions in terms of the evolution of storm surge height in a region of interest. The figure shows three snapshots of the flooded region at evolving times t_1, t_2, and t_3.



time t_1 time $t_2 > t_1$ time $t_3 > t_2$

Figure 2: Schematic description of the predicted storm surge height over time in a region of interest

The predictions can be updated in real-time as new forecasts and additional surge records at different locations become available over time. The model updating allows us to tailor the generic probabilistic model to a specific region and hurricane. Figure 3 illustrates the schematic of the modeling approach in the case of short-term predictions (Contento et al. 2021). Figure 3a shows the initial prediction of the storm surge height at an example location. Figure 3b shows the schematic of the updated prediction at the same location as the hurricane unfolds, i.e., as the position of the hurricane (at the time of the updating), its expected track changes, and new data become available.

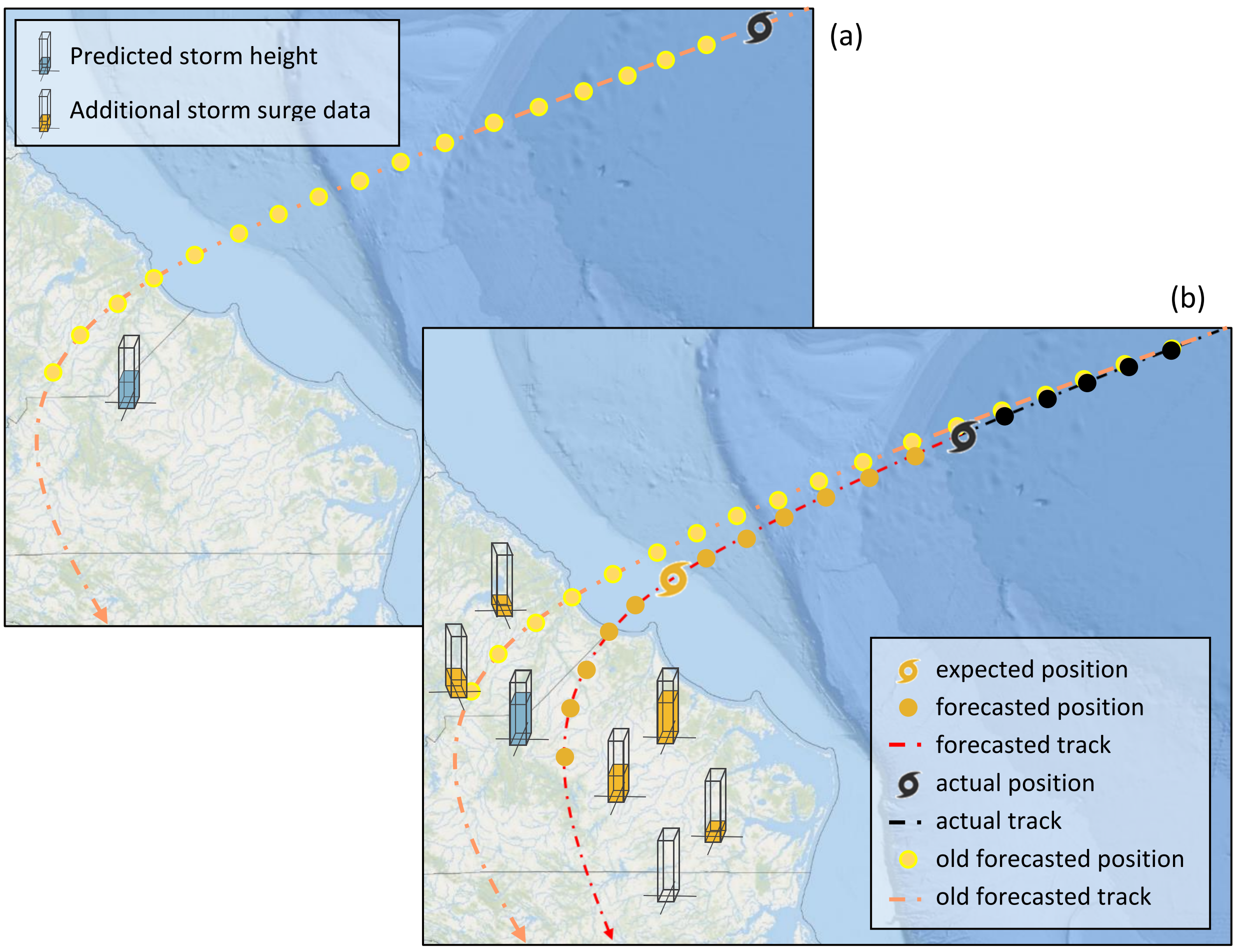


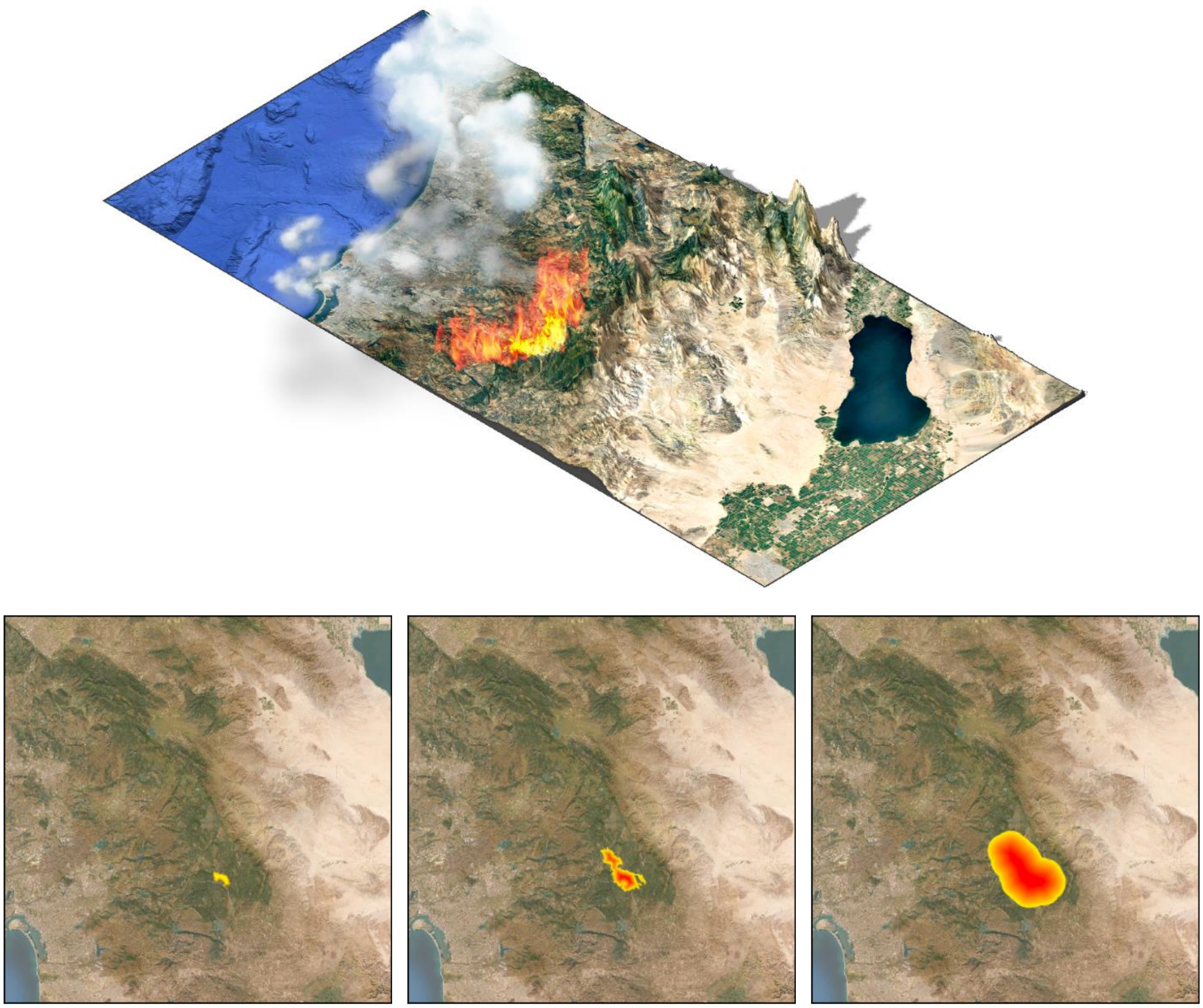
Figure 3: Schematic of the short-term storm surge height predictions as the hurricane unfolds (Adapted from Contento et al. 2021)

As an example, we made long-term predictions assuming the worst-case scenario for climate change (8.5 RCP scenario) (Contento et al. 2019). We tailored the models for a specific region in North Carolina (i.e., the area surrounding the Tar River and the Pamlico River). For each location, we predicted the probability of being flooded and the corresponding storm surge height. As an example of updating short-term predictions, we simulated the storm surge from Hurricane Michael, assuming an exact hurricane forecast. Updating the model even after a few hours since its approach to the United States coast leads to significant accuracy (Contento et al. 2021).

4.2.3. Wildfires

Wildfires are a growing concern with significant annual losses. A recent series of wildfires in Northern California became one of the deadliest and most destructive fires on record, killing at least 88 people, burning about 14,000 residences and 530 commercial structures, and causing over 12 billion dollars of total insured losses (III 2019). The changes in the frequency and intensity of wildfires and exposure conditions contribute to the growing trend of insured losses. Significant contributing factors include climate change, rapidly growing development into the wildland-urban interface (i.e., intermix of structures and infrastructure with fire-prone vegetation), and lack of wildfire suppression policies. Most catastrophic wildfires are started and sustained under extreme weather conditions, with high daytime temperatures, strong changing surface winds, and dry conditions. Future perspectives of climate change tend to favor extreme drought and alter precipitations, leading to longer fire seasons (Allen and Ingram 2002; Rochoux 2014; Kousky et al. 2018). On the exposure side, developments in the wildland-urban interface increase values at risk as well as protection costs due to the wildfire suppression (Gan et al. 2014). In turn, the accumulation of vegetation fuels on the ground due to such suppression efforts can increase likely wildfires' intensity (Gan et al. 2014).

Wildfires propagation features a complex behavior that integrates multiple physical processes across different scales of length and time (Tabandeh et al. 2021). In the governing physical processes, the vegetation scale characterizes biomass fuels, the flame scale characterizes combustion and heat transfer processes, the topographical scale characterizes terrain and vegetation boundary layer, and the meteorological scale characterizes atmospheric conditions (Rochoux 2014). Figure 4 shows a schematic description of the obtained results from the wildfire propagation model. The figure shows three snapshots of the burned region at evolving times t_1, t_2, and t_3. As shown in the figure, wildfires generally feature a front-like geometry that propagates into unburned vegetation. Vegetations ahead of the burning zone receive a significant heat flux from the flame, leading to increased temperature. The intensity of the heat flux decreases with distance from the flame. The direction and speed at which wildfire propagates result from interactions among different physical processes, namely the pyrolysis processes at the vegetation scale, combustion and flow dynamics at the flame scale, and atmospheric dynamics and chemistry meteorological scale. Firebrands' advection also contributes to wildfire propagation by spotting effects, where embers are lofted from fire and transported up to miles downwind.



time t_1 | time $t_2 > t_1$ | time $t_3 > t_2$

Figure 4: Schematic description of the predicted wildfire propagation in a region of interest

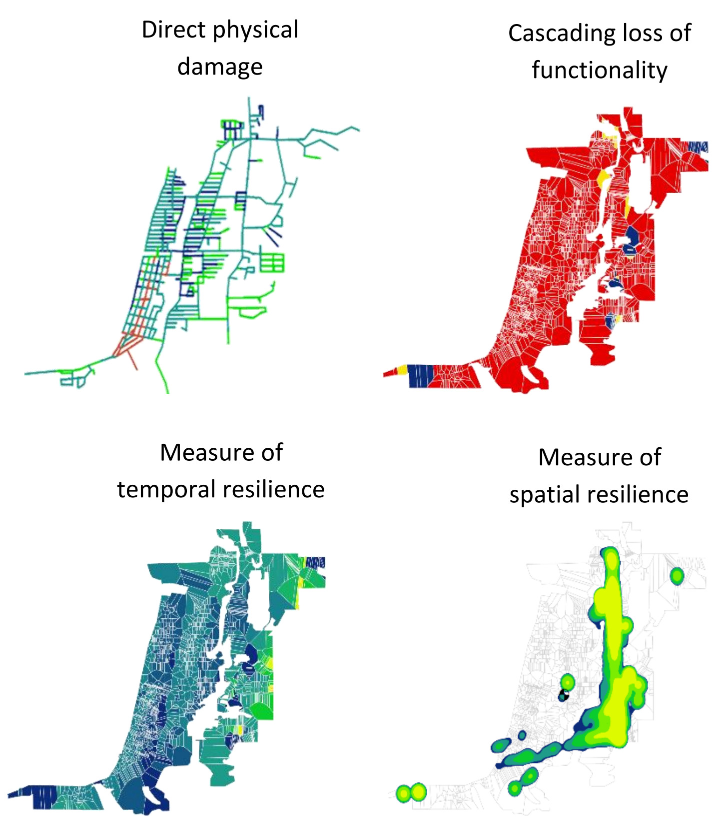
We developed a mathematical formulation to model wildfire propagation using the level-set method, a computational method to track moving fronts (Tabandeh et al. 2021). The level-set method (Osher and Sethian 1988) relies on an implicit representation of fire fronts whose dynamics are governed by a Hamilton-Jacobi partial differential equation. The governing equation captures the dependence of the propagation speed and direction on front geometrical properties such as its gradient and curvature, vegetation properties, weather conditions, and terrain topography. Specifically, we integrate available empirical models that capture the dependence of the propagation speed and direction on the governing factors into the level-set equation. These empirical models are calibrated based on general data outside the formulated level-set equation. In specific propagation cases, we may update these models using specific data at different scales. In addition to the typical advective propagation mode, the developed mathematical formulation captures the contributions of turbulent hot-air transport and fire-spotting in wildfire propagation. The obtained results are affected by various sources of uncertainty in the model inputs, including boundary and initial conditions, vegetation properties, wind intensity and direction, model parameters, and possible errors in numerical solutions. To account for these sources of uncertainties, we developed a differential equation that governs the evolution of the probability distribution of fire fronts. We also developed a novel numerical method to compute the probability distribution.

4.3. Time-varying vulnerability of interdependent systems

We developed an approach to model the time-varying vulnerability and resilience of interdependent physical assets while capturing their deteriorations (Iannacone et al. 2021). The developed approach has a hierarchical structure with three primary levels (e.g., material, structure, infrastructure). First, we developed mathematical models for the time-varying processes affecting interdependent physical assets. These models capture the effects of external drivers, including gradual deteriorations (e.g., due to corrosions), shock deteriorations (e.g., due to past extreme events), or maintenance, repair, and recovery. Such effects cause spatiotemporal changes in the variables that define physical assets (e.g., variables that define geometry, boundary conditions, and material properties, which are collected data in creating the digital twin.) Second, we developed mathematical models to predict the time-varying vulnerability of interdependent physical assets (Gardoni et al. 2002; Choe et al. 2008, 2009; Kumar and Gardoni 2014; Iannacone and Gardoni 2018; Nocera et al. 2019b; Xu and Gardoni 2020a). For this purpose, we model infrastructure as a collection of interdependent networks. For example, we developed a structural network to model a given infrastructure's vulnerability and a flow network to model its functionality (details can be found in Sharma et al. 2020). We then obtained performance measures for each network and an

Time-varying Resilience Analysis of Water infrastructure in Seaside, OR

We implemented the developed formulation to model the time-varying vulnerability of a realistic potable water infrastructure subject to earthquake excitations (Iannacone et al. 2021). The deterioration and damage models developed for water pipelines capture the corrosivity of soil, the geometry and material properties of the pipelines, hydraulic flow properties, and hazard intensity measures. The recovery model consists of a detailed schedule for the repair or replacement of damaged pipelines while considering the required crews, resources, and other scheduling constraints, as well as high-fidelity hydraulic flow analyses. The example highlights the effects of spatially-varying exposure conditions and pipelines' age on the vulnerability, functionality, recovery, and resilience of the potable water infrastructure. The resilience maps in the bottom row show a schematic description of the recovery pace (temporal resilience) and spatial disparity among the recovery pace of different sub-regions (spatial resilience). Such effects cannot be investigated using the traditional risk analysis.



aggregate performance measure for all interdependent networks. Third, we define resilience measures based on the time-varying performance measures and use them to quantify physical assets' ability to recover after disruptions (Iannacone et al. 2021). These measures of resilience capture the spatiotemporal variations of the physical assets' ability to recover. The resilience measures consider the combined effects of deterioration processes, maintenance, repair, and recovery activities in evaluating physical assets' damages due to hazards. Experimental data on deterioration and recovery are usually available at the state variables level. The developed formulation can incorporate such data to improve predictions at higher levels (i.e., up to the infrastructure level.) Implementing the governing rules of physics and mechanics at each level of the developed approach improved the models' accuracy and their applicability to assets with different characteristics.

5. Summary and Conclusions

The MAE Center at the University of Illinois at Urbana-Champaign developed a rigorous approach for risk analysis of physical assets subject to multiple hazards. The approach accurately predicts the consequences of damage to physical assets and their spatiotemporal variabilities for risk-informed decisions. The approach provides information about direct losses due to hazard damages to physical assets and indirect losses due to cascading failures and the unavailability of the physical assets' services. This paper focused on the three topics that represent current research gaps in the risk analysis of physical assets, namely, the development of a systematic approach to creating digital twins of physical assets, the modeling of the time-varying vulnerability of interdependent physical assets, and the modeling of the spatiotemporal evolution of hazards. The paper presented the significance of these gaps and how the MAE Center approach has addressed them.

Risk analysis relies on the virtual representation of physical assets. The paper presented a systematic approach for creating such a virtual representation, called digital twin, from collecting required data and generating synthetic data when data are missing and for future developments.

Specifically, the paper discussed issues related to defining the boundaries and modeling resolution when creating digital twins for specific analyses.

The paper also presented rigorous mathematical models for the spatiotemporal evolution of hazards. The paper discussed the modeling of sequences of aftershocks following a main shock for earthquakes, storm surges for hurricanes, and wildfires. The paper presented models that capture the underlying physics of the phenomena and integrate empirical data when available. Specifically, for storm surges and wildfires, using historical data and climate change predictions, the models provide long-term predictions to guide planning for future years. Using real-time data from unfolding events, the models provide short-term predictions to optimize the management of resources needed in the aftermath of a hazard.

The paper presented a physics-based formulation to model the time-varying vulnerability of physical assets while accounting for the effects of deterioration processes, repair, maintenance, and recovery activities. The developed physics-based formulation combines first principles with various data sources to closely capture physical assets' real conditions.

Acknowledgments

The research presented in this paper was supported in part by the Office of Risk Management & Insurance Research in the Department of Finance in the Gies College of Business at the University of Illinois at Urbana-Champaign through funding made available by AXIS Capital Holdings Limited. We would like to thank Lynne McChristian Director of the Office of Risk Management & Insurance Research, and Bob Quane of AXIS Capital Holdings Limited for their support throughout the project. We also benefited from discussions with David Victor at the University of California San Diego, Eric Gesick, formerly at AXIS Capital Holdings Limited and now a Visiting Scholar at the University of Minnesota, and Roger Grenier and Brent Poliquin at AIR Worldwide Corporation as well as their AIR colleagues. We appreciate the reviews and helpful comments from Colleen Murphy in the College of Law at the University of Illinois at Urbana-Champaign, and the MAE Center colleagues Alessandro Contento, Aaron Dunton, Aditya Pandey, and Yun-Chi Yu.

References

Allen, M.R. and Ingram, W.J. (2002). "Constraints on future changes in climate and the hydrologic cycle," *Nature*, 419 (6903), 228-232.

Ayyub, B. M. (2014). "Systems resilience for multi-hazard environments: Definition, metrics, and valuation for decision making," *Risk analysis*, 34(2), 340-355.

Bedford, T., and Cooke, R. (2001). *Probabilistic risk analysis: Foundations and methods*, Cambridge University Press, Cambridge, UK.

Boakye, J., Gardoni, P., and Murphy, C. (2019). "Using opportunities in big data analytics to more accurately predict societal consequences of natural disasters," *Civil Engineering and Environmental Systems*, 36(1): 1-15.

Brickley, P. (2019). "PG&E Loses Challenge to Law Holding It Liable for Fire Damage", The Wall Street Journal, 27 November. Available at: https://www.wsj.com/articles/pg-e-loses-challenge-to-law-holding-it-liable-for-fire-damage-11574910091

Choe, D., Gardoni, P., Rosowsky, D., and Haukaas, T. (2008). "Probabilistic capacity models and seismic fragility estimates for RC columns subject to corrosion," *Reliability Engineering & System Safety*, 93(3), 383-393.

Choe, D., Gardoni, P., Rosowsky, D., and Haukaas, T. (2009). "Seismic fragility estimates for reinforced concrete bridges subject to corrosion," *Structural Safety*, 31, 275-283.

Contento, A., Chhabra, T., Gardoni, P. and Dierer, S., (2017). "Analysis of the effects of climate change on insurance against hurricanes," In the *Proceedings of the 12th International Conference on Structural Safety & Reliability (ICOSSAR2017)*, Vienna, Austria.

Contento, A., Xu, H., and Gardoni, P., (2019a). "A Physics-based transportable probabilistic model for climate change dependent storm surge," In: Paolo Gardoni (Ed.), *Routledge Handbook of Sustainable and Resilient Infrastructure*, pp. 662-682, Routledge.

Contento, A., Xu, H., and Gardoni, P., (2019b). “Risk analysis for hurricanes accounting for the effects of climate change,” In: Emilio Bastidas-Arteaga and Mark Stewart (Eds.), *Climate Adaptation Engineering: Risks and Economics for Infrastructure Decision-making*, pp. 39-72, Elsevier.

Contento, A., Xu, H., and Gardoni, P. (2020). “Probabilistic formulation for storm surge predictions,” *Structure and Infrastructure Engineering*, 16, 547-566.

Contento, A., Pandey, A., and Gardoni, P. (2021). “Prediction of storm surge evolution with time-dependent feedback,” (to be submitted).

Diffenbaugh, N. S., Swain, D. L., & Touma, D. (2015). “Anthropogenic warming has increased drought risk in California,” *Proceedings of the National Academy of Sciences*, 112(13), 3931-3936.

Gan, J., Jarrett, A., and Gaither, C. J. (2014). “Wildfire risk adaptation: propensity of forestland owners to purchase wildfire insurance in the southern United States*,” Canadian Journal of Forest Research*, 44(11), 1376-1382.

Gardoni, P., Der Kiureghian, A., and Mosalam, K. (2002). “Probabilistic capacity models and fragility estimates for reinforced concrete columns based on experimental observations,” *Journal of Engineering Mechanics*, 128(10), 1024-1038.

Gardoni, P., and Murphy, C., (2014). “A scale of risk,” Risk Analysis, 34 (7), 1208-1227.

Gardoni, P., and LaFave, J., (Eds.) (2016). *Multi-hazard approaches to civil infrastructure engineering*, Springer International Publishing, Switzerland.

Gardoni, P., Murphy, C. and Rowell, A. (Eds.) (2016a). *Risk analysis of natural hazards*, Springer International Publishing, Switzerland.

Gardoni, P., Guevara-Lopez, F., and Contento, A. (2016b). “The Life Profitability Method (LPM): A financial approach to engineering decisions,” *Structural Safety*, 63, 11-20.

Gardoni, P., (Ed.), (2017). *Risk and Reliability Analysis: Theory and Applications*, Springer.

Gardoni, P. (Ed.). (2019). *Routledge Handbook of Sustainable and Resilient Infrastructure*, Routledge, New York, NY.

Gardoni, P., and Murphy, C., (2020). "Society-based design: Promoting societal well-being by designing sustainable and resilient infrastructure," *Sustainable and Resilient Infrastructure*, 5(1-2), 4-19.

Grenier, R. R., Sousounis, P., Schnedyer, J., and Raizman, D. (2020). *Quantifying the impact from climate change on US hurricane risk,* AIR Worldwide Corporation, Boston, MA, Retrieved from https://www.preventionweb.net/go/75312

Guidotti, R., Stupazzini, M., Smerzini, C., Paolucci, R., and Ramieri, P. (2011). "Numerical study on the role of basin geometry and kinematic seismic source in 3D ground motion simulation of the 22 February 2011 MW 6.2 Christchurch Earthquake," *Seismological Research Letters*, 82(6), 767-782.

Guidotti, R., Chmielewski, H., Unnikrishnan, V., Gardoni, P., McAllister, T. and van de Lindt, J. (2016). "Modeling the resilience of critical infrastructure: the role of network dependencies." *Sustainable and Resilient Infrastructure*, 1(3-4): 153-168.

Guidotti, R., Gardoni, P., and Rosenheim, N., (2019) "Integration of physical infrastructure and social systems in communities' reliability and resilience analysis," *Reliability Engineering & System Safety*, 185, 476-492.

Hofer, L., Gardoni, P., Zanini, M.A. (2019). "Risk-based CAT bond pricing considering parameter uncertainties," *Sustainable and Resilient Infrastructure*, DOI: 10.1080/23789689.2019.1667116.

Hofer, L., Zanini, M.A., and Gardoni, P., (2020). "Risk-based catastrophe bond design for a spatially distributed portfolio," *Structural Safety*, 83, 101908.

Hu, S., Gardoni, P., and Xu, L. (2018). “Stochastic procedure for the simulation of synthetic main shock-aftershock ground motion sequences,” *Earthquake Engineering & Structural Dynamics*, 47(11), 2275-2296.

Hu, S., Tabandeh, A., and Gardoni, P. (2019). “Modeling the joint probability distribution of main shock and aftershock spectral accelerations,” In *Proceedings of 13th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP 2019*, Seoul, South Korea.

Iannacone, L., and Gardoni, P. (2018). “Physics-based repair rates for pipelines subject to seismic excitations,” In *Proceedings of 16th European conference on Earthquake Engineering*, Thessaloniki, Greece.

Iannacone, L., Sharma, N., Tabandeh, A., and Gardoni, P. (2021). “Modeling time-varying reliability and resilience of deteriorating infrastructure,” *Reliability Engineering and System Safety*, (under review).

Insurance Information Institutes (III) (2019). “Facts statistics: Wildfires,” Retrieved from https://www.iii.org/fact-statistic/facts-statistics-wildfires [Accessed: October-10-2019].

Jelesnianski, C. P., Chen, J., and Shaffer, W. A. (1992). SLOSH: Sea, lake, and overland surges from hurricanes (NOAA Technical Report NWS 48). Silver Spring, MD: United States. National Oceanic and Atmospheric Administration United States. National Weather Service.

Jia, G., Tabandeh, A., and Gardoni, P. (2017). “Life-cycle analysis of engineering systems: Modeling deterioration, instantaneous reliability, and resilience,” In: Paolo Gardoni (Ed.) *Risk and reliability analysis: Theory and applications*, pp. 465-494, Springer, Cham.

Jia, G., and Gardoni, P. (2018). “State-dependent stochastic models: A general stochastic framework for modeling deteriorating engineering systems considering multiple deterioration processes and their interactions,” *Structural Safety*, 72, 99-110.

Kleiner, Y., Sadiq, R., and Rajani, B. (2006). “Modelling the deterioration of buried infrastructure as a fuzzy Markov process,” *Journal of Water Supply: Research and Technology*, 55(2), 67-80.

Kousky, C., Greig, K., Lingle, B., and Kunreuther, K. (2018). “Wildfire cost in California: The role of electric utilities,” *Changes*, 114(18), 4582-4590.

Kumar, R., and Gardoni, P., (2012). “Modeling structural degradation of RC bridge columns subject to earthquakes and their fragility estimates,” *ASCE Journal of Structural Engineering*, 138 (1), 42-51.

Kumar, R., and Gardoni, P., (2013). “Second-order logarithmic formulation for hazard curves and closed-form approximation to annual failure probability,” *Structural Safety*, 45, 18-23.

Kumar, R., and Gardoni, P., (2014a). “Effect of seismic degradation on the fragility of reinforced concrete bridges,” *Engineering Structures*, 79, 267-275.

Kumar, R., and Gardoni, P., (2014b). “Renewal theory-based life-cycle analysis of deteriorating engineering systems,” *Structural Safety*, 50, 94-102.

Kumar, R., Cline, D., and Gardoni, P. (2015). “A stochastic framework to model deterioration in engineering systems,” *Structural Safety*, 53, 36-43.

Murphy, C., and Gardoni, P., (2006). “The role of society in engineering risk analysis: A capabilities-based approach,” *Risk Analysis*, 26 (4), 1073-1083.

Murphy, C., Gardoni, P., McKim, R., (Eds.) (2018). *Climate Change and Its Impact: Risks and Inequalities*, Springer.

National Association of Insurance Commissioners (NAIC) (2020) “Business Interruption/Business Owner’s Policies (BOP)” *The Center for Insurance Policy and Research*, Retrieved from https://content.naic.org/cipr_topics/topic_business_interruptionbusinessowners_policies_bop.htm

Nocera, F., Gardoni, P., and Cimellaro, G.P. (2019a). "Time-dependent probability of exceeding a target level of recovery in resilience analysis," *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems*, 59(5), 1241-1259.

Nocera, F., Tabandeh, A., Guidotti, R., Boakye, J., and Gardoni, P. (2019b). "Physics-based fragility functions: Their mathematical formulation and use in the reliability and resilience analysis of transportation infrastructure." In: Paolo Gardoni (Ed.) *Routledge Handbook of Sustainable and Resilient Infrastructure*, pp. 239-260, Routledge.

Nocera, F., and Gardoni, P. (2019a). "A ground-up approach to estimate the likelihood of business interruption," *International Journal of Disaster Risk Reduction*, 41, 101314.

Nocera, F., and Gardoni, P. (2019b). "Modeling business interruption as a function of the reliability and resilience of physical infrastructure and social systems," In: Paolo Gardoni (Ed.) *Routledge Handbook of Sustainable and Resilient Infrastructure*, pp. 841-865, Routledge.

Nocera, F., and Gardoni, P. (2021a). "Definition of resolution for the modeling of critical infrastructure," (to be submitted).

Nocera, F., and Gardoni, P. (2021b). "Asynchronous system reliability formulation to model the duration of business interruption," (to be submitted).

Penn, I., and Eavis, P. (2020). "PG&E Pleads Guilty to 84 Counts of Manslaughter in Camp Fire Case", *The New York Times*, 16 June. Available at: https://www.nytimes.com/2020/06/16/business/energy-environment/pge-camp-fire- california-wildfires.html

Raymond, C., Horton, R. M., Zscheischler, J., Martius, O., AghaKouchak, A., Balch, J., Bowen, S. G., Camargo, S., J., Hess, J., Kornhuber, K., Oppenheimer, M., Ruane, A. C., Wahl, T., and White, K. (2020). "Understanding and managing connected extreme events," *Nature climate change*, 10(7), 611-621.

Rochoux, M. C. (2014). *Towards a more comprehensive monitoring of wildfire spread: contributions of model evaluation and data assimilation strategies*, PhD thesis, Ecole Centrale Paris, France.

Sharma, N., Tabandeh, A. and Gardoni, P. (2018). "Resilience analysis: A mathematical formulation to model resilience of engineering systems," *Sustainable and Resilient Infrastructure*, 3(2): 49-67.

Sharma, N., and Gardoni, P. (2019). "Modeling the time-varying performance of electrical infrastructure during post disaster recovery using tensors," In: Paolo Gardoni (Ed.) *Routledge Handbook of Sustainable and Resilient Infrastructure*, pp. 259-276, Routledge.

Sharma, N., Tabandeh, A., and Gardoni, P. (2020a). "Regional resilience analysis: A multiscale approach to optimize the resilience of interdependent infrastructure," *Computer-Aided Civil and Infrastructure Engineering*, 35(12), 1315-1330.

Sharma, N., Nocera, F., and Gardoni, P. (2020b). "Classification and mathematical modeling of infrastructure interdependencies," *Sustainable and Resilient Infrastructure*, 1-22.

Sharma, N., and Gardoni, P. (2021). "Mathematical modeling of interdependent infrastructure: An object-oriented approach for generalized network-system analysis," (to be submitted).

Sharma, N., Tabandeh, A., and Gardoni, P., and Murphy C. (2021). "Modeling and evaluating the impact of natural hazards on communities and their recovery," (to be submitted).

Sharma, N., Tabandeh, A., and Gardoni, P. (2019). "Regional resilience analysis: A multi-scale approach to model the recovery of interdependent infrastructure," In: Paolo Gardoni (Ed.) *Routledge Handbook of Sustainable and Resilient Infrastructure*, pp. 259-276, Routledge.

Stupazzini, M., Allmann, A., Infantino, M., Paolucci, R., Smerzini, C., Mazzieri, I., Guidotti, R., and Gardoni, P., (2019). "Footprint based PSHA: the case of Christchurch, New Zealand," *Proceedings of 2019 Pacific Conference on Earthquake Engineering (PCEE)*, April 4-6, Auckland, New Zealand.

Tabandeh, A., Sharma, N., and Gardoni, P. (2021a). "Uncertainty propagation in risk and resilience analysis of hierarchical systems," (to be submitted).

Tabandeh, A., Gardoni, P., and Masud, A. (2021b). "A variational multiscale approach to stochastic modeling of wildfire propagation," (to be submitted).

Tonn, G., Reilly, A., Czajkowski, J., Ghaedi, H., and Kunreuther, H. (2021). "US transportation infrastructure resilience: Influences of insurance, incentives, and public assistance," *Transport Policy*, 100, 108-119.

Utsu, T., and Ogata, Y. (1995). "The centenary of the Omori formula for a decay law of aftershock activity," *Journal of Physics of the Earth*, 43(1), 1-33.

Westerink, J. J., Luettich, R. A., Blain, C. A., and Scheffner, N. W. (1994). ADCIRC: An advanced three-dimensional circulation model for shelves, coasts and estuaries. Report 2: User's manual for ADCIRC-2DDI. Washington, DC: Department of the Army, US Army Corps of Engineers.

Xu, H., and Gardoni, P., (2020a). "Multi-level, multi-variate, non-stationary random field modeling and fragility analysis of engineering systems," *Structural Safety*, 87, 101999.

Xu, H., and Gardoni, P., (2020b). "Conditional random field formulation for multi-level random field calibration with incomplete data," *Reliability Engineering and System Safety*, 204, 107121.

About the MAE Center

The MAE Center develops new integrated approaches to predict the consequences of natural and anthropogenic hazards. The MAE Center has been conducting interdisciplinary research to estimate damage and vulnerability at regional and national levels, and characterize different hazards. Through these activities, the Center has been supporting different stakeholders and societal interests.

The MAE Center is at the forefront of risk research. The MAE Center uses understandings of the physics of the phenomena and the latest data analytics to develop the most comprehensive and realistic models for risk analysis considering multiple hazards including earthquakes, hurricanes, tornados, and wildfires.

Risk analysis for natural and anthropogenic hazards is particularly challenging due to the rare occurrence of extreme events and because of the complex processes of interaction of such rare events with the natural and built environment to produce a societal impact.

The information generated by the MAE Center allows for state-of-the-art informed decision- and policy-making.

Contact the MAE Center

For more information on the MAE Center please contact

Prof. Paolo Gardoni
MAE Center Director

MAE Center
3118 Newmark Civil Engineering Laboratory
205 North Mathews Avenue
Urbana, IL 61801, USA

E-mail: gardoni@illinois.edu
Phone: (217) 333-5103

Or visit us at http://mae.cee.illinois.edu