Predictive Resilience of Interdependent Water and Transportation Infrastructures: A Sociotechnical Approach

Armin Rahimi-Golkhandan[a], Babak Aslani[a,b] and Shima Mohebbi[a,b,*]

[a] *Center for Resilient and Sustainable Communities, George Mason University, Fairfax, VA*
[b] *Department of Systems Engineering and Operations Research, George Mason University, Fairfax, VA*

ARTICLE INFO

Keywords:
Infrastructure systems
Interdependency
Social vulnerability
Predictive analytics
Natural disasters
Cascading random failure
Community detection

ABSTRACT

Infrastructures are interdependent systems and their interdependency can influence their resilience to routine failures and extreme events. Even though infrastructure resilience has been widely explored, few studies have considered physical, spatial, and social dimensions simultaneously. In this paper, we propose a resilience assessment framework for interdependent water and transportation infrastructures. The framework incorporates the physical network of these infrastructures, social vulnerability indicators, and predictive analytics for a sociotechnical resilience assessment. It enables us to measure the impact of random failures due to aging infrastructures, natural disasters, and their cascading failures. We applied the proposed framework to the City of Tampa, FL. The results indicated that areas with higher social vulnerability are more prone to cascading failures caused by both random breakdowns and natural disasters. While natural disasters affect all land use classes similarly, random failures have a greater impact on residential and institutional land use. The findings of this study highlight that infrastructure interdependency and the consequences of cascading failures should be taken into account in a coordinated infrastructure resilience assessment and planning. Further, socioeconomic factors and land use features should be incorporated in interdependent resilience assessment for a more comprehensive and equitable resilience planning.

1. Introduction

Urban communities highly rely on critical infrastructures such as power, water, transportation, and communication systems. These infrastructures are crucial for the functionality of any community and a failure in these systems can threaten safety, security, public health, and economic activity (DHS, 2021). Despite the importance of infrastructures, the condition of US infrastructure systems has been poor and the American Society of Civil Engineers infrastructure report card gives a D+ score to the entire infrastructure system in the US (ASCE, 2017). The aging infrastructures in the US have made these systems fragile to failures. For instance, each year water pipelines experience an average of 25 breaks in every 100 miles of pipes (Baird, 2020). These breaks usually bring about service reduction, road traffic disruption, and affect communities (Jin Jun et al., 2020). Transportation systems are also in poor condition. For example, nearly 40% of operating bridges in the US are over their designed life span of 50 years (Tochaei et al., 2021); the collapse of the I-35W Mississippi River bridge in Minneapolis during a rush hour highlighted the catastrophic impacts that such failures in the transportation system can have on communities (Zhu et al., 2010).

Infrastructure aging, poor urban environmental planning and governance, and population growth have also made infrastructures and cities more susceptible to natural disasters (Albrito, 2012). Due to climate change, natural disasters happen more frequently and in higher intensity (Song et al., 2016) and this has put even more pressure on the unprepared aging infrastructure systems which are more critical during emergency situations. In 2017, Hurricane Irma caused a power outage to two-thirds of power customers in Florida (Sultan and Hilton, 2020) and Hurricane Harvey resulted in a significant disruption in the transportation system of Houston, Texas leaving thousands of people stranded (Gori et al., 2020). Therefore, in any community, the resilience of infrastructure systems should be improved to better cope with random infrastructure breakdowns and extreme events, quickly recover from them, and learn and adapt to future similar disturbances. Resilience enhancement in infrastructures requires assessing the capacity of sub-systems within infrastructures to respond to disturbances and how different infrastructures connect and support each other's functionality.

arahimig@gmu.edu (A. Rahimi-Golkhandan); baslani@gmu.edu (B. Aslani); smohebbi@gmu.edu (S. Mohebbi)
ORCID(s):

Infrastructures are interdependent systems. Two infrastructures are interdependent when their performance depends on one another. Although interdependencies have increased the efficiency of functions, they can make systems more prone to cascading failures (Rinaldi et al., 2001). In interdependent systems, a failure in one system can cascade to other systems; these cascading failures can cause greater service disruption, economic impact, and loss of life (Shah and Babiceanu, 2015). Specifically, in infrastructures, a failure in one infrastructure can cascade to its interdependent infrastructure systems. The unprecedented Winter Storm Uri in Texas in 2021 crippled the transportation system. This failure caused a huge impact on the food infrastructure. At the same time, the power outage by this winter storm disrupted several interdependent infrastructures such as communication and healthcare. Thus, it is crucial to assess the interdependency of infrastructure systems and their resilience to cope with cascading failures caused by both random system breakdowns and extreme events like natural disasters.

The resilience of infrastructure systems to random failures and natural disasters has been analyzed in several studies. However, due to the complexity of interdependencies among infrastructures, much fewer studies have explored infrastructure interdependency and infrastructure resilience to cascading failures (e.g., Heracleous et al. (2017); Portante et al. (2017); Zuloaga et al. (2020)). In addition, infrastructures are sociotechnical systems (Walsh et al., 2015) and the magnitude of the impact of failures in infrastructures also depends on the socioeconomic characteristics of the people using lifelines. However, these factors are often overlooked in infrastructure resilience assessments (Rahimi-Golkhandan and Garvin, 2020). For a comprehensive sociotechnical assessment of the resilience of interdependent infrastructures to cascading failures, it is essential to take into account the *social vulnerability* of people. Considering the interdependency of infrastructures along with their social and cyber aspects can enhance the resilience of cities and communities (Mohebbi et al., 2020).

In this study, we propose an algorithmic framework for resilience assessment of interdependent water and transportation infrastructures to cascading failures. Through this framework that also incorporates social vulnerability and land use factors, we assess the resilience of these two infrastructures to (i) *random failures caused by aging*, and (ii) *failures caused by a natural disaster*. Subsequently, we analyze how these infrastructures perform when failures in one of them propagate to the other one and how the collective water-transportation network responds to such cascading failures. We applied the developed framework to the water and transportation systems in the city of Tampa, Florida (FL) to demonstrate its feasibility and efficiency. To the best of our knowledge, the contributions of this study are threefold: (a) we propose an algorithmic framework for predicting the resilience of water-transportation infrastructures considering both physical and spatial characteristics; (b) the cascading effects of both random failures due to aging infrastructures and natural disasters within and across these two infrastructures are modeled; (c) we incorporated social vulnerability and community detection algorithms in our approach for a more comprehensive sociotechnical resilience assessment.

The rest of the paper is structured as follows: In section 2, the relevant literature is analyzed and the gaps are identified. Section 3 provides the detailed steps of the proposed framework. Section 4 focuses on the selected case study. Section 5 visualizes the results for the case study for both random failure and natural disaster scenarios. The design and policy-making implications as well as the limitations are included in section 6. Future directions are also discussed in section 7.

2. Background

2.1. Infrastructure Interdependency and Cascading Failures

Interdependency among infrastructures can be generally described by four types: (a) physical, (b) geographical, (c) cyber, and (d) logical (Rinaldi et al., 2001). The approaches to analyze these interdependencies are broadly classified into five groups (Ouyang, 2014): *empirical* (identify failure patterns and risk analysis), *agent-based*, *system dynamics*, *economic* (input-output and computable general equilibrium), and *network* (topology and flow). Specifically, network approaches have widely been used in the literature, and we focus on this method to investigate the interdependencies among infrastructures.

Among recent studies, Cao et al. (2021) studied the impact of an earthquake on the interdependency of infrastructure networks in Japan using a topological network-GIS approach. They developed a risk map that identifies the critical areas of the interdependent network to cascading impacts of seismic hazards. Similarly, Munikoti et al. (2021) investigated the robustness of interdependent utility infrastructures by a graph theory approach and highlighted the importance of information systems for improved robustness of infrastructure networks. The interdependency security and identity among electric and gas networks during instabilities of gas pressure, supply shortage, and gas demand surge was analyzed by Antenucci and Sansavini (2018). They proposed automation actions and safety strategies to respond to demand surges and failures in network components.

Ouyang and Wang (2015) investigated recovery strategies for the interdependent electric power and gas infrastructures after a hurricane. They concluded that while restoration plans result in higher individual resilience in these systems, the compromised recovery strategy leads to a higher overall resilience for the electric-gas systems. This highlights that while considering interdependency is critical to respond to a disturbance, it is equally important for efficient recovery. The geographical and physical interdependency of the same infrastructures and the cascading failures in them due to spatially localized attacks was explored by Ouyang (2016) to identify the most critical locations. The results demonstrated that infrastructures interdependency and radius of attacks influence critical locations in the network and such spatially localized attacks cause less vulnerability than random attacks. These findings demonstrate that interdependency among infrastructures changes the most critical/vulnerable locations in infrastructure networks compared to when infrastructures are studied separately. Identifying critical/vulnerable locations/components in interdependent infrastructure systems permits investigating how they influence the resilience of infrastructure systems and which policies can enhance resilience. Ouyang (2017) explored how protecting weak components of the interdependent networks or increasing network redundancy can improve the resilience of power and water infrastructures.

Network metrics were used by Mao and Li (2018) to assess the impact of disturbances on the robustness and recovery of power-water-telecommunication infrastructures. The results of their analysis revealed that disregarding infrastructure interdependency results in the underestimated impact of extreme events. Similar to Ouyang and Wang (2015), they concluded that interdependency among infrastructures should be taken into account for efficient recovery planning. Adequate budget, resources, and time are crucial for successful recovery plans. Among recent studies, Mohebbi et al. (2021) proposed a coalitional game theory approach coupled with an optimization model to address decentralized resource allocation in restoration planning for city-scale interdependent water and transportation networks. They demonstrated that the decentralized model outperforms the centralized counterpart in terms of computational time and the trajectory of the system performance (met demand) over time. Having strategies to protect vulnerable network components as well as plans for a quick and efficient recovery is crucial for the resilience of interdependent infrastructures. These prioritized components for system recovery might not be the most vulnerable ones to failure, but they are the most critical for service restoration to mitigate the impact of failures.

The interdependency of water infrastructure has not been fully explored (Abdel-Mottaleb et al., 2019); especially, the cascading failures between water-transportation systems have received less attention compared to the interdependency between water and other infrastructures. Dong et al. (2020) analyzed the geographic interdependency of transportation and sewer networks and cascading failures in these networks through percolation. They found that the road network is more vulnerable to failures in the collocated sewer system. Further, the robustness of this interdependent network decreases as the number of initial failed sources increases. Additionally, nodes in the sewer network either have zero or severe risk which results in two-phase percolation caused by failure due to liquefaction.

Abdel-Mottaleb et al. (2019) analyzed how critical components in the water infrastructure would vary when its interdependency with the transportation infrastructure is considered compared to when it is considered separately. Their findings revealed that when interdependency is considered, the identified critical components significantly vary from those when only the water network is analyzed. These findings highlight the importance of water-transportation interdependency and cascading failures between these systems for resilience enhancement. However, critical components might vary given the disturbance that this interdependent network experiences. In other words, the critical components to a natural disaster might not necessarily be the same as the critical components to a random failure. Thus, analyzing the interdependency of water-transportation infrastructures to both random failures and natural disasters could provide a clearer perspective of the most vulnerable components/locations in the network. Further, if other important elements such as social vulnerability are factored in for a more comprehensive analysis, the most vulnerable areas for system enhancement and recovery planning might change.

2.2. Social Vulnerability

Social vulnerability to hazards generally discusses inequalities in the ability of different groups to maintain their desired state (Kuhlicke et al., 2011). In the context of hazards and disasters, social vulnerability is the conditions and characteristics that reduce the ability of an individual or a group of people to cope with and recover from an environmental shock (Wisner et al., 2004). Social vulnerability can be described as social inequality through characteristics of people (e.g., age, sex, race/ethnicity, income) and geographical inequality that are related to communities and the built environment (e.g., economic vitality, urbanization level) (Cutter et al., 2003). In addition, the Social Vulnerability Indicator (SoVI) can be used to examine the interaction between infrastructure systems and the social aspect of urban

Table 1
Summary of studies with customized SoVI

Author(s)	Scope
Cutter et al. (2013)	To incorporate simplified SoVI into civil planning and to preserve the robustness.
Armas and Gavris (2013)	To reveal patterns of vulnerable communities to post-earthquake coping strategies.
Holand and Lujala (2013)	To adopt the existing index developed for the US to municipalities in Norway.
Aksha et al. (2019)	To assess the performance on Nepali context by adding new variables such as caste.
Sung and Liaw (2020)	To quantify the vulnerability of complex topography to environmental hazards in Taiwan.

communities (Cutter et al., 2003). SoVI can explain the social aspect of community resilience during disturbances (Nelson et al., 2015; Tate et al., 2016).

To tie social vulnerability to infrastructure resilience for sociotechnical assessment, nodes of infrastructure networks (e.g., water junctions, which represent customers' locations with their respective demand of water) can be considered as representative components for SoVI variables. If these nodes are spatially well-distributed across a community, socioeconomic factors of residents in each area can be associated with infrastructure nodes in those areas to incorporate social vulnerability in infrastructure assessments. This requires community detection that could be costly. To overcome unreasonable computational costs, node attribute-based community detection (clustering) methods have been implemented (e.g., Jia et al. (2017); Liu and Wang (2018)).

Communities interact with each other through infrastructures, both dependently and interdependently. For example, when a water junction is disrupted near a specific community, other communities might suffer from that failure if it propagates to water junctions in other communities. Such a failure could also cause a disturbance in interdependent infrastructures. For instance, if a water junction fails to operate properly, either due to a random failure or a natural disaster, the co-located interdependent roads might fail to maintain connectivity and transport demands; depending on the socioeconomic characteristics the impact of such failures might vary. Thus, incorporating social vulnerability, Karakoc et al. (2019) developed a model for the recovery of interdependent infrastructures.

A share of studies in this research stream adopted the SoVI concept and tailored this index for their case studies or tested its applicability in various contexts related to risk management and community resilience. Table 1 provides a summary of studies in this area. Socio-demographic variables, including age, sex, income level, and race, are the common elements in these studies. In addition, these studies' results reflected the fact that even though the SoVI indicator is an appealing choice for social vulnerability measurement, application and interpretation of the output related to an entirely different socioeconomic context outside the U.S. is challenging. For instance, (Holand and Lujala, 2013) reported that the adjusted index applied to a different socioeconomic context could only explain 19% of variation in the data. However, others like Aksha et al. (2019) and Sung and Liaw (2020) only focused on the results without any interpretation about the accuracy. Aksha et al. (2019) argued that the social vulnerability is higher in mountainous regions populated by Dalit (people belonging to the lowest caste) and minority communities and/or with a history of armed conflict. Sung and Liaw (2020) validated the effectiveness of SoVI concept to environmental hazards in Taiwan by GWR and provided visualization maps as essential decision-making tool in emergency planning

Although a significant part of the assessment of social vulnerability is concerned with detecting communities inside an area, such methods are not very efficient due to statistical bias, precision, and uncertainty (see Tate (2013) for a detailed explanation). Since infrastructures can be usually represented as a network of nodes (e.g., demand/supply points) and links between nodes, community detection algorithms can be implemented to identify communities within a network. However, these methods are absent in the literature of social vulnerability in the context of interdependent infrastructure networks. To bridge this gap, we adopted a well-known community detection method, joint community detection criterion (JCDC), to identify the interdependent water and transportation systems based on several social variables.

3. Resilience Assessment Framework

To assess the resilience of the interdependent water-transportation infrastructures to random failures and natural disasters, we propose an algorithmic framework (Figure 1). First, we create an interdependent network of water and transportation systems that includes social vulnerability and land use factors. Then, we develop scenarios to analyze simultaneous failures in these infrastructures. For random failure scenarios, data is generated through experimental

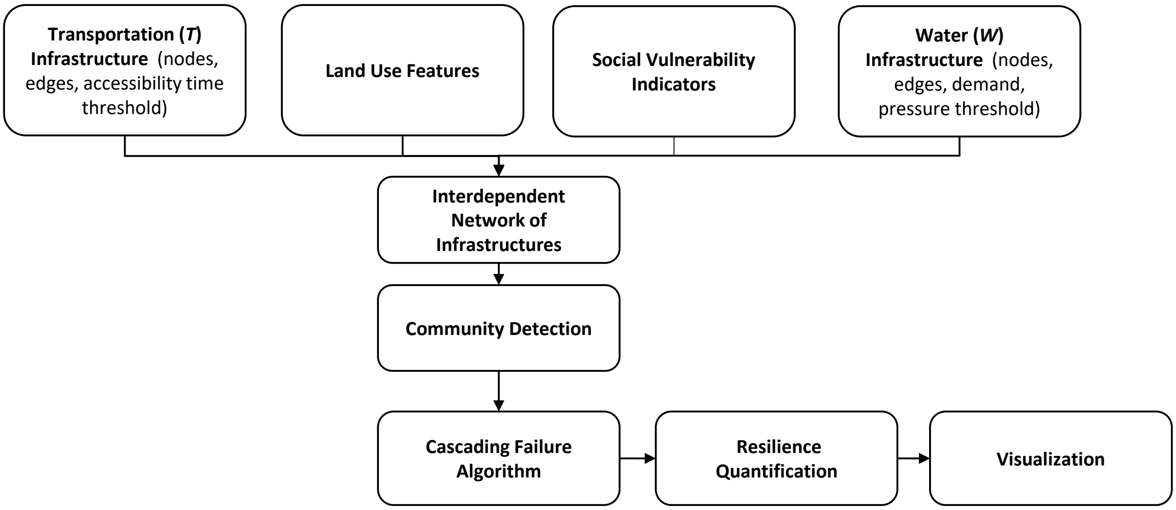


Figure 1: Proposed resilience assessment framework for interdependent water and transportation networks

design. For natural disaster scenario, we simulated the impact of Hurricane Irma. The failures propagate within each infrastructure and cascade to the other interdependent infrastructure. Finally, the framework is applied to the water and transportation infrastructures in the City of Tampa, FL.

3.1. Interdependent Network of Infrastructures

To study the interdependency among water-transportation systems, we focused on geographic co-location of these infrastructures. Pipelines and water junctions are the components of the water network, roadways and intersections represent the transportation system in our framework. The interdependent network of water-transportation systems was developed using the physical network, and geospatial data of these infrastructures. We used this base network to detect communities and overlay the built environment features onto the interdependent infrastructures.

3.1.1. Community Detection

An urban area can be described by several factors such as urban form, infrastructures, land use, and the socioeconomic characteristics of residents in that area. Here, to detect communities in the interdependent infrastructure network, we use census blocks. Census blocks are the US Census Bureau's smallest geographic unit and help us to detect communities at a fine-grained scale. This community detection will allow us to investigate the impact of a failure in infrastructures and the highlight community characteristics. The road segments in each census block are assigned to their closest water junction. In each census block, the socioeconomic characteristics of residents are assigned to the water junctions, which represent customer locations with their respective demand of water, in that block. Incorporating the socioeconomic characteristics of people in the network enables us to measure social vulnerability and its relationship with failures in the infrastructure systems, and the impact of failure propagation on communities with different socioeconomic characteristics.

Cutter et al. (2003) identified 11 factor groups that represent different socioeconomic properties to quantify the social vulnerability of a community. These 11 factor groups are categorized mostly around age, gender, race, wealth, and occupation of the residents of a community. According to these factor groups, we used 12 socioeconomic variables (Table 2). While other factors such as income, poverty rate, educational attainment, school enrolment, and employment status could be used to characterize social vulnerability in a community, here our focus is on factors related to age, sex, race/ethnicity, and housing that are key for social vulnerability during disasters. We then used JCDC (Zhang et al., 2016) to detect communities in the network. The water junctions and road segments in each community include the social vulnerability features of those communities. In addition, to take into account the built environment characteristics, land use features are incorporated.

Table 2
Social vulnerability variables

Median age by sex	Total population in occupied housing units
Population of Asian or Pacific Islander	Population of females
Percentage of female-headed households	Population of renter occupied housing units
Population of Hispanic persons	Population living in urban areas
Percentage of black population	Percentage of Native American population
Percentage of population under 5 years	Percentage of age over 65 years

3.1.2. Land Use Features

A failure in an infrastructure can have different impacts on areas with different land use characteristics. For instance, the consequences of a breakdown in a water pipe in a residential area and an industrial area might vary since the need for water in those areas differ. Thus, to be able to analyze the relationship between land use and failures in infrastructures, we incorporate land use features in the water-transportation network. Three general land use types are considered: (a) residential, (b) industrial, commercial, and service, and (c) institutional and others. These land use types are assigned to the water junctions and road segments in the network.

3.2. Cascading Failure Algorithm

The interdependent network of water and transportation infrastructures includes the characteristics of these systems as well as social vulnerability indicators and land use features. This network is the foundation for sociotechnical resilience assessment of these infrastructures. Here, we describe failure scenarios, resilience assessment metrics, and termination criteria of the algorithm. The required inputs and the main steps are outlined in algorithm 1 .

Algorithm 1 Cascading failure algorithm for interdependent water and transportation networks

Input Data

```
1: Interdependent Network of Infrastructures
2: Community Detection
3: Failure Scenarios
4: while Termination condition is not met do
5:     Collect the set of failed roads and pipes;
6:     Water network hydraulic simulation
7:         Continue failure propagation based on pressure;
8:         Fail interdependent roads with pipes;
9:     Road network
10:        Continue failure propagation based on traffic load;
11:        Fail interdependent pipes if affected by traffic load;
12: end while
```

3.2.1. Failure Scenarios

Water distribution networks are prone to different types of failures. Aging and specific pipe materials such as Ductile Iron Pipes (DIP) are common sources of failure in this infrastructure (Kabir et al., 2015). In addition, design problems such as exposing pipes to constant high hydraulic pressures can also expedite pipe deterioration and eventually failures. The majority of components in water distribution networks are typically underground, causing accessibility problems for proactive and periodic maintenance. Therefore, inadequate maintenance can be considered as another source of failure in the water network (Shirzad and Safari, 2019). In addition, most leakage incidents remain undetected until they cause severe consequences in the system. External factors such as temperature and soil features also contribute to failures in water components like pipes, valves, reservoirs, and tanks (Renzetti et al., 2013). Random failures are another primary source of breakdowns in this complex network. Specifically, water main breaks are a common failure factor in urban water distribution networks, generating a spectrum of problems from disrupting the routine functionality of this system to contamination and jeopardizing public health (Aslani et al., 2021).

In a roadway network, if a road segment closes due to excessive congestion, the traffic load will consequently be on the other roadways which could cascade the congestion to the rest of the network (Li et al., 2012). Several factors can cause congestion and closure of road segments. The main roadway congestion factors are traffic demand (normal traffic fluctuation, special events such as a football game or a concert), traffic-influencing events (weather, work zones, traffic incidents), and physical highway features (capacity bottlenecks, traffic control devices) (FHWA, 2005).

However, the consequences of a disruptive event are much broader than physical damages and service loss in critical infrastructures. When communities experience a natural disaster, they could be immediately impacted. In these situations, the primary source of social vulnerability is related to the weakness of particular groups of people to timely and effectively respond to such events. For example, communities with a higher ratio of children, elderly population, and underrepresented communities (e.g., immigrants living in suburban areas) are more prone to severe damages. Likewise, residents of more populated areas usually face difficulty for evacuation. In short, the social vulnerability adds another layer to the resilience framework and complements it to form a more holistic picture of the effects of cascading failures on interconnected community-infrastructure networks.

In this part, we explain the process of simulating failures in each network individually and in the interdependent components. We assumed that the pipe leakage and water main breaks are the primary sources of failure in the water network. Hence, we removed the affected pipes/edges from the network and ran the hydraulic simulation algorithm to capture these types of failures. Then, by comparing pressures in nodes to the maximum operational threshold, we traced the cascading impacts (see Shuang et al. (2014) for more detail on pressure-driven analyses). For transportation, we considered road closures due to pavement issues (aging infrastructure) and flooding as the main types of failures. Similar to the water network, we removed the affected roads/edges from the network and used the edge betweenness centrality to measure the cascading failures. More precisely, if traffic exceeds the capacity of a road segment (i.e., congestion), we consider that road segment as a failed component. Finally, the interactions between networks are automatically captured through interdependencies defined in our work.

As described above, the geospatial interdependency between water and transportation infrastructures might result in the propagation of failures from one infrastructure to the other. For instance, water pipe breakage can close roads and roadway congestion might cause pipeline breakdown. In general, we can describe the consequences of a failure in a component of one of these infrastructures as:

- *failures within the infrastructure*: breakdown in the directly connected components and cascading failures in the indirectly connected components, and
- *failures in the interdependent infrastructure*: cascading failures in the co-located components and propagation of that failure to other components.

To analyze the influence of these failures on the resilience of the water-transportation infrastructures, we develop scenarios based on random failures and natural disasters. The resilience of the system will be assessed in four states: (a) failures in the water network caused by a breakdown in a pipe, (b) cascading failures in the co-located road segments of the broken pipe, (c) failures in the road network due to a road segment closure or flooding, and (d) cascading failures in the co-located pipes of the closed road segment. It should be noted that these failures can happen simultaneously in both water and transportation networks, particularly during natural disasters. The initial failure in each network propagates internally due to cascading failure and spreads to the other network through interdependent components. For instance, the cascaded failure in the transportation network results from the propagation of initial road closures and can be intensified by the co-located water main break.

3.2.2. Interdependent Water-Transportation Infrastructures Resilience

To measure the resilience of the interdependent network to cascading failures, we use a metric that incorporates a failure's impact on both water and transportation systems as the failure propagates. A failure develops in water junctions or road segments and step by step propagates to the rest of the network. In the water infrastructure, the met demand (McMahon et al., 2006) determines the performance and the resilience of this infrastructure during cascading failures. Accordingly, the larger the met demand, the more resilient the system is.

In the roadway system, the spatial accessibility loss (Cantillo et al., 2019; Ortega et al., 2020) determines the resilience of this system. Here, we consider spatial accessibility (Eq. 1) (Golub and Martens, 2014; Kelobonye et al., 2020) as the number of road segments that are co-located with a water pipe and are accessible for the maintenance crew with a defined time threshold. It should be noted that this shortest path is for access by vehicles.

$$A_s = \sum I_s(j) \tag{1}$$

Where A_s is the total accessibility in state s, j denotes a road segment co-located with a pipe, and $I_s(j)$ is an indicator function. $I_s(j)$ is equal to 1 if the j^{th} road segment is accessible for maintenance crew by vehicle within a t time threshold at the step s. $I_s(j)$ is equal to 0, otherwise.

Subsequently, as failures propagate over steps, we can measure the resilience of the interdependent network of water and transportation to cascading failures through a step-wise system performance assessment (Eq.2).

$$R_{WT} = \sum_{s \in S} \frac{R_W^{(s)} + R_T^{(s)}}{2|S|} \tag{2}$$

In this equation, R_{WT} is the resilience, W denotes the water infrastructure, T represents the transportation infrastructure, and $S \in \{1, 2, ...\}$ is the set of steps with size of $|S|$ before the termination condition of the algorithm is met. $R_W^{(s)}$ and $R_T^{(s)}$ are the proportion of met demand in water, and the proportion of total accessibility in transportation at step s, respectively. Hydraulic simulation is used in our framework to evaluate pressure changes in the water network, identify components with pressure above the threshold, and quantify the met demand at each step. The pressure threshold is the pressure above which other components may break.

3.2.3. Algorithm Termination

The resilience assessment algorithm is based on the propagation of failures in water-transportation infrastructures and it terminates if failure propagation stops. Concretely, failures stop cascading in two conditions:

(a) One of the infrastructures is completely collapsed or stopped functioning. In other words, the failure is total and cannot cascade anymore. This situation happens if all water junctions or road segments fail.

(b) The infrastructures are not collapsed and the failure does not cascade anymore. In this situation, the failure is contained within the system. Therefore, if the failure does not cascade in two consecutive steps, the algorithm terminates. We used this standard termination condition for cascading failures (see Shuang et al. (2014) and Shuang et al. (2017a)), assuming that when the system reaches a stable state, the failure propagation stops, and we do not observe any new failed component. In other words, if new failures are not observed after two iterations, we will not have any more failures in any further steps.

3.3. Data Generation for Random Failures

The algorithmic framework enables us to analyze the resilience of complex network of infrastructures to failures. Although replication of data for analyzing network-specific disruption criteria is feasible, it is time-consuming. Moreover, analyzing every possible failure scenario is not practical. Thus, to overcome the computational limitations, we use Design of Experiment (DOE) to replicate failure data. DOE is a well-known systematic method to determine the relationship between factors affecting a process and its output. More precisely, it allows for manipulating multiple input factors, and determining their effect on the output. DOE has been implemented in designing resilience assessment framework for infrastructures. For instance, Najarian and Lim (2019) adopted DOE for presenting a new resilience metric for general complex systems. Nan et al. (2014) also used DOE for developing a holistic and integrated metric for resilience quantification of interdependent infrastructure systems. DOE was incorporated in Lopez et al. (2019) to maximize the resilience of the unbalanced electrical distributions network. In this study, we considered four factors in the DOE process with three levels for all of them. Two factors are related to the spatial aspect of the interdependent network (communities and land use features). The other two factors are the magnitude of failure in water and transportation networks to capture cascading failures. This setting accounts for simultaneous failures in both water and transportation networks. Table 3 shows the factors and their associated levels in the DOE.

Table 3
Factors and levels for design of experiment

Factors	Type	Levels	Values
Land use type	Categorical	3	1, 2, 3
Communities	Categorical	3	1, 2, 3
Magnitude of failure in water infrastructure	Continuous	3	17,50,83
Magnitude of failure in transportation infrastructure	Continuous	3	27,54,82

Table 4
Description of predictive models

Predictive Model	**Description**
Bayesian Additive Regression Trees (BART)	A non-parametric Bayesian regression approach to fitting a variety of regression models while avoiding strong parametric assumptions. BART enables full posterior inference including point and interval estimates of the unknown regression function as well as the marginal effects of potential predictors.
Random Forest (RF)	An ensemble machine learning method that consists of many individual cooperating decision trees. The algorithm adopts bagging and feature randomness in building individual trees to create an uncorrelated forest of trees with a more accurate grouped prediction.
Boosted Regression Tree (BRT)	BRT is similar to RF in fitting many decision trees to improve prediction accuracy, but uses boosting to weight the input data in subsequent trees. BRT is robust to outliers, detects best fit automatically, and it is stochastic that improves predictive performance results.
Multivariate Adaptive Regression Splines (MARS)	A non-parametric regression method that builds a piece-wise linear model across the range of predictors and is based on knots. It automatically searches for the best spots to place the knots, performs well with many predictor variables, and automatically detects interactions between variables.
Artificial Neural Networks (ANN)	A computational approach inspired by biological nervous systems process. ANNs are adaptive and capable of handling complex systems to identify patterns and learn to make predictions. This method is flexible and learns in an iterative process by adjusting inputs' weights and biases.

3.4. Impact Estimation for Natural Disasters (Hurricane Irma)

To estimate the impact of a natural disaster on the resilience of the water-transportation network in Tampa, we used FEMA's dataset of flooding depth level caused by Hurricane Irma in 2017. First, we assigned a flooding elevation level to each section (polygons based on U.S. Census Bureau shapefile) of Tampa based on the nearest neighborhood function. Having the estimated levels, we compared the values with the threshold defined by FEMA (FEMA Mitigation Assessment Team Report Hurricane Irma in Florida) [1]. Any region with a level higher than 0.25 ft water height should be categorized as an affected area (FEMA). Then, we labeled the pipes and roads that their centers are inside the affected areas as the initially failed components. Finally, we executed the cascading failure algorithm to trace the impact of these initial disruptions on the networks.

3.5. Resilience Quantification

3.5.1. Predictive Analytics for Random Failures

After identifying the statistically significant interactions among factors as the output of the DOE, we implemented several predictive models to quantify resilience in different configurations. Table 4 provides a brief description of each predictive model. A detailed description of BART and other predictive models is provided in Tan and Roy (2019) and Aslani et al. (2021), respectively.

[1]FEMA P-2023 report is available at https://www.hsdl.org/?abstractdid=828548

3.5.2. Geospatial Predictive Analytics

To capture the impact of natural disasters, spatial predictive modeling is selected to quantify the resilience of different regions across Tampa. In this study, we developed a GWR model as the spatial predictive model. GWR has been widely adopted as a powerful tool to capture spatial features in the resilience assessment of interdependent infrastructure to natural disasters. For instance, Chun et al. (2017) used GWR and developed an assessment model for social resilience by measuring the heterogeneity indicators related to disaster risk. Similarly, Fahy et al. (2019) employed GWR in a proposed GIS framework and developed a combined index to test the relationships between sociodemographic variables and environmental hazard potential. Using GWR, economic resilience, social resilience, and community capital resilience were aggregated into socioeconomic community resilience to investigate the baseline resilience to natural hazards Sung and Liaw (2021).

This method is an extension of multiple linear regression model, in which regression coefficients are local rather than global estimators. In other words, the coefficients of the regression model form continuous surfaces that are assessed at certain spatial points:

$$y_i = \beta_0(u_i, v_i) + \sum_{n=k}^{p} \beta_k(u_i, v_i)x_{ik} + \epsilon_i \tag{3}$$

Where (u_i, v_i) are the geographical coordinates.

Another important component of GWR is a matrix of weights such that pairwise weights are assigned to every two observations. The observations closer to each other are given greater weight than observations further away. Finally, a kernel function should be selected as another parameter of the predictive model (see Wang et al. (2013) for more detailed explanation). We selected adaptive bandwidth and the Gaussian kernel family as the inputs of the developed model. We also adopted a non-spatial Random Forest predictive model to compare the quality of the prediction to a geospatial one.

4. Study Area

To implement our proposed methodology, we modeled water and transportation infrastructures in the city of Tampa. Tampa is a coastal city with nearly a population of 400, 000. It is prone to different natural hazards such as hurricanes, floods, and tornadoes; this makes Tampa an ideal place to implement the proposed resilience assessment framework. Tampa's water distribution network has 1,658 junctions (nodes) that are connected by 1,976 pipelines (edges). The road network in Tampa has 2,652 nodes and 5,484 vertices. The junctions of the water distribution network and roadways are labeled by communities as well as the type of land use. To specify the characteristics of the components of both networks, we collected social vulnerability variables for all census blocks in Tampa from the American Community Survey (ACS) of the US Census Bureau. The geospatial data of land use was collected from the Florida Department of Environmental Protection Geo-spatial Open Data (FDEP, 2021).

5. Results and Analysis

5.1. Interdependent Water-Transportation Network

The social vulnerability and land use factors were assigned to the nodes in the water-transportation network and communities were detected. Figure 2 illustrates the three communities in the network overlaid on water junctions. Community 1 has 66% of the nodes in the network while communities 2 and 3 have 18% and 16% of nodes, respectively. We chose three communities to follow the L_9 orthogonal array rule in our design of experiment. Table 5 represents the categorical disorderliness of each social vulnerability variable that we used for community detection. These values are transformed from continuous values of Entropy to categorical ones (see Ghahramani (2006)). It can be observed that the majority of the variables have less impact to shape the second community. In other words, compared to other communities, the disorderliness is relatively higher in the second community. The first community has the lowest disorderliness of the majority of variables, which shows that this community is socially more vulnerable compared to the other two communities.

5.2. Infrastructure Failures

The failure of pipelines and junctions in the water distribution network might propagate over other interconnected components of the network (Shuang et al., 2017b). We considered this *within* infrastructure cascading failure in our

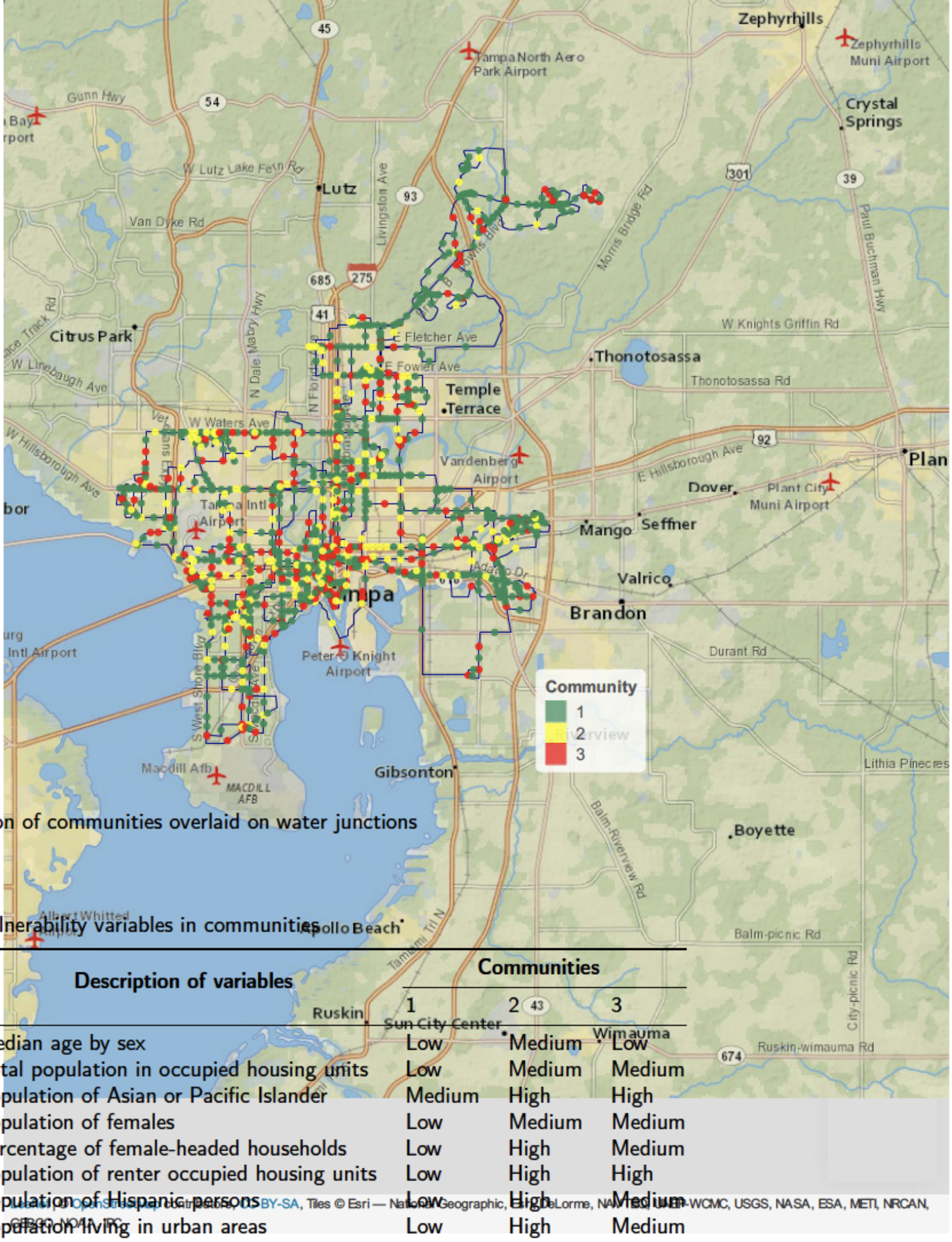


Figure 2: The distribution of communities overlaid on water junctions

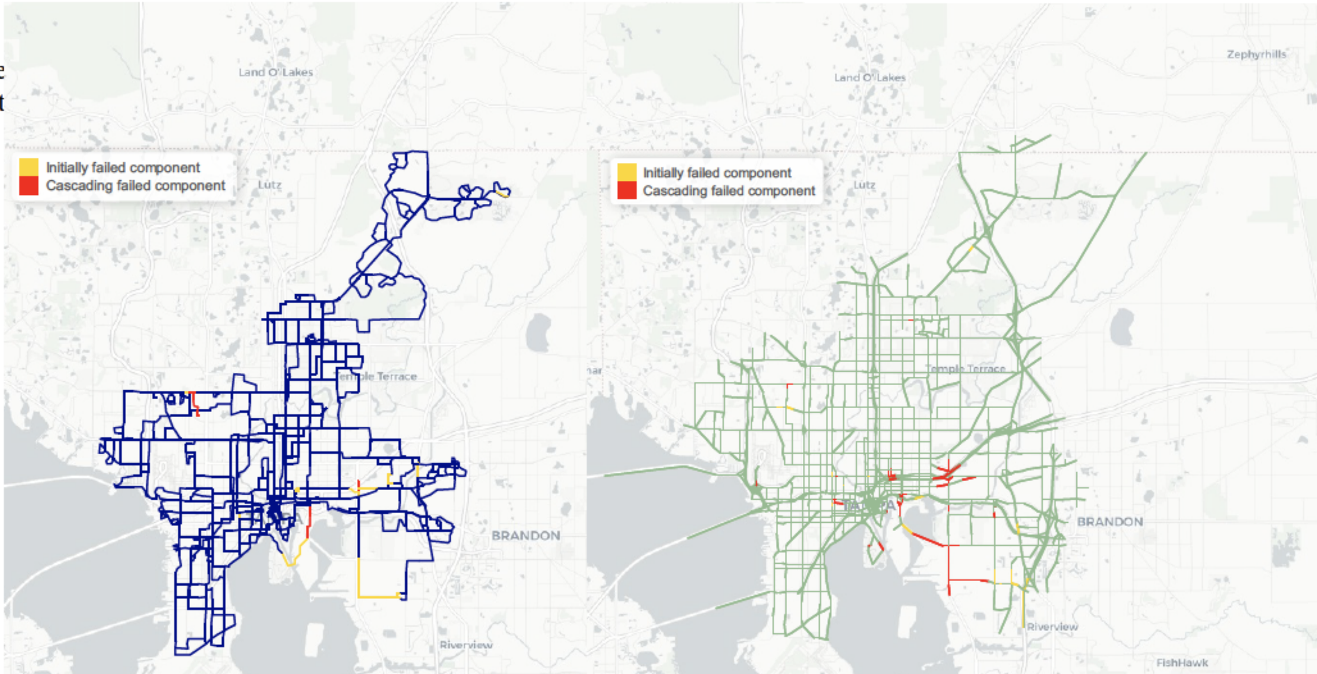
Table 5
Signification of social vulnerability variables in communities

Description of variables	Communities		
	1	2	3
Median age by sex	Low	Medium	Low
Total population in occupied housing units	Low	Medium	Medium
Population of Asian or Pacific Islander	Medium	High	High
Population of females	Low	Medium	Medium
Percentage of female-headed households	Low	High	Medium
Population of renter occupied housing units	Low	High	High
Population of Hispanic persons	Low	High	Medium
Population living in urban areas	Low	High	Medium
Percentage of black population	Low	High	High
Percentage of Native American population	Low	High	High
Percentage of population under 5 years	Low	High	Medium
Percentage of age over 65 years	Low	Medium	Medium

algorithm using WNTR hydraulic simulation engine (Klise et al., 2017; Ka et al., 2017; Klise, 2018). If a cascading failure spreads within an infrastructure, it could cause failures after several steps that might result in the collapse of the whole system. We monitored these consequential failures to assess infrastructure resilience through our proposed algorithm. For example, Figures (3a) and (3b) illustrate how failures in the components of Tampa's water and transportation network propagate over these networks. This scenario demonstrates failures triggered in the residential area in the second community where 50 water junctions and 54 roads failed. The yellow color represents initially failed components and the red color shows the cascading failed components.

In Tampa's water network, the majority of pipelines (85%) are DIP pipes. DIP pipes are stable against breakage due

of t



(a) Failure propagation in water network (b) Failure propagation in transportation network

Figure 3: Failure propagation in infrastructure networks

5.3. Generated Random Failures

We implement a Taguchi-based DOE method to generate data for random failures. We selected the $L9$ Taguchi design, which includes 9 experiments for 4 factors with 3 levels for all of them. Each experiment was replicated four times to improve the accuracy of DOE and the consequent predictive models. Table 6 and 7 are the outputs of the DOE process. The first table indicates that the effects of all of the chosen factors are statistically significant (based on p-values). The interaction table also reveals that the three interactions among factors are statistically significant and these interaction terms should be added to the predictive models.

Figure 7 in the Appendix provides more information about the interactions among factors. First, the transportation variable has interactions with all the other three variables, but they are not statistically significant. Second, residential (0) and industrial (1) land use are more vulnerable to extreme failure scenarios in the water network. However, medium failure in the water network has a higher impact on institutional (2) land use. Furthermore, communities 1 and 2 are more vulnerable to higher degrees of failure in the water network. This effect is significantly lower for the Level 1 failure scenario in water for community 2. The interaction among land use and communities shows that in residential and institutional land use, higher vulnerability is associated with community 2, while for industrial land use, the first community is related to higher degrees of vulnerability. On the other hand, the low-level failure scenario for water has a greater impact on community 1 and institutional land use. Medium and extreme situations are more disruptive for institutional and residential land use, respectively. Finally, community 2 is the most vulnerable to medium and high degrees of failure in the water network.

5.4. Cascading Impact of Random Failures

We used a data set of 70 randomly generated failures by different settings as the input for the proposed cascading failure algorithm. The output of the algorithm, the system resilience, is considered as the response variable for the machine learning algorithms. The predictor variables are the factors and their interactions identified as significant in the DOE process in Table 7. As a result, we used 6 predictor variables for random failures, including community, the magnitude of failure in both networks, and the interactions of land use and community, land use and water, and community and water. We adopted the one-hot-encoding technique to handle the categorical variables in the modeling phase and used *caret* and *dbarts* packages in R to develop the predictive models for random failures. As a common

Table 6
ANOVA Table for DOE

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	P-Value
Community	2	0.02380	0.02380	0.011898	5.82	0.008
Magnitude of failure in Water	2	0.10590	0.10590	0.052951	25.92	0.000
Magnitude of failure in Transportation	2	0.13632	0.13632	0.068161	33.36	0.000
Land Use	2	0.05735	0.05735	0.028673	14.03	0.000
Error	27	0.05516	0.05516	0.002043	nan	nan
Total	35	0.37853	nan	nan	nan	nan

Table 7
ANOVA Table for interactions for DOE

	Df	SS	F value	Pr(>F)
Land Use	1	2.81E-03	1.096709	3.04E-01
Community	1	1.39E-02	5.428965	2.72E-02*
Magnitude of failure in Water	1	8.96E-02	34.9102	2.34E-06***
Magnitude of failure in Transportation	1	1.20E-02	4.659513	3.96E-02*
Land Use*Community	1	1.15E-01	44.99883	2.78E-07***
Land Use*Water	1	2.99E-02	11.65247	1.97E-03**
Community *Water	1	4.31E-02	16.8055	3.22E-04***
Residuals	28	7.18E-02	NA	NA
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				

Table 8
Performance Measures of predictive models

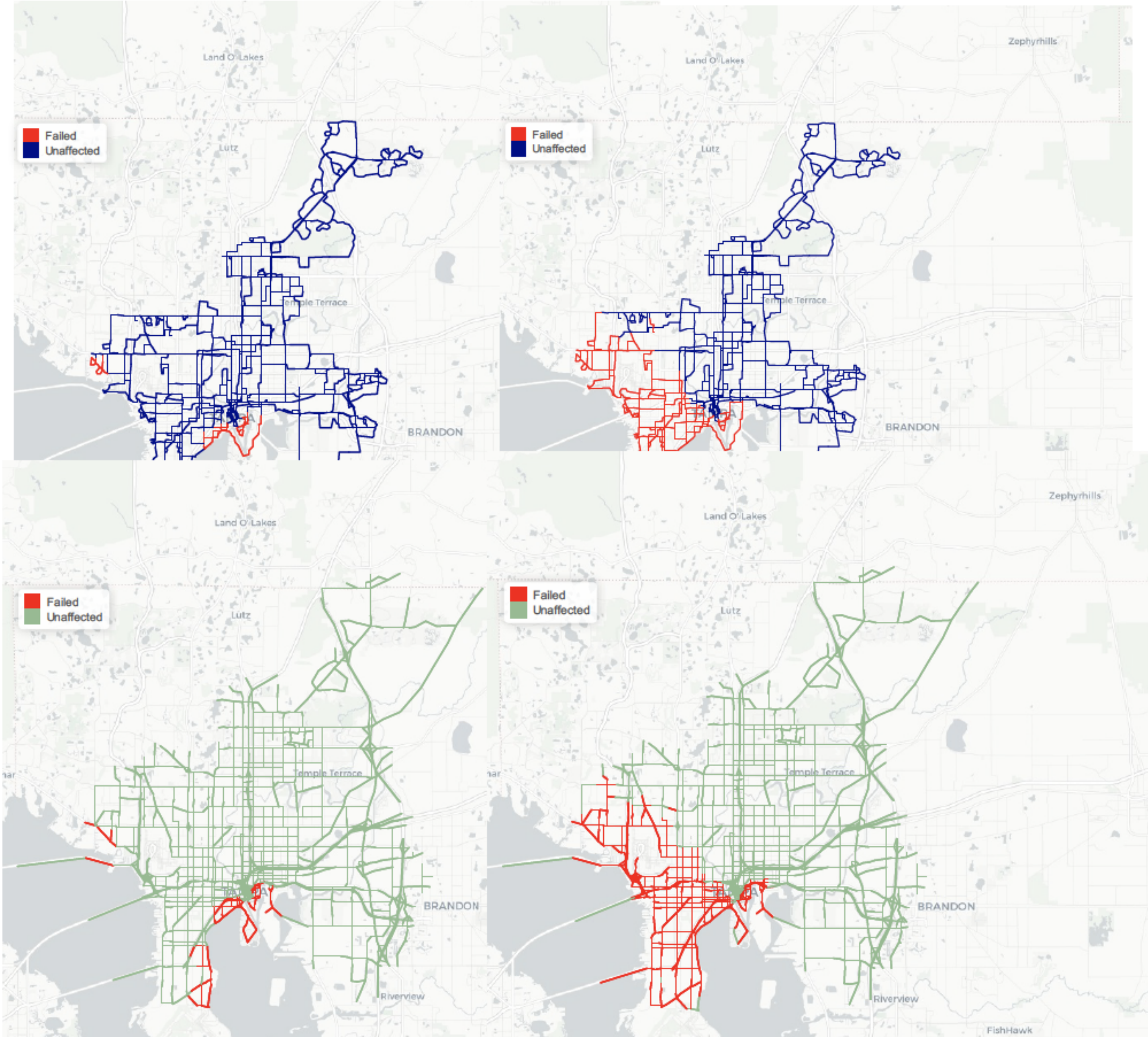
	Performance Measure						
Method	MAE train	RMSE train	MAE test	RMSE test	ICOMP	AIC	CAIC
BART	**0.0002**	**0.0002**	**0.012**	**0.015**	**54.740**	**100.210**	**147.234**
MARS	0.071	0.094	0.066	0.096	58.608	104.021	151.044
ANN	0.078	0.310	0.091	0.120	58.992	104.448	151.472
RF	0.065	0.093	0.087	0.106	58.798	104.245	151.269
BRT	0.067	0.089	0.087	0.117	58.218	103.682	150.706

practice, we split the data to 70/30 for training and testing the models, and used a 5-fold cross-validation process. The performance of the developed predictive models for random failure scenarios is compared (Table 8) based on MAE and RMSE measures as well as three information-based criteria (refer to Mohebbi et al. (2019), Akaike's classic Information Criterion (AIC), Information Complexity (ICOMP), and Consistent Akaike's AIC (CAIC). Based on these criteria, BART is selected as the best predictive model.

5.5. Cascading Impact of Natural Disasters (Hurricane Irma)

Fig. 4 shows the initial failure in water and transportation networks and the propagated failures in the interdependent network caused by Hurricane Irma. These failures happen simultaneously in both water and transportation networks. We calculated the resilience of the interdependent network in each polygon. We considered a similar resilience index to that of the random failures (the total met demand in water and transportation networks). A threshold of 0.4 was defined to distinguish areas affected by Irma. An area is labeled affected if more than 40% of the total demand is lost. Fig. 5 depicts the resilience distribution for the affected region in Tampa. The darker shades in this figure indicate the areas with the least resilience. It is clear that the hurricane mainly impacted the southwestern areas of the city which are closer to the coastline and were in Irma's path.

To capture the spatial autocorrelation and heterogeneity, we first fit a linear regression model and mapped the residuals to scrutinize the spatial patterns. Moreover, we calculated the local Moran's I index to evaluate the spatial



(c) Initial failure in transportation network

(d) Cascaded failure in transportation network

Figure 4: Cascading failure for historic data of hurricane Irma

autocorrelation in the study region. Fig. 8 in the Appendix shows the results of these pre-processing techniques. As there are noticeable spatial clusters in both of these cases, we can use GWR as a reliable predictive model to capture the spatial non-stationarity features of our case study. Initially, we considered 15 variables of social factors, land use, community data, and failure ratio as the predictors for GWR. Then, we implemented a bi-directional stepwise model selection by AIC (stepAIC) to select the best group of predictors. The result of this step is 6 significant predictor variables summarized in Table 10. The response variable for GWR is the resilience index for each polygon. We developed the GWR model for cascading failures of the natural disaster using the *spgwr* package in R.

Table 9 presents the performance measures for these models. We can see that GWR outperforms the RF model in all performance measures. Therefore, GWR is the best predictive model to capture the spatial aspects of the data related to this natural disaster. However, this specific geospatial predictive model can be also applied to other similar cases with various sizes.

We used the developed GWR predictive model to provide the resilience map in the study area. Fig. 6 shows the overlaid map of water and transportation networks and the predicted resilience in Tampa. Darker shades in this figure show the areas with the least resilience.

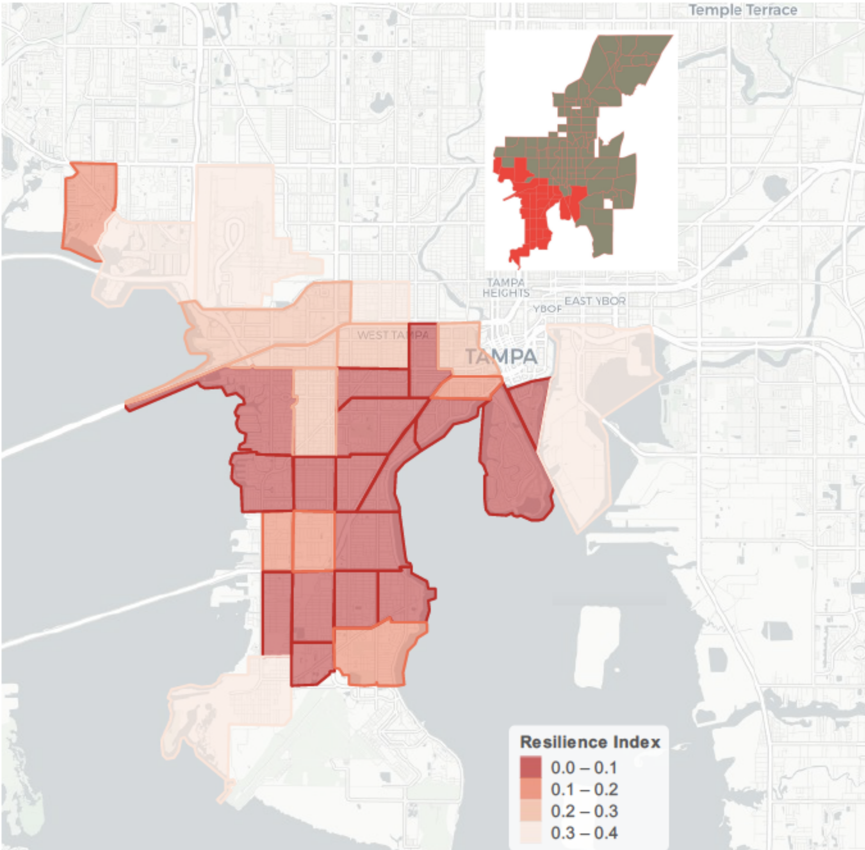


Figure 5: Resilience map of the affected area of Tampa by Hurricane Irma

Table 9
Performance measures of GWR and non-spatial RF predictive models

	Performance Measure			
Model	MAE	MSE	RMSE	R-squared
GWR	**0.087**	**0.013**	**0.114**	**0.899**
RF	0.113	0.024	0.154	0.839

6. Discussion

The performance of infrastructure systems can be disrupted by random failures and natural disasters. These disruptions can cascade to interdependent infrastructures and cause greater damage. Thus, it is crucial to analyze the resilience of interdependent infrastructures to cascading failures. In general, the results of our study showed that while the nature of random failures and natural disasters differ, they might have a similar impact on areas with specific sociotechnical characteristics. For both water and transportation networks, higher degrees of random failures in an area, propagate more rapidly in that area. Likewise, areas closer to the origin of Hurricane Irma had a higher rate of failure. These findings indicate that identifying the most vulnerable areas in the interdependent water-transportation network and resilience planning to timely respond to failures in this network will likely mitigate failure propagation and service disruption in the rest of the network.

The results of random failures showed that nodes in community 2 are the most vulnerable ones to medium and high degrees of failure in the water network. In the natural disaster scenario, areas closer to the shore are the most vulnerable. However, incorporating social vulnerability indicators in the final GWR model in the natural disaster scenario showed that spatial proximity to the origin of the hurricane was not the only important factor in the vulnerability of areas to Hurricane Irma. Interestingly, the level of all significant social variables in the final GWR model is high in this

Table 10
Significat variables in GWR model

Description of variables
Failure ratio
Average number of people per household
Percentage of Asian or Pacific Islander
Percentage of females

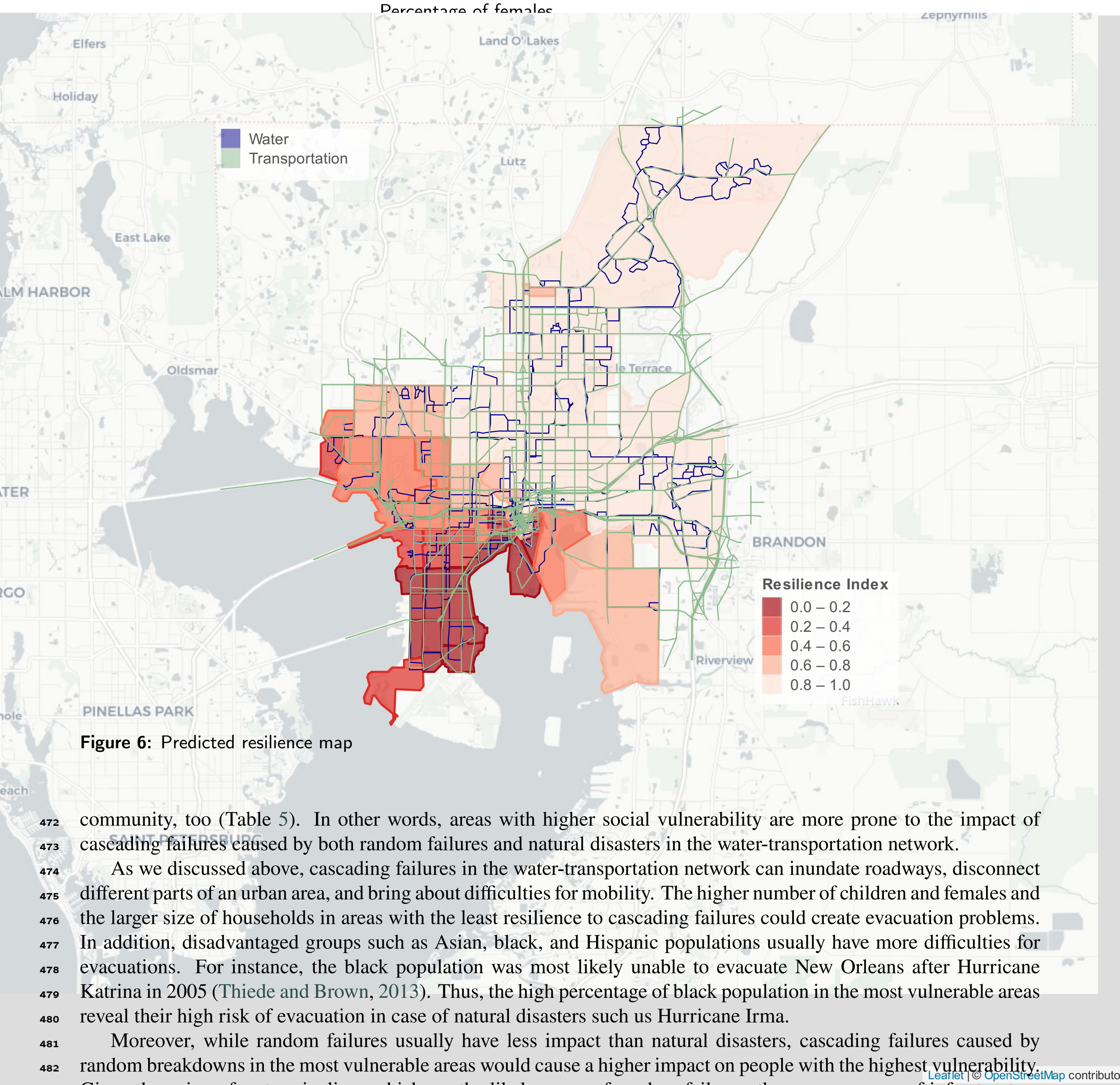


Figure 6: Predicted resilience map

community, too (Table 5). In other words, areas with higher social vulnerability are more prone to the impact of cascading failures caused by both random failures and natural disasters in the water-transportation network.

As we discussed above, cascading failures in the water-transportation network can inundate roadways, disconnect different parts of an urban area, and bring about difficulties for mobility. The higher number of children and females and the larger size of households in areas with the least resilience to cascading failures could create evacuation problems. In addition, disadvantaged groups such as Asian, black, and Hispanic populations usually have more difficulties for evacuations. For instance, the black population was most likely unable to evacuate New Orleans after Hurricane Katrina in 2005 (Thiede and Brown, 2013). Thus, the high percentage of black population in the most vulnerable areas reveal their high risk of evacuation in case of natural disasters such us Hurricane Irma.

Moreover, while random failures usually have less impact than natural disasters, cascading failures caused by random breakdowns in the most vulnerable areas would cause a higher impact on people with the highest vulnerability. Given the aging of water pipelines which are the likely cause of random failures, the consequences of infrastructure aging and random failures are disproportionately on the most vulnerable people. This imbalance in the distribution of impacts suggests that infrastructure rehabilitation and resilience planning to random failures should take into account the social aspect of infrastructures. The comparison of the cascading impact of random failures and natural disasters also showed that while random failures affect residential and industrial land use more, a natural disaster propagates uniformly in areas with different land use. This difference underlines the necessity to have resilience plans for both random failures and natural disasters and indicates which land use should be prioritized.

6.1. Resilience-Informed Infrastructure Design

The results of this study is informative for decision-makers at municipal levels to improve infrastructure design. Considering geospatial interdependencies, the design features and specifications of water and transportation infrastructures in vulnerable regions can be explored for network resilience improvements. Increasing network redundancy is a key design strategy to enhance the resilience of both water (Matthews, 2016; Di Nardo et al., 2017; Diao, 2020) and transportation networks (Chan and Schofer, 2016; Xu et al., 2018; Sun et al., 2020). The approach we used in this study pinpoints vulnerable areas in the interdependent water-transportation system and can inform redundancy enhancement in both infrastructures. In the water distribution network, decentralization is another effective design strategy to improve the efficiency and reliability of water supply and the resilience of the network to random failures and natural disasters (Vázquez-Rowe et al., 2017; Leigh and Lee, 2019; Vegas Niño et al., 2021). The impact of failures in the water distribution network that we analyzed demonstrates that decentralization and valves can be useful to contain failures locally and prevent failure propagation to other areas. Our findings also informs transportation resilience designs such as pavement designs (Bowers and Gu, 2021) that take into account traffic load (Almeida et al., 2021) and flooding (Khan et al., 2017; Lu et al., 2017), roadway intersection design such as roundabouts instead of traffic signals (Bengigi, 2020), and implementation of intelligent transportation systems (Dey et al., 2014) to support mobility during extreme weather situations.

Furthermore, geographical and environmental features can be inspected in vulnerable areas to improve resilience. Soil characteristics and proximity to a shoreline can result in less resilience to flooding events; hence, different areas might need different inspection, monitoring, and fortification planning. For instance, landscape morphology, soil moisture, and soil type in vulnerable road sections can be analyzed to identify network sections that need improved drainage system and monitoring (Kalantari et al., 2019). Likewise, the type, corrosivity, and moisture of soil around the most vulnerable pipelines can be investigated for better pipe inspection and monitoring planning (Yamijala et al., 2009).

System breakdowns in water and transportation infrastructures under normal conditions can cause service disruptions. Timely and effective maintenance and rehabilitation of these aging infrastructures are key to decrease the likelihood of such disruptions and their impact on routine infrastructure performance. Our approach in analyzing water-transportation systems can be implemented to maintain and rehabilitate these infrastructures for more reliable service during normal situations. Prioritization of rehabilitation efforts for areas prone to cascading failures will help to mitigate cascading failures within each infrastructure and across their interdependent network. Moreover, recovery plans should focus on the interdependent components as they are the critical points for failure propagation across infrastructures. Consequently, these efforts during normal situations eventually contribute to higher infrastructure resilience during extreme events (Levenberg et al., 2017; Boulos, 2017). From the social point of view, we identified the profile of vulnerable communities to both types of failures. While prioritizing these communities in evacuation plans is a crucial reactive strategy, empowering these communities by assigning financial and social supports before a disruptive event will significantly increase their preparedness and their ability to cope with such events.

The results of cascading failures caused by both random breakdowns and Hurricane Irma confirm that overlooking infrastructure interdependency will result in underestimated assessment of the impact of disturbances (Mao and Li, 2018). These results reinforce previous findings in other infrastructures that resilience assessment and planning for infrastructure systems require considering their interdependencies. Separate resilience planning for water and transportation infrastructures might lead to a higher resilience within those infrastructures. However, the analysis of recovery strategies in electric power and gas infrastructures (Ouyang and Wang, 2015) indicated that considering infrastructure interdependency in a joint infrastructure recovery plan is more effective. Therefore, a compromised resilience plan for water-transportation infrastructures that considers their interdepenednecy will likely result in a higher overall resilience in these infrastructures. Indeed, such resilience plans should go beyond the traditional technical strategies that focus on the physical aspect of these infrastructures and incorporate community profiles based on social vulnerability. This sociotechnical approach enables decision makers to strategize targeted fortification plans to improve the resilience of the interdependent infrastructures and to support more vulnerable communities to improve the overall preparedness for future incidents that could also expedite recovery from such incidents.

6.2. Policy-Making Implications

Top-down approaches have traditionally been the common strategy of governments for community resilience planning (Fitzpatrick and Molloy, 2014; Ashmawy, 2021). However, each urban community is a unique sociotechnical system, and local stakeholders that are directly involved in the everyday functioning of a community and its challenges can make more effective community-specific resilience decision-making. These local stakeholders could be city officials, legislators, planners, and community representatives. The involvement, cooperation, and collaboration of these stakeholders have been a challenge for resilience planning (Bostick et al., 2017) as they have different interests (McConnell and Drennan, 2006). This could also be partly due to the confusion of stakeholders on how infrastructures should be improved and what the risks of disturbances are on infrastructure performance (Macaskill and Guthrie, 2018; Chester et al., 2019, 2021). Identifying infrastructure vulnerabilities to different types of failures and their impact on society is fundamental for resilience decision-making. These decision-makings can get complicated when stakeholders from each infrastructure domain compete for limited resources. The approach we presented in this study for the resilience assessment of interdependent water and transportation infrastructures supports stakeholders of these infrastructures for collaborative decision-making. Our approach enables stakeholders to understand and identify vulnerable sections of both water and transportation infrastructures to random failures and natural disasters. In addition, it highlights the interdependent components in these infrastructures that can trigger cascading failures.

A city can entirely be resilient if social equity is considered in its resilience planning (Meerow et al., 2019). Therefore, the impact of infrastructure failures on residents, as a key stakeholder in infrastructure and community resilience, should be taken into account in resilience decision-making. Our sociotechnical approach in this study offers residents stakeholders and representatives a clear picture of the social vulnerability of communities to random failures and natural disasters in water-transportation infrastructures. This social vulnerability dimension provides means for a more holistic and equitable infrastructure resilience decision-making.

A large number of critical infrastructures in the US are owned and operated by private entities (Boin and McConnell, 2007). However, private sectors and the role they can play in resilience planning are usually overlooked (McKnight and Linnenluecke, 2016; Ashmawy, 2021). Engaging private sectors is necessary for successful resilience decision-making (Marana et al., 2018). This engagement could be more successful if private entities have knowledge about the fragility of their infrastructure and the cascading failures triggered in other interdependent infrastructures. Another key private-sector stakeholder for infrastructure and community resilience is insurance. Data-driven approaches for infrastructure resilience assessment can also inform insurance companies of climate insurance actions (Rumson and Hallett, 2019). Thus, the interdependent infrastructure resilience approach proposed in this study can be adopted by city officials and insurers to facilitate more strategic financial protection of government facilities, businesses, and individuals rather than unreliable and insufficient post-disaster funding (see Surminski et al. (2016)). Such climate insurance actions will support reducing disaster losses and quicker recovery (Tonn et al., 2021).

6.3. Limitations

This study proposed an adaptable framework to assess the resilience of interdependent water-transportation infrastructures. We showed and tested its applicability through a case study in the City of Tampa. The framework can be applied to other case studies and scenarios for further analyses. For instance, we used FEMA's flooding data after Hurricane Irma for natural disaster scenarios. While hurricanes are one of the main natural disasters threatening Tampa, other natural disasters might have a different impact on the water-transportation network. Further, hurricanes with varying intensities and trajectories might cause different levels of flooding in different areas of a city; in the case of Tampa, these flooding levels might be different from what Hurricane Irma caused. Thus, a sensitivity analysis of the impact of hurricanes with different intensities will likely provide a clearer perspective of the resilience of the water-transportation network in Tampa.

Additionally, our analysis indicated that areas with higher social vulnerability are more prone to cascading failures caused by both random failures and natural disasters. While this finding provides valuable information for a more equitable resilience planning in the water-transportation network of Tampa, we recognize that other cities should be analyzed to determine if a similar relationship exists in other communities.

In this study, based on the characteristics and materials of water pipelines in Tampa, the failures that road congestion (traffic load) can cause on pipelines were small and negligible. However, it should be noted that in larger cities such as Washington, New York City, Los Angeles, and Boston that experience the highest level of congestion in the nation

(INRIX, 2021), heavy traffic especially in areas with low roadway resilience to congestion (Khaghani et al., 2019) can cause cascading failures in the water network.

7. Conclusions

Infrastructure resilience studies generally analyze a single infrastructure and its response, recovery, or adaptation to a disturbance which is mainly an extreme event such as a natural disaster. These studies have improved our understanding of infrastructure systems and their capacities to cope with disturbances. However, infrastructures are interdependent systems, and this interdependency influences infrastructure resilience. In this study, we presented a comprehensive algorithmic framework and analyzed the resilience of the water and transportation infrastructures to extreme events and random failures. The contributions of this study can be described in three areas.

First, we developed an algorithmic framework to assess the resilience of water-transportation infrastructures. We created an interdependent network of these infrastructures that allowed us to investigate the impact of failures on both infrastructures. Since infrastructures experience both random failures and natural disasters, we analyzed the impact of these disturbances on the resilience of the interdependent water-transportation network. For both infrastructures, we measured resilience as the maintained level of service after a disruption. The analysis of the impact of both random failures and natural disasters on this interdependent network highlighted the similarities and differences between these failures and provided a clearer understanding of the resilience of these infrastructures.

In addition, we studied the cascading effects of failures caused by both random failures and Hurricane Irma within and across infrastructures and identified areas that are more vulnerable to cascading failures. For random failures, we used the Taguchi method for the experimental design of failure scenarios. For the impact of Hurricane Irma, two predictive models were designed to quantify resilience. We developed geospatial GWR and non-spatial RF models and compared the results. The GWR model performed better than RF, meaning it can appropriately capture the spatial autocorrelation and heterogeneity of data. This geospatial model can help the administrators to predict the level of damage from future natural disasters and strengthen the weak spots to mitigate the impact. Besides, by estimating the residual water heights of flooding in different parts of Tampa, we distinguished the regions that were impacted the most. Pinpointing these areas underlines the necessity of coordinated and joint resilience planning for these infrastructures to mitigate the impact of failures and their propagation. The approach we used in this study can be extended to other infrastructures, other types of interdependencies, and other disturbances for a more complete resilience assessment among the entire critical infrastructure systems in an urban area and a more comprehensive resilience planning for infrastructures and communities.

The resilience of infrastructures and communities are entangled and a comprehensive resilience assessment and planning should incorporate community features. Therefore, in this study, we took a sociotechnical approach and incorporated social vulnerability and land use factors in our interdependent resilience assessment framework. The results showed the disproportionately greater impact of random failures and natural disasters in areas with higher social vulnerability and in residential land use. These findings confirm the intertwined relationship between infrastructure and community resilience and emphasize the incorporation of socioeconomic and land use factors in resilience assessment for thorough, rigorous, and equitable resilience planning. Moreover, the resilience assessment approach we used in this study can be extended to include the consequent costs incurred to the systems by failures, which could provide more insights for decision-makers.

Acknowledgements

This work was supported by the US National Science Foundation under Grant Number 1638301. Any opinions, Findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abdel-Mottaleb, N., Ghasemi Saghand, P., Charkhgard, H., and Zhang, Q. (2019). An exact multiobjective optimization approach for evaluating water distribution infrastructure criticality and geospatial interdependence. *Water Resources Research*, 55(7):5255–5276.

Aksha, S. K., Juran, L., Resler, L. M., and Zhang, Y. (2019). An analysis of social vulnerability to natural hazards in nepal using a modified social vulnerability index. *International Journal of Disaster Risk Science*, 10(1):103–116.

Albrito, P. (2012). Making cities resilient: Increasing resilience to disasters at the local level. *Journal of business continuity & emergency planning*, 5(4):291–297.

Almeida, A., Moreira, J. J., Silva, J. P., and Viteri, C. G. (2021). Impact of traffic loads on flexible pavements considering ecuador's traffic and pavement condition. *International Journal of Pavement Engineering*, 22(6):700–707.

Antenucci, A. and Sansavini, G. (2018). Adequacy and security analysis of interdependent electric and gas networks. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 232(2):121–139.

Armas, I. and Gavris, A. (2013). Social vulnerability assessment using spatial multi-criteria analysis (sevi model) and the social vulnerability index (sovi model)–a case study for bucharest, romania. *Nat. Hazards Earth Syst. Sci*, 13(6):1481–1499.

ASCE (2017). 2017 infrastructure report card. ASCE Reston, VA.

Ashmawy, I. K. I. (2021). Stakeholder involvement in community resilience: evidence from egypt. *Environment, Development and Sustainability*, 23(5):7996–8011.

Aslani, B., Mohebbi, S., and Axthelm, H. (2021). Predictive analytics for water main breaks using spatiotemporal data. *Urban Water Journal*, 18(6):433–448.

Așchilean, I., Iliescu, M., Ciont, N., and Giurca, I. (2018). The unfavourable impact of street traffic on water distribution pipelines. *Water*, 10(8):1086.

Baird, G. M. (2020). New us and international water main break studies: More detailed pipe analysis but what are we doing with the data? In *Pipelines 2020*, pages 316–325. American Society of Civil Engineers Reston, VA.

Bengigi, E. (2020). Efficiency and resilience trade-offs for roadway intersection design in the us virgin islands. Technical report, Naval Postgraduate School.

Boin, A. and McConnell, A. (2007). Preparing for critical infrastructure breakdowns: the limits of crisis management and the need for resilience. *Journal of contingencies and crisis management*, 15(1):50–59.

Bostick, T. P., Holzer, T. H., and Sarkani, S. (2017). Enabling stakeholder involvement in coastal disaster resilience planning. *Risk analysis*, 37(6):1181–1200.

Boulos, P. F. (2017). Smart water network modeling for sustainable and resilient infrastructure. *Water Resources Management*, 31(10):3177–3188.

Bowers, B. F. and Gu, F. (2021). Resilient asphalt pavements: Industry solutions for the resilience goal. *Sustainability in Practice*, (105).

Cantillo, V., Macea, L. F., and Jaller, M. (2019). Assessing vulnerability of transportation networks for disaster response operations. *Networks and Spatial Economics*, 19(1):243–273.

Cao, Y.-Y., Liu, R.-R., Jia, C.-X., and Wang, B.-H. (2021). Percolation in multilayer complex networks with connectivity and interdependency topological structures. *Communications in Nonlinear Science and Numerical Simulation*, 92:105492.

Chan, R. and Schofer, J. L. (2016). Measuring transportation system resilience: Response of rail transit to weather disruptions. *Natural Hazards Review*, 17(1):05015004.

Chester, M. V., Allenby, B., Iles, A., and Chang, M. E. (2019). Infrastructure as a wicked complex process. *Elementa: Science of the Anthropocene*, 7.

Chester, M. V., El Asmar, M., Hayes, S., and Desha, C. (2021). Post-disaster infrastructure delivery for resilience. *Sustainability*, 13(6):3458.

Chun, H., Chi, S., and Hwang, B. G. (2017). A spatial disaster assessment model of social resilience based on geographically weighted regression. *Sustainability*, 9(12):2222.

Cutter, S., Emrich, C., Morath, D., and Dunning, C. (2013). Integrating social vulnerability into federal flood risk management planning. *Journal of Flood Risk Management*, 6(4):332–344.

Cutter, S. L., Boruff, B. J., and Shirley, W. L. (2003). Social vulnerability to environmental hazards*. *Social Science Quarterly*, 84(2):242–261.

Dey, K. C., Mishra, A., and Chowdhury, M. (2014). Potential of intelligent transportation systems in mitigating adverse weather impacts on road mobility: A review. *IEEE Transactions on Intelligent Transportation Systems*, 16(3):1107–1119.

DHS (2021). Us department of homeland security, critical infrastructure sectors. Accessed: 2021-03-04.

Di Nardo, A., Di Natale, M., Giudicianni, C., Musmarra, D., Varela, J. R., Santonastaso, G., Simone, A., and Tzatchkov, V. (2017). Redundancy features of water distribution systems. *Procedia Engineering*, 186:412–419.

Diao, K. (2020). Multiscale resilience in water distribution and drainage systems. *Water*, 12(6):1521.

Dong, S., Wang, H., Mostafizi, A., and Song, X. (2020). A network-of-networks percolation analysis of cascading failures in spatially co-located road-sewer infrastructure networks. *Physica A: Statistical Mechanics and Its Applications*, 538:122971.

Fahy, B., Brenneman, E., Chang, H., and Shandas, V. (2019). Spatial analysis of urban flooding and extreme heat hazard potential in portland, or. *International journal of disaster risk reduction*, 39:101117.

FDEP (2021). Florida department of environmental protection geospatial open data. `https://geodata.dep.state.fl.us/`. Accessed: 2020-01-30.

FHWA, C. (2005). Traffic congestion and reliability: Trends and advanced strategies for congestion mitigation. Technical report, United States. Federal Highway Administration.

Fitzpatrick, T. and Molloy, J. (2014). The role of ngos in building sustainable community resilience. *International Journal of Disaster Resilience in the Built Environment*.

Ghahramani, Z. (2006). *Information Theory*. American Cancer Society.

Golub, A. and Martens, K. (2014). Using principles of justice to assess the modal equity of regional transportation plans. *Journal of Transport Geography*, 41:10–20.

Gori, A., Gidaris, I., Elliott, J. R., Padgett, J., Loughran, K., Bedient, P., Panakkal, P., and Juan, A. (2020). Accessibility and recovery assessment of houston's roadway network due to fluvial flooding during hurricane harvey. *Natural hazards review*, 21(2):04020005.

Heracleous, C., Kolios, P., Panayiotou, C. G., Ellinas, G., and Polycarpou, M. M. (2017). Hybrid systems modeling for critical infrastructures interdependency analysis. *Reliability Engineering & System Safety*, 165:89–101.

Holand, I. S. and Lujala, P. (2013). Replicating and adapting an index of social vulnerability to a new context: a comparison study for norway. *The Professional Geographer*, 65(2):312–328.

INRIX (2021). https://inrix.com/. Accessed: 2021-03-04.

Jia, C., Li, Y., Carson, M. B., Wang, X., and Yu, J. (2017). Node attribute-enhanced community detection in complex networks. *Scientific reports*, 7(1):2626.

Jin Jun, H., Park, J. K., and Ho Bae, C. (2020). Economic valuation of aging water main improvements. *Journal of Pipeline Systems Engineering and Practice*, 11(1):04019053.

Ka, K., M, B., D, M., and R, M. (2017). A software framework for assessing the resilience of drinking water systems to disasters with an example earthquake case study.

Kabir, G., Tesfamariam, S., Francisque, A., and Sadiq, R. (2015). Evaluating risk of water mains failure using a bayesian belief network model. *European Journal of Operational Research*, 240(1):220–234.

Kalantari, Z., Ferreira, C. S. S., Koutsouris, A. J., Ahlmer, A.-K., Cerdà, A., and Destouni, G. (2019). Assessing flood probability for transportation infrastructure based on catchment characteristics, sediment connectivity and remotely sensed soil moisture. *Science of the total environment*, 661:393–406.

Karakoc, D. B., Almoghathawi, Y., Barker, K., González, A. D., and Mohebbi, S. (2019). Community resilience-driven restoration model for interdependent infrastructure networks. *International Journal of Disaster Risk Reduction*, 38:101228.

Kelobonye, K., Zhou, H., McCarney, G., and Xia, J. C. (2020). Measuring the accessibility and spatial equity of urban services under competition using the cumulative opportunities measure. *Journal of Transport Geography*, 85:102706.

Khaghani, F., Rahimi-Golkhandan, A., Jazizadeh, F., and Garvin, M. J. (2019). Urban transportation system resilience and diversity coupling using large-scale taxicab gps data. In *Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*, pages 165–168.

Khan, M. U., Mesbah, M., Ferreira, L., and Williams, D. J. (2017). Estimating pavement's flood resilience. *Journal of Transportation Engineering, Part B: Pavements*, 143(3):04017009.

Klise, K., Hart, D., Moriarty, D., Bynum, M., Murray, R., Burkhardt, J., and Haxton, T. (2017). Water network tool for resilience (wntr) user manual.

Klise, K. A. (2018). An overview of the water network tool for resilience (wntr):. *WDSA / CCWI Joint Conference Proceedings*, 1.

Kuhlicke, C., Scolobig, A., Tapsell, S., Steinführer, A., and De Marchi, B. (2011). Contextualizing social vulnerability: findings from case studies across europe. *Natural Hazards*, 58(2):789–810.

Leigh, N. G. and Lee, H. (2019). Sustainable and resilient urban water systems: The role of decentralization and planning. *Sustainability*, 11(3):918.

Levenberg, E., Miller-Hooks, E., Asadabadi, A., and Faturechi, R. (2017). Resilience of networked infrastructure with evolving component conditions: Pavement network application. *Journal of Computing in Civil Engineering*, 31(3):04016060.

Li, S., Li, L., Yang, Y., and Luo, Q. (2012). Revealing the process of edge-based-attack cascading failures. *Nonlinear Dynamics*, 69(3):837–845.

Liu, H. and Wang, J. (2018). Vulnerability assessment for cascading failure in the highway traffic system. *Sustainability*, 10(7):2333.

Lopez, L., Afanador, L., Martinez, L., Jiménez, E., Oliveros, I., Castillo, R., Soto, J., Calle, M., and Ripoll, L. (2019). Sizing of renewable energy sources to support resilience in distribution networks. *Procedia Computer Science*, 155:535–542.

Lu, D., Tighe, S. L., and Xie, W.-C. (2017). Pavement fragility modeling framework and build-in resilience strategies for flood hazard. Technical report.

Macaskill, K. and Guthrie, P. (2018). Funding mechanisms for disaster recovery: can we afford to build back better? *Procedia engineering*, 212:451–458.

Mao, Q. and Li, N. (2018). Assessment of the impact of interdependencies on the resilience of networked critical infrastructure systems. *Natural hazards*, 93(1):315–337.

Marana, P., Labaka, L., and Sarriegi, J. M. (2018). A framework for public-private-people partnerships in the city resilience-building process. *Safety science*, 110:39–50.

Matthews, J. C. (2016). Disaster resilience of critical water infrastructure systems. *Journal of Structural Engineering*, 142(8):C6015001.

McConnell, A. and Drennan, L. (2006). Mission impossible? planning and preparing for crisis 1. *Journal of Contingencies and Crisis management*, 14(2):59–70.

McKnight, B. and Linnenluecke, M. K. (2016). How firm responses to natural disasters strengthen community resilience: A stakeholder-based perspective. *Organization & Environment*, 29(3):290–307.

McMahon, T. A., Adeloye, A. J., and Zhou, S.-L. (2006). Understanding performance measures of reservoirs. *Journal of Hydrology*, 324(1-4):359–382.

Meerow, S., Pajouhesh, P., and Miller, T. R. (2019). Social equity in urban resilience planning. *Local Environment*, 24(9):793–808.

Mohebbi, S., Barnett, K., and Aslani, B. (2021). Decentralized resource allocation for interdependent infrastructures resilience: a cooperative game approach. *International Transactions in Operational Research*, 28(6):3394–3415.

Mohebbi, S., Pamukcu, E., and Bozdogan, H. (2019). A new data adaptive elastic net predictive model using hybridized smoothed covariance estimators with information complexity. *Journal of Statistical Computation and Simulation*, 89(6):1060–1089.

Mohebbi, S., Zhang, Q., Wells, E. C., Zhao, T., Nguyen, H., Li, M., Abdel-Mottaleb, N., Uddin, S., Lu, Q., Wakhungu, M., et al. (2020). Cyber-physical-social interdependencies and organizational resilience: A review of water, transportation, and cyber infrastructure systems and processes. *Sustainable Cities and Society*, page 102327.

Munikoti, S., Lai, K., and Natarajan, B. (2021). Robustness assessment of hetero-functional graph theory based model of interdependent urban utility networks. *Reliability Engineering System Safety*, 212:107627.

Najarian, M. and Lim, G. J. (2019). Design and assessment methodology for system resilience metrics. *Risk Analysis*, 39(9):1885–1898.

Nan, C., Sansavini, G., and Kröger, W. (2014). Building an integrated metric for quantifying the resilience of interdependent infrastructure systems. In *International Conference on Critical Information Infrastructures Security*, pages 159–171. Springer.

Nelson, K. S., Abkowitz, M. D., and Camp, J. V. (2015). A method for creating high resolution maps of social vulnerability in the context of environmental hazards. *Applied Geography*, 63:89–100.

Ortega, E., Martín, B., and Aparicio, Á. (2020). Identification of critical sections of the spanish transport system due to climate scenarios. *Journal of Transport Geography*, 84:102691.

Ouyang, M. (2014). Review on modeling and simulation of interdependent critical infrastructure systems. *Reliability Engineering & System Safety*, 121:43–60.

Ouyang, M. (2016). Critical location identification and vulnerability analysis of interdependent infrastructure systems under spatially localized attacks. *Reliability Engineering & System Safety*, 154:106–116.

Ouyang, M. (2017). A mathematical framework to optimize resilience of interdependent critical infrastructure systems under spatially localized attacks. *European Journal of Operational Research*, 262(3):1072–1084.

Ouyang, M. and Wang, Z. (2015). Resilience assessment of interdependent infrastructure systems: With a focus on joint restoration modeling and analysis. *Reliability Engineering & System Safety*, 141:74–82.

Portante, E. C., Kavicky, J. A., Craig, B. A., Talaber, L. E., and Folga, S. M. (2017). Modeling electric power and natural gas system interdependencies. *Journal of Infrastructure Systems*, 23(4):04017035.

Rahimi-Golkhandan, A. and Garvin, M. J. (2020). A socio-economic comparison of urban areas with different transportation system diversity. In *Construction Research Congress 2020: Infrastructure Systems and Sustainability*, pages 771–780. American Society of Civil Engineers Reston, VA.

Renzetti, S., Dupont, D., and Dupont, D. P. (2013). Buried treasure: The economics of leak detection and water loss prevention in ontario. *Rep. No. ESRC-2013*, 1.

Rinaldi, S. M., Peerenboom, J. P., and Kelly, T. K. (2001). Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE control systems magazine*, 21(6):11–25.

Rumson, A. G. and Hallett, S. H. (2019). Innovations in the use of data facilitating insurance as a resilience mechanism for coastal flood risk. *Science of the Total Environment*, 661:598–612.

Shah, S. S. and Babiceanu, R. F. (2015). Resilience modeling and analysis of interdependent infrastructure systems. In *2015 systems and information engineering design symposium*, pages 154–158. IEEE.

Shirzad, A. and Safari, M. J. S. (2019). Pipe failure rate prediction in water distribution networks using multivariate adaptive regression splines and random forest techniques. *Urban Water Journal*, 16(9):653–661.

Shuang, Q., Liu, Y., Tang, Y., Liu, J., and Shuang, K. (2017a). System reliability evaluation in water distribution networks with the impact of valves experiencing cascading failures. *Water*, 9(6):413.

Shuang, Q., Liu, Y., Tang, Y., Liu, J., and Shuang, K. (2017b). System reliability evaluation in water distribution networks with the impact of valves experiencing cascading failures. *Water*, 9(6):413.

Shuang, Q., Zhang, M., and Yuan, Y. (2014). Node vulnerability of water distribution networks under cascading failures. *Reliability Engineering & System Safety*, 124:132–141.

Song, X., Zhang, Q., Sekimoto, Y., Shibasaki, R., Yuan, N. J., and Xie, X. (2016). Prediction and simulation of human mobility following natural disasters. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 8(2):1–23.

Sultan, V. and Hilton, B. (2020). A spatial analytics framework to investigate electric power-failure events and their causes. *ISPRS International journal of geo-information*, 9(1):54.

Sun, W., Bocchini, P., and Davison, B. D. (2020). Resilience metrics and measurement methods for transportation infrastructure: the state of the art. *Sustainable and Resilient Infrastructure*, 5(3):168–199.

Sung, C.-H. and Liaw, S.-C. (2020). A gis-based approach for assessing social vulnerability to flood and debris flow hazards. *International Journal of Disaster Risk Reduction*, 46:101531.

Sung, C.-H. and Liaw, S.-C. (2021). Using spatial pattern analysis to explore the relationship between vulnerability and resilience to natural hazards. *International journal of environmental research and public health*, 18(11):5634.

Surminski, S., Bouwer, L. M., and Linnerooth-Bayer, J. (2016). How insurance can support climate resilience. *Nature Climate Change*, 6(4):333–334.

Tan, Y. V. and Roy, J. (2019). Bayesian additive regression trees and the general bart model. *Statistics in medicine*, 38(25):5048–5069.

Tate, E. (2013). Uncertainty analysis for a social vulnerability index. *Annals of the Association of American Geographers*, 103(3):526–543.

Tate, E., Strong, A., Kraus, T., and Xiong, H. (2016). Flood recovery and property acquisition in cedar rapids, iowa. *Natural Hazards*, 80(3):2055–2079.

Thiede, B. C. and Brown, D. L. (2013). Hurricane katrina: Who stayed and why? *Population Research and Policy Review*, 32(6):803–824.

Tochaei, E. N., Fang, Z., Taylor, T., Babanajad, S., and Ansari, F. (2021). Structural monitoring and remaining fatigue life estimation of typical welded crack details in the manhattan bridge. *Engineering Structures*, 231:111760.

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.

Vázquez-Rowe, I., Kahhat, R., and Lorenzo-Toja, Y. (2017). Natural disasters and climate change call for the urgent decentralization of urban water systems. *Science of the total environment*, 605:246–250.

Vegas Niño, O. T., Martínez Alzamora, F., and Tzatchkov, V. G. (2021). A decision support tool for water supply system decentralization via distribution network sectorization. *Processes*, 9(4):642.

Walsh, C., Glendinning, S., Castán-Broto, V., Dewberry, E., and Powell, M. (2015). Are wildcard events on infrastructure systems opportunities for transformational change? *Futures*, 67:1–10.

Wang, K., Zhang, C., and Li, W. (2013). Predictive mapping of soil total nitrogen at a regional scale: A comparison between geographically

weighted regression and cokriging. *Applied Geography*, 42:73–85.
Wisner, B., Blaikie, P., Cannon, T., and Davis, I. (2004). People's vulnerability and disasters.
Xu, X., Chen, A., Jansuwan, S., Yang, C., and Ryu, S. (2018). Transportation network redundancy: Complementary measures and computational methods. *Transportation Research Part B: Methodological*, 114:68–85.
Yamijala, S., Guikema, S. D., and Brumbelow, K. (2009). Statistical models for the analysis of water distribution system pipe break data. *Reliability Engineering & System Safety*, 94(2):282–293.
Zhang, Y., Levina, E., and Zhu, J. (2016). Community detection in networks with node features. *Electronic Journal of Statistics*, 10(2):3153–3178.
Zhu, S., Levinson, D., Liu, H. X., and Harder, K. (2010). The traffic and behavioral effects of the i-35w mississippi river bridge collapse. *Transportation research part A: policy and practice*, 44(10):771–784.
Zuloaga, S., Khatavkar, P., Vittal, V., and Mays, L. W. (2020). Interdependent electric and water infrastructure modelling, optimisation and control. *IET Energy Systems Integration*, 2(1):9–21.

A. Appendix

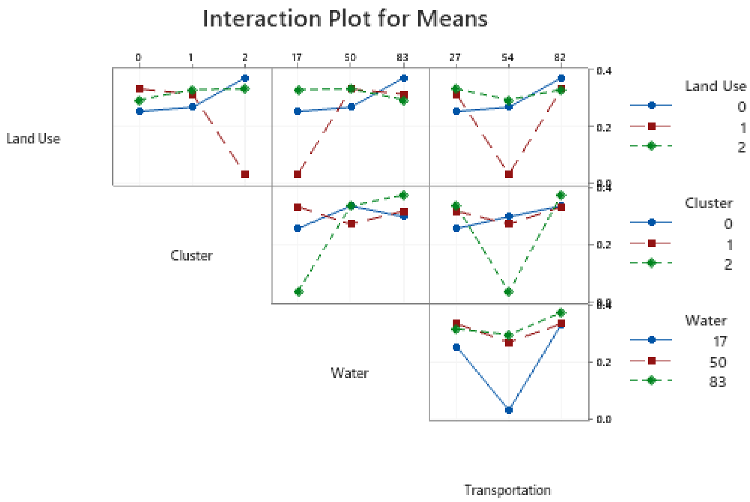
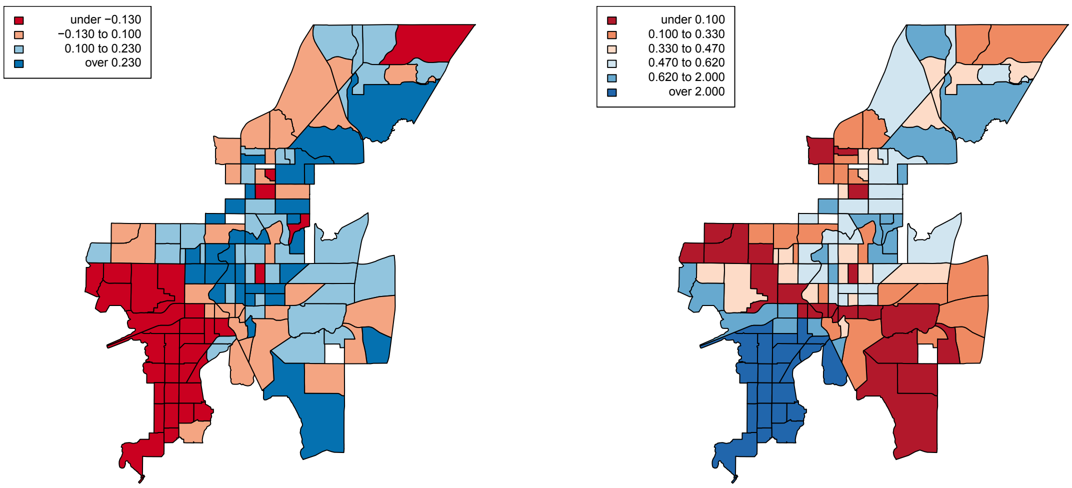


Figure 7: Interaction plots for DOE



(a) Residual of linear regression

(b) Local Moran's I

Figure 8: Spatial autocorrelation maps