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Social vulnerability and equity perspectives on interdependent infrastructure network component importance

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ABSTRACT

Critical infrastructure networks are often described as (i) interdependent in nature for operability, (ii) vulnerable against multiple natural or human-made hazards, and (iii) vital for providing the essential needs and ensuring the functionality of societies. Developing a plan for infrastructure network resilience is enabled by the identification of the most critical components that have the largest impact on the performance interdependent networks, as well as on society in terms of serving its needs. In this work, we propose a component importance measure that is driven by the social aspects of resilience, which quantifies the impact of equitable restoration activities on components of interdependent infrastructure networks. To integrate the social expectations from various perspectives in the restoration scheduling of interdependent infrastructure networks, we combine this component importance measure with multiple social vulnerability measures that define different socio-economic characteristics in a society. Finally, we implement a multi-criteria decision analysis technique to determine the final importance ranking of the components and illustrate our approach with two critical infrastructure networks in Shelby County, TN. To our knowledge, our proposed methodology is the first to incorporate both social equity and social vulnerability concepts with the component importance measures of critical interdependent infrastructure network restoration scheduling.

1. Introduction

Critical infrastructure networks, including electric power, water distribution, gas, telecommunication, and transportation, ensure the economic activities, healthcare, security, and overall quality of life of society. These networks and their components, which are crucial for the daily operations of communities, are vulnerable against multiple stressors (e.g., natural disasters, malevolent attacks, random failures, and system aging) that could interrupt their proper functioning. For the last two decades, the importance of ensuring that infrastructure networks are secure and prepared for any unexpected threats are highlighted in the literature. The Report of the President's Commission on Critical Infrastructure Protection (1997), The Infrastructure Security Partnership (2011), the National Infrastructure Protection Plan (Department of Homeland Security, 2013), White House (2013) and many other scientific reports emphasized on how important the critical infrastructures are for society, what type of properties should they contain, and how resilient critical infrastructures should perform in case of disruptive events.

In the study of critical infrastructure resilience, Ahern (2011) suggests that the focus of the proposed research methodologies recently shifted from "fail-safe" to "safe-to-fail" networks. Rather than protecting reliable infrastructure networks, emphasis has shifted to preparing for and developing resilient infrastructures that are designed with the reality of possible disruptions in mind so that these networks can ensure recovery and can achieve a certain level of performance in a timely manner even after being subjected to inoperability (Turnquist and Vugrin, 2013).

Planning for resilient infrastructure networks requires accounting for their interdependent nature, as infrastructure networks often rely on each other for operability. Two infrastructure networks are classified as interdependent if the state of one network is correlated with or influenced by the state of the other network (Rinaldi et al. 2001). For example, the electricity generated and transported in the power network could also be used in supplying energy to water pumps, and the water that is pumped and transported in the water network could be used to cool off generators in the power network. Disruptions in one network could affects others, and the restoration of one network could be

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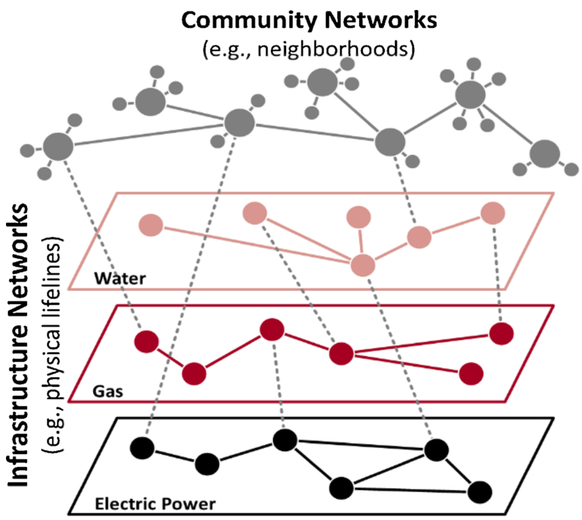

Fig. 1. Illustration of the interconnection between physical infrastructure and community networks.
adapted from Barker et al. (2017).

required for the full restoration of others.

Barker et al. (2017) note the difference between infrastructure networks, the engineered cyber-physical systems that enable essential "lifeline" services for society, and community networks, the interconnected society that such lifeline networks support (e.g., relationships among people and communities). The relationship between these networks is depicted generally in Fig. 1. Because infrastructure networks exist not for their own purposes but because networks of communities rely upon them, it is important to understand how physical disruptions impact communities and thus how physical infrastructure resilience enables community resilience. Community resilience defined as the ability of a community to successfully cope with disruptions and to coordinate recovery activities (Rotmans et al., 2003), and it is very much a function of the resilience of underlying infrastructure networks.

In the most recent literature, incorporating the social aspects and impacts become a highly relevant concern in applications dealing with (i) climate change mitigation and adaptation studies (Kontokosta and Malik 2018, Dulal et al. 2009), (ii) critical infrastructure functionality and protection analysis (Chen et al. 2019; France-Mensah et al.2019), and (iii) developing and planning resilient cities (Bibri and Krogstie 2017, Cariolet et al. 2019, Marana et al. 2019, Ribeiro and Gonçalves 2019, and Zhou et al. 2019). Through these studies, both social equity and community resilience concepts are highlighted to represent the social concerns related to urban resilience and healthy functionality of urban systems. More specifically, Rosenheim et al. (2017) integrated the household characteristics with the modeling of infrastructure network post-hazard resilience, Gardoni and Murphy (2018) defined sustainability and resilience of interdependent infrastructure networks, and promoted certain engineering tools for developing them which aims to promote societal well-being. Koliou et al. (2018) suggested extensions to existing modeling methodologies aimed at developing an improved, integrated understanding of community resilience. Karakoc et al. (2019) integrated social vulnerability to adapt community resilience with the restoration scheduling of interdependent infrastructure networks, Tabandeh et al. (2018) developed probabilistic models to predict the societal impact of disruptive events and a mathematical formulation for societal resilience analysis. Kammouh et al. (2019) defined an indicator-based method for measuring urban community resilience. Yang et al. (2020) developed an approach to assess pre-event socio-technical community resilience that integrates a topological-based evaluation, a physics-based performance simulation, and multi-criteria decision analysis.

From another aspect of considering the societal dimension, integrating social equity through preparedness and recovery activities against disruptions is another critical humanitarian approach that has also been introduced in the literature (Gralla et al. 2014, Huang et al. 2012). Especially in disaster relief efforts and humanitarian supply chain management, social equity is addressed such that (i) the optimal distribution of relief goods or demanded commodities to the effected society ensures that an equitable amount of goods are provided to each portion of the community (Davis et al. 2013, Noyan et al., 2015) or (ii) the relief efforts and allocation of resources are reshaped based on the varying vulnerability, expectations, and social demographics of the different groups (Arnette and Zobel 2019, and Zolfaghari and Peyghaleh 2015).

Different components in the infrastructure networks can have different impacts on its own network, as well as other interdependent infrastructure and community networks. For example, the outage of a particular electric power substation could adversely impact the entire power grid, the water and telecommunications networks that require electricity, and several populations, such as elderly, disabled, young children, and those without economic means, which could be vulnerable during times of disruption since they are potentially unable to function well on their own and they lack ability to evacuate without substantial assistance (Tierney 2006). As such, it is important to identify the critical components of the infrastructure networks to understand their impacts and to effectively plan for their restoration. The identification of critical components has been aided by component importance measures (CIMs), long studied in the reliability engineering literature. Particularly for networks, topology-driven CIMs rank components by average path length (Newman et al., 2006) and network efficiency (Nagurney and Qiang 2009), while flow-driven CIMs have been developed for various vulnerability measures (Nicholson et al. 2016, Ouyang, 2014, Rocco et al., 2010). Several importance measures have been developed to capture network resilience (Barker et al. 2013, Whitson and Ramirez-Marquez 2009), including recoverability-driven CIMs identified by their optimal repair time and their role in reducing resilience (Fang et al. 2016). Several CIMs have been developed for interdependent networks, including: (i) interdependent rank ordering, which considers physical interdependency among and ranks each node separately for multiple importance criteria (i.e., network connectivity, flow transfer, network vulnerability, flow traversal), (ii) geographic valued worth, which ranks geographic locations by the disruption impact of that location over the multiple, geographically interdependent networks, (iii) a CIM that ranks components in interdependent networks according to their synergistic consequences over the total synergistic consequences for a specific failure set (Johansson and Hassel 2010), and (iv) a CIM that evaluates network components according to the drop in the network performance that is caused by their one-at-a-time disruption (Wang et al. 2013).

In this study, we develop a resilience-driven CIM that combines (i) interdependent infrastructure network restoration with (ii) impact on the community that those infrastructure network components serve. This is a new contribution to the literature, to the best of our knowledge, in that we consider several indicators of social aspects of the resilience of physical infrastructures system where both types of social equity (i.e. vertical and horizontal) and the multiple dimensions of social vulnerability, driven by the Social Vulnerability Index (Cutter et al. 2003), are integrated with the resilience-driven CIM. In this study, the components of the interdependent infrastructure networks are separately ranked according to those social vulnerability dimensions of the CIM, and then these rankings are aggregated with a multi-criteria decision analysis technique. This proposed approach provides a new perspective on infrastructure network component importance that ties heavily to social equity and community resilience, incorporating the social reliance on critical infrastructure resilience for a more comprehensive understanding of the relationship between physical and social urban systems.

The remainder of this paper is organized as follows. In Section 2, we explain the methodological background that our proposed approach is built upon, in Section 3 we introduce our mixed-integer multi-objective resilience-driven optimization model for interdependent infrastructure network restoration problem. In Section 4, we define the adopted component importance measure in our study and in Section 5 the illustrative example of our proposed study is included over the critical infrastructure networks in Shelby County, TN. Finally, Section 5 is followed by the concluding remarks of our paper.

2. Background

In this section, we discuss some literature that motivates our development of a new approach to developing mainly community-driven component importance measures for interdependent infrastructure networks.

2.1. Network resilience

Network resilience is often accepted as the ability of the system to withstand, adapt to, and recover from a disruption to reach the desired level of performance (Obama, 2013). Many approaches have been proposed to quantify the resilience level of a system (Hosseini et al. 2016). Such approaches calculate resilience as the normalized area under the performance function (Bruneau et al. 2003, Cimellaro et al. 2010), as the ratio of expected degradation over network performance (Rose 2007), and as the probability of failure recovery (Li and Lence 2007), among several others. More recently, Ouyang and Dueñas-Osorio (2012) introduced a time-dependent resilience measure for assessment and improvement for urban infrastructure systems, Ouyang et al. (2012) developed a three-stage resilience analysis framework for urban infrastructure systems, and Panteli et al. (2017a), Panteli et al. (2017b) introduced a resilience trapezoid to quantify the time-dependent resilience metrics to capture its dynamic nature.

In this study, we adopt the resilience paradigm proposed by Henry and Ramirez-Marquez (2012), where resilience at a given time is quantified as the recovery in the network performance by the restoration over the performance loss due to a disruption. That is, resilience is formulated as $Я(t|e^j) = \text{Recovery}(t)/\text{Loss}(t_d)$ where e^j is the disruptive event and $t_d < t < t_f$ as illustrated in Fig. 2. Also depicted in Fig. 2 are the two primary dimensions of network resilience: *vulnerability*, or the magnitude of damage in network performance due to a disruption (Jönsson et al. 2008), and *recoverability*, or the speed at which the network reaches to a desired performance level (Rose 2007).

The CIM proposed in this paper is primarily motivated by the recoverability dimension of Fig. 2. In the last decade, the study focus is shifted to the recovery state of the critical infrastructure networks and planning their restoration after a disruptive event. Many approaches have been proposed for infrastructure network restoration scheduling from a network optimization perspective, including a mixed-integer model developed by Nurre et al. (2012) that maximizes the cumulative weighted network flow through recovery by assigning disrupted components to available work crews; a dynamic path based mathematical model by Aksu and Ozdamar (2014) that maximizes the accessibility of the network by removing the disruption debris, and a bi-level optimization model by Vugrin et al. (2014) that provides the optimum recovery schedule to maximize the network flow. Sharkey et al. (2015) proposed a mixed-integer programming that determines the disrupted components that should be restored and assigns them to work crews according to minimal cost of total flow, restoration, and unmet demand. González et al. (2016) proposed an interdependent infrastructure design problem to compute the optimum recovery schedule with the consideration of operational, budget, and resource availability constraints. Lastly, Almoghathawi et al. (2019) formulated a multi-objective mixed integer programming that returns the optimal restoration schedule of disrupted components by maximizing the resilience and minimizing the total restoration cost of the interdependent infrastructure networks.

More recently, from a different modeling perspective, Guidotti et al. (2016) developed a unified theoretical methodology that models interdependent infrastructure networks to assess the resilience of the system of networks with a probabilistic procedure. Panteli et al. (2017a), Panteli et al. (2017b) proposed a sequential Monte Carlo-based time-series simulation model to measure the resilience of power infrastructure network as a context of system of systems. Nan and Sansavini (2017) defined a quantitative method for assessing system resilience that integrates a hybrid modeling approach to represent failure behavior of infrastructure systems. Batouli and Mostafavi (2018) created a complex system modeling framework that integrates stochastic simulation for stressor effects, a dynamic modeling for infrastructure conditions, and a decision-theoretic model of infrastructure management to analyze the resilience of road infrastructure against sea-level rise.

The examined approaches and many more are based on developing a system of resilient infrastructure networks so that these systems would be able to mitigate with the inevitable risk of disruption in a timely manner to maintain their functioning at a certain desired level.

2.2. Social vulnerability

In defining network vulnerability in a holistic way, Mileti (1999) focused on the impacts of the surrounding environment vulnerabilities from three perspectives: (i) the physical environment, (ii) the

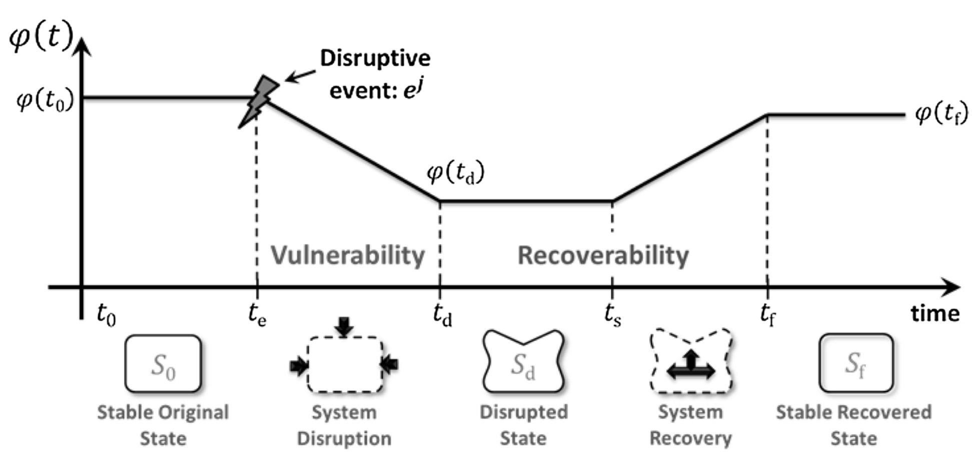

Fig. 2. Illustration of network performance, $\varphi(t)$, across different transition states. adopted from Henry and Ramirez-Marquez (2012).

constructed structures, and (iii) the served society. The first perspective deals with the spatial characteristics of the setting of an infrastructure network and could be quantified with spatially-explicit information (i.e. location of the network components) (Mileti 1999) and the evacuation potential of the study region (in arterial miles/mi^2) (National Research Council, 2006). The second perspective deals with the vulnerability of structures, which could be quantified by housing age (National Research Council, 2006) and the tree trimming frequency of the region (Guikema et al. 2006). With regard to the third perspective, on understanding the vulnerability level of the served society, more human and community characteristics are considered. For example, in terms of the adequacy of restoration resources for a given community, some studies considered the number of available resources (i.e., restoration work crews and equipment, physicians and emergency responders) (Norris et al., 2007), the shelter capacity (Tierney 2009), and the medical capacity (Auf der Heide and Scanlon 2007), among others. Other studies have emphasized the importance of socio-economic demographics to describe the vulnerability of the served society. For example, Norris et al. (2007) and Cutter et al. (2008) focused on racial and ethnic inequalities in communities, Norris et al. (2007) and Morrow (2002) focused on educational inequality, and Cutter et al. (2008) analyzed previous disaster experience. Cutter et al. (2008) and Silver and Andrey (2014) suggest that if the community learns from the previous hazard event and utilizes the opportunity to improve its preparedness, it is likely to increase its inherent resilience before the next event occurs.

Social vulnerability is defined as the set of characteristics of an individual or a group that influences their capacity to anticipate, cope with, resist, and recover from the impact of a hazard (Blaikie et al. 1994). Many take a socio-economic approach to model social vulnerability, as such socio-economic measures that represent the inherent vulnerabilities of certain demographic groups where due to these different natures, the consequences of the same disruption over different communities would not be same (Cutter et al. 2003, Morrow 2002, Cutter et al. 2008, Tierney 2009). One such model is the Social Vulnerability Index (SoVI). Cutter et al. (2003) developed the SoVI algorithm to identify the socially more vulnerable groups in society and formulate a final aggregated index describing the cumulative effect of individual socioeconomic characteristics. In the SoVI algorithm, the 42 distinct socio-economic characteristics are defined as social vulnerability variables as each one of them represent a different sub-group in the society. Also, these variables are grouped into eleven social vulnerability factors and they are listed in Table 1.

According to their definition, these factors and the social vulnerability variables either contradict or contribute to the vulnerability of community networks. According to Cutter et al. (2003), these socio-economic characteristics and the communities that are as socially vulnerable could require more and prior restoration resources (e.g., additional communication during times of crisis, expedited restoration) to cope with and recover from a disruption in a timely manner. Thus, including these various expectations and differing needs of communities would guide pre-disruption preparedness plans as well as post-disruption restoration schedules.

Table 1
The 11 social vulnerability factors that are pre-determined by Cutter et al. (2003) to account for all the possible socially more vulnerable sub-groups in the society.

Age	Occupation
Density of the built environment	Personal wealth
Ethnicity (Hispanic)	Race (African-American)
Ethnicity (Native American)	Race (Asian)
Housing stock and tenancy	Single-sector economic dependence
Infrastructure dependence	

2.3. Social equity

The concept of equity has been divided into two categories: (i) horizontal and (ii) vertical equity. Joseph et al. (2016) defined *horizontal equity* as the equal treatment of equals and *vertical equity* as unequal treatment of unequals. Horizontal equity could be expressed as each individual or group in the society being able to meet their needs since they have access to the same amount of resources separately. Vertical equity could be expressed as providing each individual or group in the society a varying amount of resources that is proportional with the level of their needs and vulnerabilities.

Horizontal equity is included in the study of urban systems as Cai (2008) studied a water delivery system from fiscal, social, economic, and environmental aspects to identify the required policy and reforms that ensure equal access of water among communities at all levels. Additionally, Yan and Shih (2009) optimized the scheduling of emergency railroad repair such that the relief of multiple commodities to each location is equalized. Also, Cao et al. (2016) optimized humanitarian relief distribution in a service network where meeting demand is considered for three different granularity including regional and national priorities.

For vertical equity in the study of interdependent infrastructure networks, Thomopoulos et al. (2009) proposed a support tool to assist decision makers in differentiating their choice of equity perspectives and principles. Also, Manaugh and El-Geneidy (2012) developed a transportation network methodology that allows accessibility and less travel time for the varying socio-economic groups, Ogryczak et al. (2014) conducted a survey study for fair optimization methodology that is applied to the interdependent communication networks where these equitable models provide an unequal amount of system service based on operations-dependent relations. Additionally, Zolfaghari and Peyghaleh (2015) proposed a two-stage stochastic programming method for resource allocation for regional earthquake risk mitigation where the equity consideration led to variability in mitigation expenditures by geographic and structural vulnerability, Manaugh et al. (2015) evaluated the concept of equity and its integration into transportation network planning objectives and measures in terms of satisfying the various expectations of different social groups. Finally, Arnette and Zobel (2019) developed a risk-based optimization model to improve the disaster relief asset pre-positioning based on the varying residual risk measure of each location.

Some works have included both horizontal and vertical equity in urban infrastructure systems. Fauconnier (1999) conducted a review on the theoretical and policy debates on the water and sanitation infrastructure service privatization, where equity is defined as physical access, economical affordability, and access to planning for services. Doctor (1994) defined and explained the institutional arrangements in the communication infrastructure that are needed to spread the benefits of information technologies to all segments of the population. Ahmed et al. (2008) focused on the comparative social equity assessment of urban development and characteristics of the supply versus demand on transportation infrastructure to suggest new strategies for sustainable and equitable urban transportation systems. Thomopoulos et al. (2009) conducted a literature review on the current practices in transportation infrastructure with the consideration of equity and proposed a new framework that offers additional support tool to decision makers based on the type of equity concern they have through transportation infrastructure network practices. Thomopoulos and Grant-Muller (2012) proposed a method to incorporate a multi-criteria analysis and composite indicator to assess the impacts of equity through the two large EU transportation infrastructure. Mehta and Kalra (2013) analyzed some of the initiatives taken by institutions and organizations for information and communications technology projects to achieve social objectives and identified the technological solutions to improve the education, health, government and financial services of the society. Lastly, Tahmasbi et al. (2019) integrated both horizontal and social equity concepts into the transportation infrastructure to assess its availability to the served community.

3. Proposed methodology

In this paper, we propose an integration of multiple social aspects on the restoration of critical interdependent infrastructure networks to introduce a social equity-based component importance measure that ranks the critical components of interdependent infrastructure networks based on various social vulnerability dimensions. The optimization model is an extended version of the approach modified by Karakoc et al. (2019) where the two objectives of the model are to (i) maximize the resilience of the set of interdependent networks, and to (ii) minimize the total cost associated with the restoration process while accounting for the community resilience of the studied area. Additionally, as a completely new and more comprehensive extension, we formulate a third objective for the existing work to represent social equity among the community. Therefore, this work includes both social equity and social vulnerability measures with the resilience-based component importance measure of urban infrastructure systems. While the proposed interdependent infrastructure network restoration model could be integrated with various methods to measure social vulnerability, we adopt the algorithm introduced by Cutter et al. (2013).

3.1. Notation and assumptions

In the multi-objective mixed-integer programming model that we extend for the interdependent infrastructure network restoration problem, the following assumptions hold: (i) there is no partial disruption in the nodes and links (hereafter, components) of the critical infrastructure networks through the disruption phase, (ii) there is no partial operability in the components of the critical infrastructure networks through the restoration phase, (iii) the required restoration duration differs for each component in the critical infrastructure networks, (iv) the amount of demand and supply is known for the nodes in the system, (v) the optimal amount of flow is known for each link in the system, (vi) the fixed unmet demand penalty cost (i.e., disruption cost) is assigned for each demand node in the networks, (vii) the varying restoration costs are assigned for each disrupted component in the networks, (viii) the varying unit flow cost that is proportional with the length of the disrupted component is assigned to each link, (ix) the physical interdependency allows a component to be either fully operational or not operational based on the status of the components required for interdependency, and (x) known and fixed number of restoration crews are assigned to each network separately where each work crew can restore a single component at a given time through the restoration process.

For the network model, $T = \{1, \ldots, \tau\}$ represents the available time periods for the restoration and $K = \{1,\ldots,\varkappa\}$ represents the set of interdependent infrastructure networks in the system. For network $k \in K$, the set of nodes is represented with N^k, where the set of supply and demand nodes are denoted by $N_s^k \subseteq N^k$ and $N_d^k \subseteq N^k$, respectively, and the set of links is represented with L^k. The sets of disrupted nodes and disrupted links are denoted by $N^{'k}$ and $L^{'k}$, respectively. b_i^k represents the maximum amount of flow from node $i \in N_s^k$ to all the demand nodes $i \in N_d^k$ in network $k \in K$. s_{it}^k represents the amount of total unmet demand (i.e., slack demand) in the demand node $i \in N_d^k$ in network $k \in K$ at time $t \in T$. Hence, $\sum_{i \in N_d^k} s_{it}^k$ represents the total unsatisfied demand in all the demand nodes in network $k \in K$ at time $t \in T$. Q_i^k represents the amount of unmet demand in node $i \in N_d^k$ after the disruptive event occurs. Finally, the weight of each demand node in each critical infrastructure network is represented by w_i^k for network $k \in K$ where $\sum_{k \in K} \sum_{i \in N_d^k} w_i^k = 1$.

The time required for the restoration of disrupted node $i \in N^{'k}$ and disrupted link $(i, j) \in L^{'k}$ is denoted by dn_i^k and dl_{ij}^k, respectively, where the various restoration durations are determined proportional to the length and capacity of the disrupted components. u_{ij}^k denotes the undisrupted flow capacity of link $(i, j) \in L^k$ in network $k \in K$. The operability status of the node $i \in N^k$ and link $(i, j) \in L^k$ in network $k \in K$ at time $t \in T$ are denoted by binary variables β_{it}^k and α_{ijt}^k, respectively, where if the component is operational at time $t \in T$, the related binary variable takes the value 1 and otherwise takes the value 0. R^k represents the set of available work crews with the specific skills and capabilities for each network $k \in K$ separately through the restoration schedule. The scheduling variables for disrupted node $i \in N^{'k}$ and disrupted link $(i, j) \in L^{'k}$ in network $k \in K$ at time $t \in T$ are denoted by the binary variables γ_{it}^{kr} and δ_{ijt}^{kr}, respectively, where if the restoration of the disrupted component is completed by work crew $r \in R^k$ and by time $t \in T$, the related binary variable takes the value 1 and otherwise takes the value 0. Lastly, the interdependency between the networks is represented by $((i, k), (\bar{i}, \bar{k})) \in \Psi$ where it stands that in terms of functionality node $\bar{i} \in N^{\bar{k}}$ in network $\bar{k} \in K$ is physically dependent to node $i \in N^k$ in network $k \in K$.

In minimizing the total cost associated with the restoration process objective, fn_i^k and fl_{ij}^k represent the restoration cost of disrupted node $i \in N^{'k}$ and disrupted link $(i, j) \in L^{'k}$ in network $k \in K$, respectively. The unitary unmet demand penalty cost for demand node $i \in N_d^k$ in network $k \in K$ is represented by p_i^k, where unitary flow cost through link $(i, j) \in L^k$ is denoted by c_{ij}^k. The non-negative variable x_{ijt}^k represents the total flow through link $(i, j) \in L^k$ in network $k \in K$ at time $t \in T$. The restoration status of the disrupted node $i \in N^{'k}$ and link $(i, j) \in L^{'k}$ are denoted by binary variables z_i^k and y_{ij}^k, respectively, where if the disrupted component is restored through the restoration process, the related binary variable takes the value 1 and otherwise takes the value 0.

3.2. Community resilience

We integrate the community resilience perspective into our interdependent infrastructure network restoration model by utilizing the SoVI methodology, which measures the baseline characteristics of communities that foster resilience (Cutter et al. 2010). We define a parameter, $SoVI_{ic}^k$ for each demand node $i \in N_d^k$ in network $k \in K$ for social vulnerability variable $c \in C$, where this parameter represents an index between 0 and 1. The value of $SoVI_{ic}^k$ is calculated separately for social vulnerability variable $c \in C$ according to the SoVI-Lite algorithm (Cutter et al. 2013, Evans et al. 2014) with the following steps: (i) the percentage of population that is covered by each social vulnerability variable is calculated for each geographic region, (ii) the percentages are standardized into z-scores with variable mean and standard deviation, and (iii) the standardized z-scores are normalized between 0 and 1 with Eq. (1). A $SoVI_{ic}^k$ value of 1 represents node i being located in the most socially vulnerable geographic region and likewise a value equal of 0, the least socially vulnerable region.

$$\frac{z - \min(X)}{\max(X) - \min(X)}, \ \forall \ z \in X \tag{1}$$

We adopt an exponential formulation to assign relatively higher importance to more socially vulnerable areas, as shown in Eq. (2) with social vulnerability score, V_{ic}^k, for demand node $i \in N_d^k$ in network $k \in K$ for social vulnerability variable $c \in C$ (Barker et al. 2018). Hence, the increase in the social vulnerability indices in the socially more vulnerable regions would be penalized highly.

$$V_{ic}^k = e^{a \times SoVI_{ic}^k}, \ \forall \ i \in N_d^k, \, a \in Z^+ \tag{2}$$

Additionally, to better represent the magnitude of affected populations, we introduce the parameter, P_i^k, which defines the human occupancy level of the service area of each demand node $i \in N_d^k$ in network $k \in K$ as shown in Eq. (3). As such, the social vulnerability of as well as the size of the served society is accounted for.

$$P_i^k = \frac{\text{population of the service area served by demand node } i}{\text{total population of all service areas}}, \ \forall \ i \in N_d^k \tag{3}$$

3.3. Interdependent infrastructure network restoration model

The previously updated optimization model by Karakoc et al. (2019) that contains two conflicting objective functions (i) to maximize the resilience of the set of interdependent infrastructure networks, and (ii) to minimize the total cost associated with the restoration of these critical infrastructure networks while accounting for social vulnerability of the impacted community. In this study we extend this work one more step to include an additional objective (iii) to plan the recovery schedule of the disrupted communities according to the vertical social equity distribution among them, along with horizontal equity throughout the rest of the formulation. We believe that, with this newly proposed model which integrates a social equity-driven objective function and overall horizontal equity aspect through the method, the critical infrastructure resilience studies would be introduced with a more heavily emphasized social dimension through planning of recovery and resilience enhancement activities.

The resilience of interdependent infrastructure networks is formulated as a function of unmet demand, s_{it}^k, for demand node $i \in N_d^k$ in each network $k \in K$ through the recovery time $t \in T$. As a disruptive event occurs, the amount of unmet demand would increase since the system wouldn't be able to perform in its optimum level. Hence, the increase in the unmet demand due to disruption represents the loss in the maximum flow (i.e., loss in system performance). Since Q_i^k represents the amount of unmet demand at demand node $i \in N_d^k$ in network $k \in K$ after the disruption and before the restoration process, the total amount of unmet demand in the network is measured as $\sum_{i \in N_d^k} Q_i^k$. Additionally, to represent the effect of unmet demand on different communities, we assign the social vulnerability score V_{ic}^k and population density P_i^k, to the demand node $i \in N_d^k$ in network $k \in K$.

We formulate the recovery of the community-weighted infrastructure networks as the increase in the maximum flow in the system, or the difference in the total unmet demand before the restoration and at time t during the restoration process. In the objective function, $\sum_{k \in K} \sum_{i \in N_d^k} ((Q_i^k V_{ic}^k P_i^k) - (s_{it}^k V_{ic}^k P_i^k))$ represents the total amount of unmet demand that is restored during the time period $t \in T$ in restoration process. The assigned weights of social vulnerability and population density measures are only responsible for prioritizing the restoration of components where the actual amount of served demand is not affected by the integration of community resilience measures. The actual sum of the change in the amount of unmet demand in each demand node in each time period through the restoration duration is included as $[\sum_{t=1}^{\tau} [t((Q_i^k V_{ic}^k P_i^k) - (s_{it}^k V_{ic}^k P_i^k)) - (t-1)((Q_i^k V_{ic}^k P_i^k) - (s_{i(t-1)}^k V_{ic}^k P_i^k))]]$ in the objective function. That is, the amount of demand that is recovered is represented as the difference between the amount of slack demand after the disruption and the amount of slack at time t, as shown in Eq. (4) during restoration. As the decrease in the amount of unmet demand in the networks stand for an increase in the amount of total flow that is transferred through the network, it is also suggested as an increase in the network performance. The total performance loss is represented in the denominator of the objective function as $\sum_{i \in N_d^k} \frac{w_i^k}{\tau(Q_i^k V_{ic}^k P_i^k)}$ which is the total amount of unmet demand in the network before the restoration begins. Thus, the ratio of the amount of recovery over the amount of performance lost at each time period through the total available restoration process, is a measure of resilience where the networks are recovering from an inoperability in a certain time period and trying to achieve a certain desired level of performance. This serves as the first objective in the optimization problem.

$$\max \sum_{k \in K} \sum_{i \in N_d^k} \frac{w_i^k}{\tau(Q_i^k V_{ic}^k P_i^k)} \Big[\sum_{t=1}^{\tau} [t((Q_i^k V_{ic}^k P_i^k) - (s_{it}^k V_{ic}^k P_i^k)) - (t-1)((Q_i^k V_{ic}^k P_i^k) - (s_{i(t-1)}^k V_{ic}^k P_i^k))] \Big] \tag{4}$$

For the second objective, we account for three different costs associated with the restoration process: (i) the flow cost in each link, (ii) the restoration cost of each disrupted node and link, and (iii) the penalty cost of unmet demand in each demand node in each interdependent infrastructure network. The flow cost is calculated by the unitary flow cost, c_{ij}^k, and the amount of flow, x_{ij}^k that is transmitted through link $(i, j) \in L^k$ in the network $k \in K$. The varying restoration cost of fn_i^k for disrupted node $i \in N'^k$ and fl_{ij}^k for disrupted link $(i, j) \in L'^k$ denotes the cost associated with the available restoration work crews and their utilization through the restoration process. These varying restoration costs, fn_i^k and fl_{ij}^k are quantified by the capacity and the size of the disrupted components in the interdependent infrastructure networks. Lastly, p_i^k for demand node $i \in N_d^k$ quantifies the disruption cost, i.e. the unmet demand penalty cost in each demand node in the infrastructure network due to disruption. As shown in Eq. (5), we also integrate the social vulnerability scores and population density measures in the unmet demand penalty cost part of the cost minimization objective so that restoration of the disrupted components that serve more socially vulnerable groups would be prioritized.

$$\min \sum_{k \in K} \left(\sum_{i \in N'^k} fn_i^k z_i^k + \sum_{(i,j) \in L'^k} fl_{ij}^k y_{ij}^k + \sum_{t \in T} \left[\sum_{(i,j) \in L^k} c_{ij}^k x_{ij}^k + \sum_{i \in N_d^k} p_i^k s_{it}^k V_{ic}^k P_i^k \right] \right) \tag{5}$$

To account for social equity, we incorporate both horizontal and vertical equity concepts for network restoration planning. Horizontal equity is introduced in the model by formulating two additional constraints which ensure that all the disrupted components must be restored through the restoration period. Hence, the demand of all disrupted communities is met in the system as all the components are operational with full capacity. To account for vertical equity, a third objective is formulated to guide the restoration process to start with more heavily disrupted communities. To achieve this, the resilience of each demand node $i \in N_d^k$ at each time t is calculated as $\frac{t(Q_i^k - s_{it}^k) - (t-1)(Q_i^k - s_{i(t-1)}^k)}{\tau(Q_i^k)}$, and the resilience residual of each demand node is measured by subtracting the demand node resilience at time t from the optimal resilience level of 1. Then the total system residual through the duration of complete restoration is minimized. Additionally, to emphasize more heavily on the vertical equity, the demand node residual at each time t is weighted with social vulnerability score, V_{ic}^k, and population density, P_i^k, of the effected community. The social equity-motivated objective is formulated in Eq. (6).

$$\min \sum_{t \in T} \left(\sum_{i \in N_d^k} \left(\left(1 - \frac{t(Q_i^k - s_{it}^k) - (t-1)(Q_i^k - s_{i(t-1)}^k)}{\tau(Q_i^k)} \right) V_{ic}^k P_i^k \right) \right) \tag{6}$$

The constraints that are balanced for the above-explained three objectives are as follows.

$$\sum_{(i,j) \in L^k} x_{ijt}^k \le b_i^k, \quad \sum_{(i,j) \in L^k} x_{ijt}^k \le b_i^k, \tag{7}$$

$$\sum_{(i,j) \in L^k} x_{ijt}^k - \sum_{(j,i) \in L^k} x_{jit}^k = 0, \ \ \forall \ i \in N^k \backslash \{N_s^k, N_d^k\}, \ k \in K, \ t \in T \tag{8}$$

$$\sum_{(j,i) \in L^k} x_{jit}^k + s_{it}^k = b_i^k, \ \ \forall \ i \in N_d^k, \ k \in K, \ t \in T \tag{9}$$

$$x_{ijt}^k - u_{ij}^k \le 0, \quad \forall \ (i,j) \in L^k, k \in K, t \in T \tag{10}$$

$$x_{ijt}^k - u_{ij}^k \beta_{it}^k \le 0, \quad \forall \ (i,j) \in L^k, i \in N^k, k \in K, t \in T \tag{11}$$

$$x_{ijt}^k - u_{ij}^k \beta_{jt}^k \le 0, \quad \forall\ (i,j) \in L^k, i \in N^k, k \in K, t \in T \tag{12}$$

$$x_{ijt}^k - u_{ij}^k \alpha_{ijt}^k \le 0 \quad \forall\ (i,j) \in L'^k, k \in K, t \in T \tag{13}$$

$$\beta_{\bar{i}t}^{\bar{k}} - \beta_{it}^k \le 0, \quad \forall\ ((i,k),(\bar{i},\bar{k})) \in \Psi, t \in T \tag{14}$$

$$y_{ij}^k = \sum_{r \in R^k} \sum_{t \in T} \delta_{ijt}^{kr}, \quad \forall\ (i,j) \in L'^k, k \in K \tag{15}$$

$$z_i^k = \sum_{r \in R^k} \sum_{t \in T} \gamma_{it}^{kr}, \quad \forall\ i \in N'^k, k \in K \tag{16}$$

$$\alpha_{ijt}^k \le \sum_{r \in R^k} \sum_{l=1}^{t} \delta_{ijl}^{kr}, \quad \forall\ (i,j) \in L'^k, k \in K, t \in T \tag{17}$$

$$\beta_{it}^k \le \sum_{r \in R^k} \sum_{l=1}^{t} \gamma_{il}^{kr}, \quad \forall\ i \in N'^k, k \in K, t \in T \tag{18}$$

$$\sum_{(i,j) \in L'^k} \sum_{l=t}^{\min(\tau, t+dl_{ij}^k-1)} \delta_{ijl}^{kr} + \sum_{i \in N'^k} \sum_{l=t}^{\min(\tau, t+dn_i^k-1)} \gamma_{il}^{kr} \le 1, \quad \forall\ k \in K, r \in R^k, t \in T \tag{19}$$

$$\sum_{t=1}^{dl_{ij}^k-1} \alpha_{ijt}^k = 0, \quad \forall\ (i,j) \in L'^k, k \in K \tag{20}$$

$$\sum_{t=1}^{dn_i^k-1} \beta_{it}^k = 0 \quad \forall\ i \in N'^k,\ k \in K \tag{21}$$

$$\sum_{r \in R^k} \sum_{t=1}^{dl_{ij}^k-1} \delta_{ijt}^{kr} = 0, \quad \forall\ (i,j) \in L'^k, k \in K \tag{22}$$

$$\sum_{r \in R^k} \sum_{t=1}^{dn_i^k-1} \gamma_{it}^{kr} = 0, \quad \forall\ i \in N'^k, k \in K \tag{23}$$

$$\sum_{r \in R^k} \sum_{t=1}^{\tau} \delta_{ijt}^{kr} = 1, \quad \forall\ (i,j) \in L'^k, k \in K \tag{24}$$

$$\sum_{r \in R^k} \sum_{t=1}^{\tau} \gamma_{it}^{kr} = 1, \quad \forall\ i \in N'^k, k \in K \tag{25}$$

$$s_{it}^k \ge 0, \quad \forall\ i \in N_d^k, k \in K, t \in T \tag{26}$$

$$x_{ijt}^k \ge 0, \quad \forall\ (i,j) \in L^k, k \in K, t \in T \tag{27}$$

$$y_{ij}^k \in \{0,1\}, \quad \forall\ (i,j) \in L'^k, k \in K \tag{28}$$

$$z_i^k \in \{0,1\}, \quad \forall\ i \in N^k, k \in K \tag{29}$$

$$\alpha_{ijt}^k \in \{0,1\}, \quad \forall\ (i,j) \in L'^k, k \in K, t \in T \tag{30}$$

$$\beta_{it}^k \in \{0,1\}, \quad \forall\ i \in N^k, k \in K, t \in T \tag{31}$$

$$\delta_{ijt}^{kr} \in \{0,1\}, \quad \forall\ (i,j) \in L'^k, k \in K, t \in T, r \in R^k \tag{32}$$

$$\gamma_{it}^{kr} \in \{0,1\}, \quad \forall\ i \in N'^k, k \in K, t \in T, r \in R^k \tag{33}$$

The first set of constraints in Eqs. (7)–(9) represent the flow conservation in node $i \in N^k$. The second set of constraints in Eqs. (10)–(13) is for the capacity control of disrupted and undisrupted components, where Eq (10) controls the undisrupted links, Eqs. (11)–(12) control the disrupted nodes, and Eq. (13) controls the disrupted links. Eq. (14) represents the physical interdependency between the nodes of two infrastructure networks where this constraint ensures that the operability status of the node $\bar{i} \in N^{\bar{k}}$ in network $\bar{k} \in K$ at time $t \in T$ is fully dependent on the status of the node $i \in N^k$ in network $k \in K$ at time $t \in T$. Eqs. (15)–(25) ensure the scheduling of and assignment of the work crews to disrupted components, where Eqs. (15)–(16) ensure work crew assignment, Eqs. (17)–(18) ensure the operability of restored components, Eq. (19) governs the restoration of a single component at a specific time by a single work crew, and Eqs. (20)–(25) control the completion of the restoration of a disrupted component by a work crew for it to be functional. Eqs. (24)–(25) ensure that all the disrupted components are restored. Since it is assumed that system operates with no slack demand before a disruption, the demand of each community would be met to support the horizontal equity motivation. Finally, Eqs. (26)–(33) constrain the nature of the decision variables.

3.4. Component importance measure

To integrate a resilience-based component importance measure with the community resilience perspective through the restoration scheduling of interdependent infrastructure networks, we utilized Optimal Recovery Time (ORT), an extension (to multiple interdependent infrastructure networks) of a CIM introduced by Fang et al. (2016). This CIM is integrated into the proposed optimization model since ORT is defined as the optimal time to recover a disrupted component such that the resilience of the interdependent infrastructure networks is maximized over the recovery time horizon (Almoghathawi and Barker 2017). The ORT measure prioritizes the disrupted components, both the nodes and links, with the higher impact on the resilience of the interdependent infrastructure networks and schedules the restoration process accordingly. With this CIM, decision makers can rank the disrupted components according to their latest restoration completion time through the available restoration duration. The earlier the disrupted component is scheduled for restoration, a higher importance is assigned to it, and thus, the critical components of the interdependent infrastructure networks would be scheduled for restoration, since they have a higher impact on the resilience of the networks. The formal definition and the mathematical formulation of the ORT component importance measure is located below.

The ORT of a disrupted component $e \in E'^k = N'^k \cup L'^k$ in network $k \in K$ is represented as I_e^{ORT}, as shown in Eqs. (33) and (34). In the formulation, μ_{et}^k denotes the operability status of component $e \in E'^k$ in network $k \in K$ at time $t \in T$. If μ_{et}^k is equal to 1, then the disrupted component is operational at time $t \in T$ and 0 otherwise.

$$I_e^{ORT} = 1 + \sum_{t \in T} (1 - \mu_{et}^k) \tag{34}$$

where

$$\mu_{et}^k = \begin{cases} z_{it}^k, & \text{if } e \text{ is a node},\ e = i \\ y_{ijt}^k, & \text{if } e \text{ is a link},\ e = (i,j) \end{cases} \tag{35}$$

In this paper, we integrate the adopted CIM with the community resilience-driven interdependent infrastructure network restoration model. The critical components are identified and ranked for each social vulnerability measure individually by utilizing the ORT, then these independent rankings are aggregated to form a final overall ranking of the critical components.

3.5. Multi-criteria decision analysis technique for aggregated ranking

Multi-criteria decision analysis (MCDA) techniques are particularly useful for aiding in selecting from one of several discrete alternatives when several criteria are being considered (Lootsma 1999). In this study, we utilize the Technique for Order Preferences by Similarity to an Ideal Solution (TOPSIS), which ranks alternatives that balance

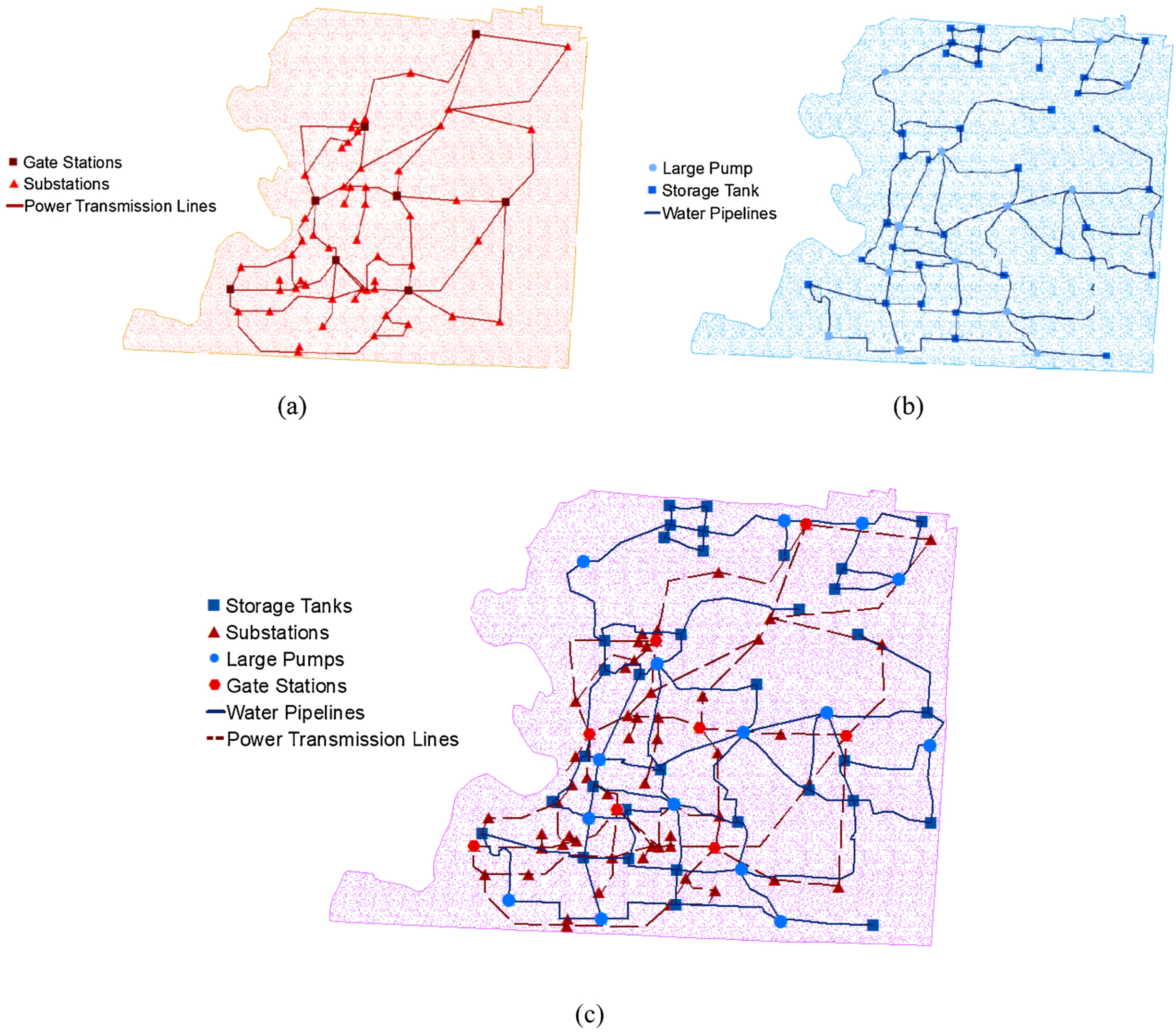

Fig. 3. The geographic layout of power and water distribution systems in Shelby County, TN independently and interdependently, respectively. adapted from González et al. (2016).

closeness to the best solution and distance from the worst (Hwang and Yoon 1981). Sets $A = \{A_e | e = 1, \ldots, n\}$ and $C = \{C_c | c = 1, \ldots, m\}$ denote respectively the set of possible alternatives and criteria, respectively. Additionally, $Y = \{y_{ec} | e = 1, \ldots, n;\ c = 1, \ldots, m\}$ denotes the set of performance scores of the alternatives for each criterion. Finally, $\omega = \{\omega_c | c = 1, \ldots, m\}$ denotes the set of criteria weights, where $\omega_c \geq 0$ and $\sum_{c=1}^{m} \omega_c = 1$ such that larger value of ω_c suggests that criterion c is more important to the decision maker. Eq. (35) is defined to scale the performance scores of the alternatives, as often criteria are measured on different scales. Eq. (36) represents how the criteria weights are assigned to the scaled aggregation scores in TOPSIS.

$$r_{ec}(y) = \frac{y_{ec}}{\sqrt{\sum_{e=1}^{n} y_{ec}^2}}, \quad e = 1, \ldots, n; \ c = 1, \ldots, m \tag{36}$$

$$v_{ec}(y) = \omega_c r_{ec}(y), \ e = 1, \ldots, n; \ c = 1, \ldots, m \tag{37}$$

In the next step, the positive ideal solution, A^+, and the negative ideal solution, A^-, are determined by the collection of most preferred and the least preferred weighted and scaled aggregation score, v_{ec}, for each criterion, respectively. Eqs. (37) and (38) represent the formula for finding the PIS and NIS respectively, where C^+ represents the set of benefit criteria and C^- represents the cost criteria.

$$A^+ = \{v_1^+(y), \ldots, v_m^+(y)\} = \{(\max_{l \leq e \leq n} v_{eC}(y) | c \in C^+), (\min_{l \leq e \leq n} v_{ec}(y) | c \in C^-)\} \tag{38}$$

$$A^- = \{v_1^-(y), \ldots, v_m^-(y)\} = \{(\min_{l \leq e \leq n} v_{ec}(y) | c \in C^+), (\max_{l \leq e \leq n} v_{ec}(y) | c \in C^-)\} \tag{39}$$

Next, the distance, D_e^+, between alternative A_e and the positive ideal solution is calculated with Euclidean distance in Eq. (39). Similarly, the distance, D_e^-, between the same alternative, A_e and the negative ideal solution is found in Eq. (40). Finally, the balance between positive and negative ideal solutions is calculated with Eq. (41), where higher S_e^+ values suggest a higher similarity to the positive ideal solution. A ranking of alternatives could be produced from an ordering of highest to lowest S_e^+ values.

$$D_e^+ = \sqrt{\sum_{c=1}^{m} [v_{ec}(y) - v_c^+(y)]^2}, \ e = 1, \ldots, n \tag{40}$$

$$D_e^- = \sqrt{\sum_{c=1}^{m} [v_{ec}(y) - v_c^-(y)]^2}, \ e = 1, \ldots, n \tag{41}$$

$$S_e^+ = \frac{D_e^-}{D_e^+ + D_e^-}, \ e = 1, \ldots, n \tag{42}$$

In our study, the set of alternatives, A, are the disrupted components of the critical infrastructure networks and the set of criteria, C, are the multiple social vulnerability variables. The performance scores of the alternatives over each criteria, v_{ec}, are the rank of the disrupted components in the restoration schedule of interdependent infrastructure networks that are based on each social vulnerability variable independently.

We believe that our proposed methodology that incorporates interdependent infrastructure restoration scheduling model and a community resilience-driven component importance measure with (i) social equity and (ii) social vulnerability measures to represent an aggregated final ranking of the system components is a new comprehensive approach that could be insightful for decision makers to reshape the pre-event investment policies and post-event recovery strategies with a higher humanitarian concern.

4. Illustrative example: interdependent infrastructure networks in Shelby County, TN

In this study, we implement our community resilience-driven CIM with data describing the interdependent infrastructure networks in Shelby County, Tennessee, which is subject to earthquake scenarios due to its risky geographic location in the New Madrid Seismic Zone (González et al. 2016). We consider two physically interdependent infrastructure networks, water distribution and electric power networks, the geographic layout of which is represented in Fig. 3, both independently and combined. The two infrastructure networks contain a total of 108 nodes, including 15 demand nodes in the water network and 9 demand nodes in the power network. From both of these interdependent infrastructure networks, there are a total of 288 links and through the restoration process. We assign six work crews separately for each network.

4.1. Social vulnerability variables

The social vulnerability measures included in the SoVI algorithm (Cutter et al. 2003) were collected for Shelby County, TN. Most of the 11 social vulnerability factors in Table 1 are accounted for with the eight social vulnerability variables listed in Table 2.

To provide a high level of granularity in social vulnerability measures in Shelby County, we collect social vulnerability data at the block group level, defined as a statistical division of census tracts that consists of clusters of blocks that generally contain 600 to 3000 residents of the contiguous area (US Census Bureau, 2010). In Shelby County, TN there are 621 block groups that contain a total of 928,794 residents. Ten block groups that contain around 4000 residents were eliminated from the study because they lacked certain demographic information required for the social vulnerability measures. Shown in Fig. 4, a correlation analysis was conducted on the eight social vulnerability variables that are available for block groups. An initial study (Karakoc et al. 2019) and the current results suggest that certain social vulnerability variables have a reasonably high positive correlation with each other in our case.

As it is represented in Fig. 4, the social vulnerability variables that are coded as “75000,” “African-American,” “Single-Female,” and “Poverty” contain relatively high positive correlation among each other

Table 2
The considered eight social vulnerability variables in Shelby County, TN that are defined as the percentages by Cutter et al. (2003).

Households earning under $75,000 annually
Population under the age of 5
Population over the age of 65
Population living below the poverty line
Population that is Asian
Population that is Hispanic
Population that is African American
Single-female based households

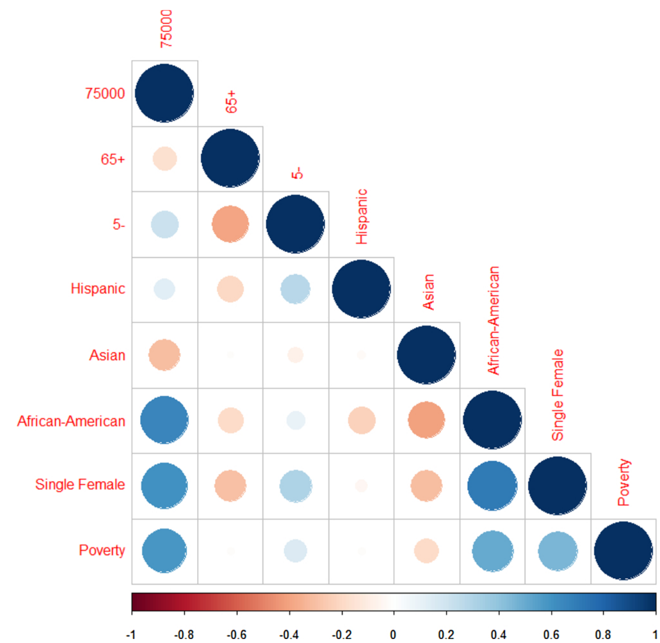

Fig. 4. Illustration of the correlation analysis that is conducted for block group level social vulnerability variables that are defined by Cutter et al. (2003). The darker purple shade represents a higher positive correlation where darker orange shade represents a higher negative correlation among two variables.

such that the value of the correlation coefficient value is around 0.7 for all of their pairwise combinations. These social vulnerability variables represent the percentage of households earning under $75,000 annually, the percentage of the population that is African-American, the percentage of single-female based households, and the percentage of households that are in poverty, respectively. To eliminate excess redundancy and re-counting of certain populations due to their correlated socio-economic characteristics, variables “75000″ and “African-American” were removed. Moreover, the remaining components ensure at least one variable from each highly correlated group of variables is still included in the study and almost all the factor groups are represented as well. The variable “Asian” was also removed from the study since it did not produce a significant value due to the extremely low percentage of the population that it represents in Shelby County, TN. The final complete list of five social vulnerability variables that are included in this study is represented in Table 3.

To assign the social vulnerability scores, V_{ic}^{k}, to the demand nodes at the block group level, we define specific geographic regions that represent the coverage area of each demand node in the infrastructure networks. We utilize the Voronoi diagram approach (Okabe et al. 2008) to estimate the geographic boundaries of the coverage area of each demand node. The estimated Voronoi coverage areas for each demand node in the two critical infrastructure networks appear as the dark boundaries in Fig. 5 and they lay on top of the block groups. The shading of the block groups indicates the strength of social vulnerability index, $SoVI_{ic}^{k}$, for each of the five variables, which are encoded as “65 + ,” “5-,” “Hispanic,” “Single-Female,” and “Poverty.” To assign the

Table 3
The complete final list of the social vulnerability variables that are utilized in the community resilience study of Shelby County, TN which are defined by Cutter et al. (2003) as the percentages.

Population over the age of 65
Population under the age of 5
Population that is Hispanic
Single-female based households
Households that are in poverty

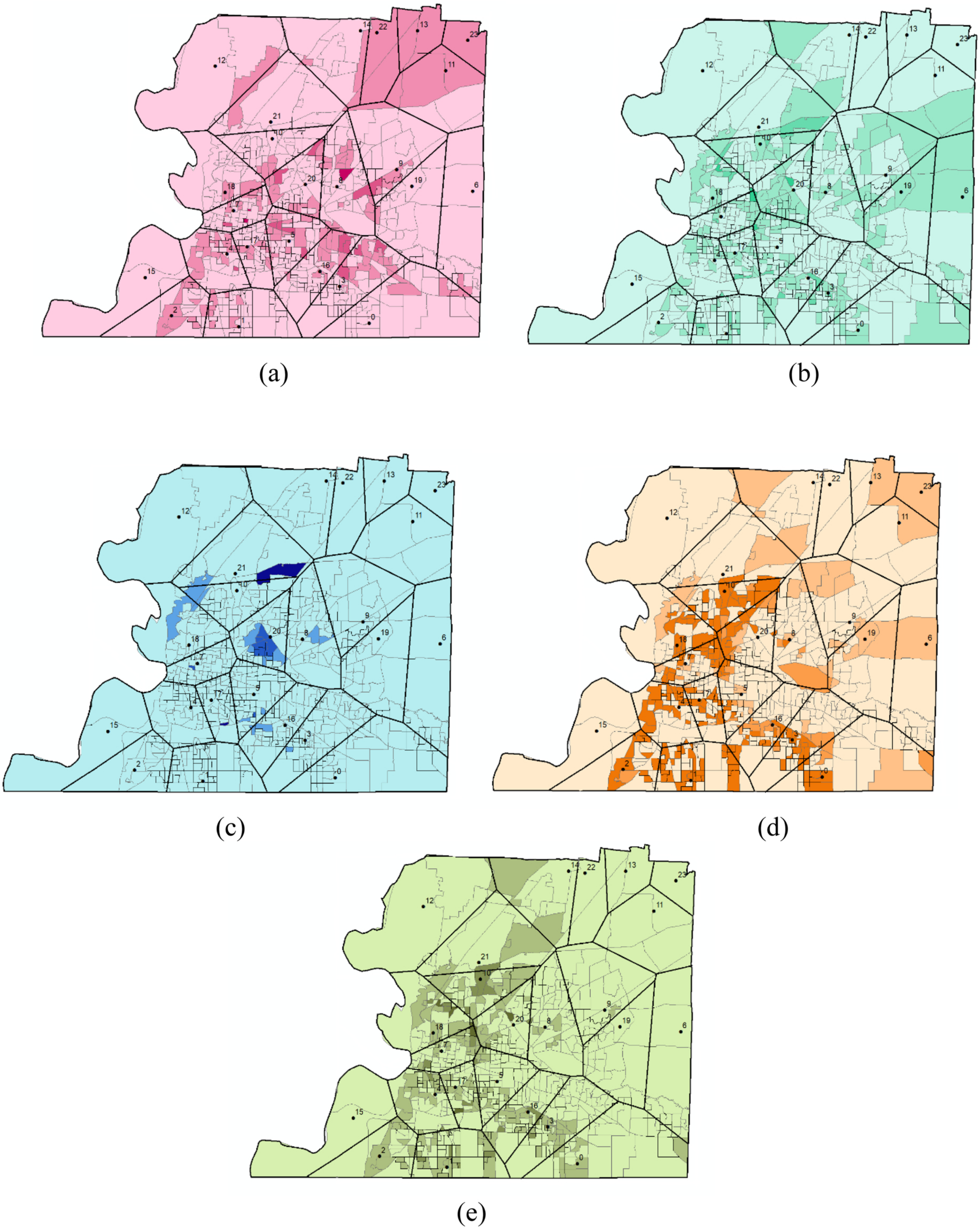

Fig. 5. The distribution of social vulnerability scores over the block groups in Shelby County, TN based on the population that is (a) under age five, (b) over age sixty-five, (c) Hispanic, (d) living in poverty, and (e) living in a single-female household whereas with the darker shades, socially more vulnerable region is represented.

associated social vulnerability indices to the demand nodes, we take the average of the indices of the block groups that are located in the Voronoi coverage area of each demand node. Additionally, we also assign the associated population density values to demand nodes based on the proportional population density of each Voronoi coverage area.

For variable $c \in C$, the value of V_{ic}^{k} is scaled between zero and one, and the social vulnerability scores are grouped in the following four intervals: 0-0.25, 0.25-0.5, 0.5-0.75 and 0.75–1, ranging from the least socially vulnerable to the most socially vulnerable region. The darker the map shading, the higher the social vulnerability is illustrated. As illustrated in Fig. 5, some block groups are especially vulnerable with respect to some variables and not with others, suggesting that considering only one variable may not provide a sufficient perspective.

To solve the multi-objective interdependent infrastructure network restoration problem, we utilize the ε-constraint approach (Chankong and Haimes 2008). In our proposed method, maximizing social equity is kept as the core objective of the model, and the resilience maximization objective is converted into a constraint, shown in Eq.(44), as the resilience measure naturally ranges from 0 to 1. Also, minimizing the total cost associated with the restoration process objective is converted into a budget constraint as in Eq. (45) in our case, where the budget limit, D, is determined by the decision maker.

$$\sum_{k\in K}\sum_{i\in N_d^k}\frac{w_i^k}{\tau(Q_i^k V_{ic}^k P_i^k)}\Big[\sum\nolimits_{t=1}^{\tau}[t((Q_i^k V_{ic}^k P_i^k)-(s_{it}^k V_{ic}^k P_i^k)) - (t-1)((Q_i^k V_{ic}^k P_i^k)-(s_{i(t-1)}^k V_{ic}^k P_i^k))]\Big]\le \varepsilon \tag{43}$$

$$\sum_{k\in K}\left(\sum_{i\in N'^k} fn_i^k z_i^k + \sum_{(i,j)\in L'^k} fl_{ij}^k y_{ij}^k + \sum_{t\in T}\left[\sum_{(i,j)\in L^k} c_{ij}^k x_{ij}^k + \sum_{i\in N_d^k} p_i^k s_{it}^k V_{ic}^k P_i^k\right]\right)\le D \tag{44}$$

4.2. Disruption scenarios

In this study, we consider a single disruption scenario of a magnitude 7.0 earthquake, $M_w = 7$. Were a lone earthquake scenario considered, the number of disrupted components would be fixed and the resulting rankings would be specific just to that particular disruption. To capture a more holistic ranking of (most of) the components, we simulate 50 different disruptions with varying disrupted components. In each one of these 50 different cases, the disrupted components are determined according to a previously conducted simulation study by González et al. (2016), and a certain disruption probability is assigned to each component to simulate one of the 50 magnitude 7.0 earthquakes. Across the 50 disruptions, a total of 397 components were disrupted, 109 of which are nodes and the remaining 288 are links. Among these 109 of the nodes, 49 of them belong to the water network and the remaining 60 of them belong to the power network. Among the 288 links, 142 belong to the water network and the remaining 146 from the power network. The number of disrupted components range from 28 to 60 in the individual disruption scenario simulations. In this study, we run the proposed restoration scheduling of interdependent infrastructure network model for 50 disruption scenarios with varying disrupted components. This step is repeated five times to reflect the optimal restoration scheduling for each of the five social vulnerability variable perspectives. As such, we calculate the ORT for each variable separately, where disrupted components with smaller restoration completion time earn higher priority and receive smaller rank values. As the restoration completion time of the disrupted components increase, their priority decrease and the components are assigned with higher ranking values, thus lower importance levels.

To aggregate the 50 different disruption scenarios, we develop an aggregation index that determines the final rank of each disrupted component. This index is calculated with the following: (i) the disrupted components in each disruption scenario are ranked separately using ORT, (ii) the ranks of each disrupted component are represented with $\frac{i}{g}$, where i refers to the rank of the disrupted component and g refers to the total number of disrupted components in each scenario, such that $g \in [28, 60]$ (Kolesárová et al. 2007), and finally (iii) the $\frac{i}{g}$ values are averaged based on the number of scenarios that each component is disrupted (Muralidharan et al. 2002; Ho et al., 2010). That is, even though there are a total of 50 disruption scenarios, if a single component is disrupted in only a of these scenarios, we calculate the average based on the h, where $h \le g$, scenarios such that the randomness of the simulation does not influence a component's ranking. The aggregation index applies simple arithmetic on the ordinal data, however this practice is motivated by the literature (Kolesárová et al. 2007, Muralidharan et al. 2002, Ho et al., 2010).

4.3. Integration of rankings with TOPSIS

Discussed previously, different network components are important from different social vulnerability perspectives. To aggregate these different perspectives into a comprehensive ranking of infrastructure components that affect community resilience, we implement a multi-criteria decision analysis technique, TOPSIS. Recall that with TOPSIS, the set of alternatives, A, is ranked across multiple criteria, C. With the application of TOPSIS in our study, the alternatives to be ranked consist of the set of 397 disrupted components, and the multiple criteria consist of the set of the five social vulnerability variables. The performance scores of the set of alternatives under each criteria, Y_{ec}, represents the aggregation index of the ranks of the disrupted components whose values range from [0.017,1]. The five social vulnerability variables represent "costs" (e.g., values to be minimized) from an MCDA perspective. And since a better ranking is the result of a smaller aggregation index, the positive ideal solution for each variable is its smallest aggregation index.

To find the weights of each social vulnerability variable, ω_c, we utilize the Principle Component Analysis (PCA) technique, a widely used approach to aggregate multiple inputs with the minimum loss of information (Adler and Golany 2001). The PCA method explains the variance structure of data through linear combinations of variables (Johnson and Wichern 1982), where the dynamics of the information exist along directions with the largest variance (Shlens 2014). Hence, it is not uncommon to use the "percent variation in a dependent variable explained by an independent variable" to measure the importance of the effect of the independent one on the dependent one (Rosenthal and Rubin 1979). Similarly, we assume that the amount of variance that is captured by each social vulnerability variable could stand for the importance of that variable relative to the others. More information about the formulation and definition of the PCA approach can be found in Holland (2008).

To ensure that the weight, the largest variance coverage stands for the most important variable, is consistent with the previous steps of our study where a lower ranking value represents a more important component, we apply the following scaling approach: (i) calculate the inverse of the original weight of each social vulnerability variable found from PCA, (ii) sum these inverse values, and (iii) scale them with the ratio of each over their sum. As such, the newly calculated weight values are consistent with the ranking of the components based on their importance (i.e., higher weight values suggest less important social vulnerability variable) and have a sum that is equal to 1. The explained scaling approach with the final criteria weights, $\omega_c^{''}$ is formulated in Eq. (45)–(47) where $\sum_{c=1}^{m}\omega_c^{''} = 1$, and the calculated final weights of the five social vulnerability variables are listed in Table 4.

$$\omega_c^{'} = \frac{1}{\omega_c},\ c = 1,\ \ldots, m \tag{45}$$

$$S = \sum_c \omega_c^{'}, \tag{46}$$

$$\omega_c^{''} = \frac{\omega_c^{'}}{S},\ c = 1,\ \ldots, m \tag{47}$$

Table 4 suggests that the weights that are assigned to each social vulnerability variable are relatively similar. Despite the PCA weights of social vulnerability variables being close to each other, a systematic and data-driven approach was used, allowing for a better informed decision making process relative to random (or strictly equal) weights.

Table 4
The representation of the weights of the social vulnerability variables that are determined by PCA method and utilized in TOPSIS algorithm.

Population that is over the age 65	0.22
Population that is under the age 5	0.22
Population that is Hispanic	0.23
Single-female parent based households	0.17
Households living under the poverty line	0.16

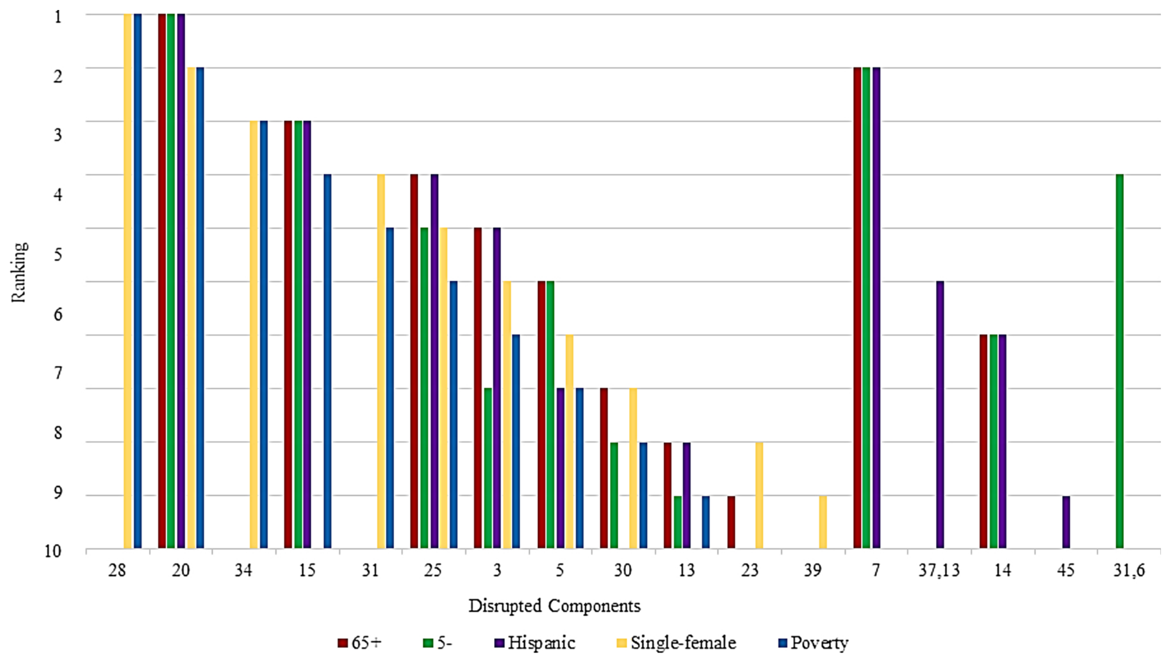

Fig. 6. The ranking of the subset of water network components (both nodes and links are listed) are represented independently based on each social vulnerability variable.

4.4. Critical components of Shelby County, TN

The components that make up the top 10 rankings for each social vulnerability variable are depicted in Fig. 6 and Fig. 7 for the water and power networks, respectively. For the power network, we see some variability in ranking among the components for the different social vulnerability variables (e.g., most of the top five components have very similar ranks for each variable), perhaps suggesting that social vulnerability does have a little impact restoration order for that network. The water network, however, demonstrates more variability: there is a wider variety of components and different types of components (i.e., both links and nodes) in the top ten. In both networks, the most important component according to ORT stands out across social vulnerability variables. Note that of the 32 components that appear across the top 10 rankings of the two networks, only two of them are links, and as the component rankings are aggregated based on a multi-criteria decision analysis technique, the top ten components result as all nodes. The obtained results suggest that nodes are overwhelmingly more critical from ORT and social vulnerability perspectives.

Integrating the rankings with TOPSIS results in Table 5. The integrated rankings are quite similar to Fig. 6 and Fig. 7, due in part to the lack of variability in the individual rankings of many of the social vulnerability variables and due to the similarity of variable weights from Table 4. As it can be seen from the above figures, the water network has relatively higher variance than power network in terms of the ranking of the critical components under different social vulnerability measures. This could be due to the difference in size and connectivity of the two networks.

Therefore, as the results of our case study implies, importance of the components differ based on the equity and social vulnerability

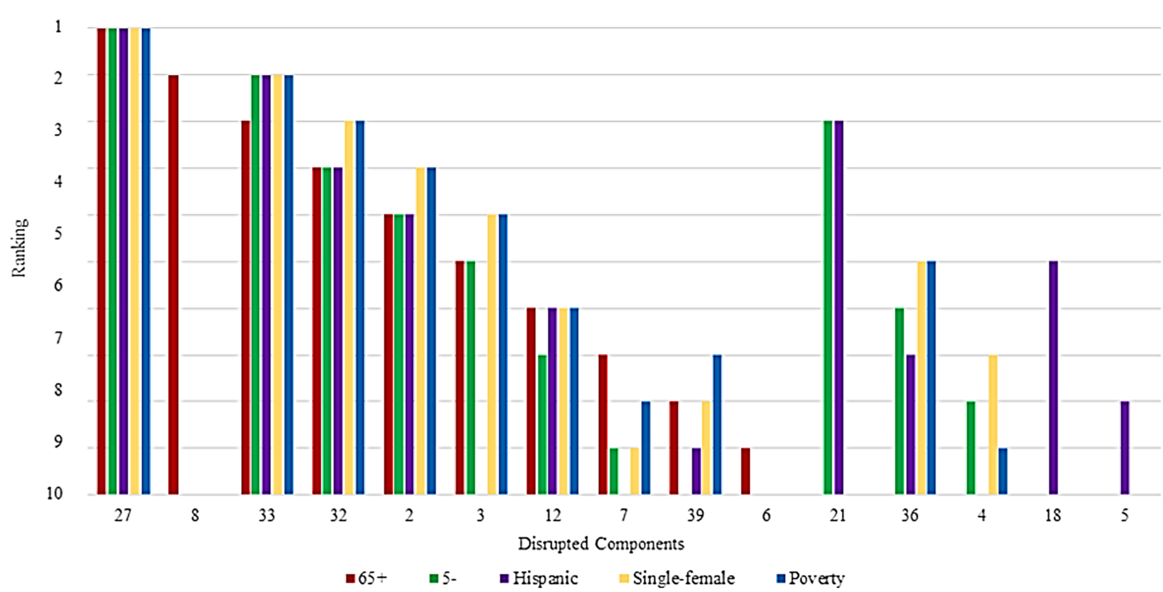

Fig. 7. The ranking of the subset of the power network components (both nodes and links are listed) are represented independently based on each social vulnerability variable.

Table 5
A subset of the critical components (both nodes and links are considered) in the water and power network based on all the available social vulnerability measures together.

Rank by ORT	Water network components	Power network components
1	Node 20	Node 27
2	Node 25	Node 33
3	Node 15	Node 32
4	Node 3	Node 2
5	Node 5	Node 12
6	Node 45	Node 7
7	Node 8	Node 3
8	Node 4	Node 19
9	Node 18	Node 6
10	Node 6	Node 39

measures of various socioeconomic characteristics in the population that they serve. Through the process of post-disruption restoration planning and resource investment, our proposed approach could be informative and supportive to the prioritization and importance assessment of component-based tasks according to the community resilience view of the decision maker. Also, as different importance rankings of components converge through various social vulnerability variables, this multi-criteria approach could be a different insightful resource for a more aggregated concept of community resilience through the planning of post-disruption activities.

5. Concluding remarks

Societies heavily rely on the critical infrastructures to ensure their proper function. However, due to the globalization and the technological developments of infrastructure networks (Castells 1996, Graham 2000 and Rinaldi et al. 2001), such critical networks have become more dependent on each other. As the interdependent nature of the networks become more common, their vulnerability to a variety of disruptive events has increased. Further, the bi-directional relationship among these physical networks and the surrounding community networks, disruptions can impact the communities significantly. Thus, the recovery planning of interdependent infrastructure networks with the consideration of community resilience has become more important to study.

Understanding the relationship between the certain socio-economic characteristics and the different components of the networks is the first step to identifying component criticality. We study the interdependent infrastructure networks restoration problem and the identification of critical components in the system where we propose a multi-objective optimization model from the community resilience perspective that (i) maximizes the overall system resilience for a given restoration horizon, (ii) minimizes the total cost associated with the restoration process, and (iii) maximizes the social equity through the scheduling of restoration process. The proposed model plans for the restoration schedule of the interdependent infrastructure networks by prioritizing the disrupted components that serve socially less advantageous communities based on their social demographics and resilience levels. This approach ensures that the restoration process of the interdependent infrastructure networks is motivated by social equity and community resilience perspectives. Additionally, the proposed model considers various social vulnerability measures where each demand node in the critical networks are assigned with (i) a specific social vulnerability score for each social vulnerability variable separately, and (ii) population density of its related service area in order to represent the service expectations from community perspective. In our study, the proposed approach allows us to determine the critical infrastructure components according to the planned restoration schedule with the utilization of resilience-based component importance measure, ORT. The critical components are ranked according to their restoration time due based on multiple social vulnerability measures. For the results of our study, we observe that through the restoration of two critical infrastructures in Shelby County, the majority of the earlier periods of the restoration horizon are reserved for the nodes of the networks as they are responsible for more drastic increase in the system resilience both for the case of considering each social vulnerability measure independently and together where they are aggregated by TOPSIS algorithm. Hence, through the pre-disruption preparedness planning and the post-disruption recovery process, the decision makers could schedule the restoration of the disrupted nodes prior to the disrupted links. For the schedule of the nodes among each other, in that case, the decision makers can base their implementations on the relative importance of the social vulnerability measures.

For the further work, additional resilience-based component importance measures could be considered to determine and rank the critical components of the interdependent infrastructure networks. Moreover, more critical infrastructure networks that are interdependent in nature could be included in the study with various types of interdependencies, and the community resilience perspective could be extended to incorporate with different types of interdependencies to provide a more comprehensive study of interdependent infrastructure network restoration and component importance measures problem. Additionally, to address some of the limitations of the proposed study, the future work could focus on the uncertainties in the system and incorporate a stochastic method to account for physical network related parameter uncertainties. Lastly, a more dynamic approach to capture the continuously changing state of the social vulnerability, hence social equity measure of community could be introduced in the further studies.

Declaration of Competing Interest

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.

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References

Adler, N., & Golany, B. (2001). Evaluation of deregulated airline networks using data envelopment analysis combined with principal component analysis with an application to Western Europe. *European Journal of Operations Research, 132*(2), 260–273.
Ahern, J. (2011). From fail-safe to safe-to-fail: Sustainability and resilience in the new urban world. *Landscape and Urban Planning, 100*(4), 341–343.
Ahmed, Q. I., Lu, H., & Ye, S. (2008). Urban transportation and equity: A case study of Beijing and Karachi. *Transportation Research Part A, Policy and Practice, 42*(1), 125–139.
Aksu, D. T., & Ozdamar, L. (2014). A mathematical model for post-disaster road restoration: Enabling accessibility and evacuation. *Transportation Research Part E Logistics and Transportation Review, 61*(1), 56–67.
Almoghathawi, Y., & Barker, K. (2017). *Component importance measures for interdependent infrastructure network resilience.* In Press.
Almoghathawi, Y., Barker, K., & Albert, L. (2019). Resilience-driven restoration model for interdependent infrastructure networks. *Reliability Engineering & System Safety, 185*, 12–23.
Arnette, A. N., & Zobel, C. W. (2019). A Risk-Based Approach to Improving Disaster Relief Asset Pre-Positioning. *Production and Operations Management, 28*(2), 457–478.
Auf der Heide, E., & Scanlon, J. (2007). Health and medical preparedness and response. *Emergency management: Principles and practice for local government,* 183–206.
Barker, K., Lambert, J. H., Zobel, C. W., Tapia, A. H., Ramirez-Marquez, J. E., McLay, L. A., Nicholson, C. D., & Caragea, C. (2017). Defining resilience analytics for interdependent cyber physical-social networks. *Sustainable and Resilient Infrastructure, 2*(2), 59–67.
Barker, K., Ramirez-Marquez, J. E., & Rocco, C. M. (2013). Resilience-based network component importance measures. *Reliability Engineering & System Safety, 117*, 89–97.
Barker, K., Karakoc, D. B., & Almoghathawi, Y. (2018). Interdependent infrastructure network restoration from a Community resilience perspective. *Proceedings of the European Safety and Reliability Conference* (pp. 1261–1267).

Batouli, M., & Mostafavi, A. (2018). Multiagent simulation for complex adaptive modeling of road infrastructure resilience to sea-level rise. *Computer-Aided Civil and Infrastructure Engineering, 33*(5), 393–410.

Bibri, S. E., & Krogstie, J. (2017). On the social shaping dimensions of smart sustainable cities: A study in science, technology, and society. *Sustainable Cities and Society, 29*, 219–246.

Blaikie, P., Cannon, T., Davis, I., & Wisner, B. (1994). *At risk: Natural hazards, people's vulnerability and disasters.* Routledge.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A., & von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra, 19*(4), 733–752.

Cai, X. (2008). Water stress, water transfer and social equity in Northern China Implications for policy reforms. *Journal of Environmental Management, 87*(1), 14–25.

Cao, W., Çelik, M., Ergun, O., Swann, J., & Viljoen, N. (2016). Challenges in service network expansion: An application in donated breastmilk banking in South Africa. *Socio-economic Planning Sciences, 53*, 33–48.

Cariolet, J. M., Vuillet, M., & Diab, Y. (2019). Mapping urban resilience to disasters–a review. *Sustainable Cities and Society*101746.

Castells, M. (1996). *The rise of the network society. The information age: Economy, society, and culture volume I (Information age series).* London: Blackwell.

Chankong, V., & Haimes, Y. Y. (2008). *Multiobjective decision making: Theory and methodology. Dover books on engineering.* Courier Dover Publications.

Chen, Y., Bouferguene, A., Shen, Y., & Al-Hussein, M. (2019). Assessing accessibility-based service effectiveness (ABSEV) and social equity for urban bus transit: A sustainability perspective. *Sustainable Cities and Society, 44*, 499–510.

Cimellaro, G., Reinhorn, A., & Bruneau, M. (2010). Seismic resilience of a hospital system. *Structure and Infrastructure Engineering, 6*(1), 127–144.

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

Cutter, S. L., Burton, C. G., & Emrich, C. T. (2010). Disaster resilience indicators for benchmarking baseline conditions. *Journal of Homeland Security and Emergency Management, 7*(1).

Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. *Global Environmental Change Part A, 18*(4), 598–606.

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. *Social Science Quarterly, 84*(1), 242–261.

Davis, L. B., Samanlioglu, F., Qu, X., & Root, S. (2013). Inventory planning and coordination in disaster relief efforts. *International Journal of Production Economics, 141*(2), 561–573.

Department of Homeland Security (2013). National preparedness report. *The National Infrastructure Protection Plan*.

Doctor, R. D. (1994). Seeking equity in the national information infrastructure. *Internet Research, 4*(3), 9–22.

Dulal, H., Shah, K., & Ahmad, N. (2009). Social equity considerations in the implementation of Caribbean climate change adaptation policies. *Sustainability, 1*(3), 363–383.

Evans, J. M., Hardy, D., & Hauer, M. (2014). *Assessing social vulnerability using "SoVI-Lite:" a demonstration study at Glynn County, GA*.

Fang, Y. P., Pedroni, N., & Zio, E. (2016). Resilience-based component importance measures for critical infrastructure network systems. *IEEE Transactions on Reliability, 65*(2), 502–512.

Fauconnier, I. (1999). The privatization of residential water supply and sanitation services: Social equity issues in the California and international context. *Berkeley Planning Journal, 13*(1).

France-Mensah, J., Kothari, C., O'Brien, W. J., & Jiao, J. (2019). Integrating social equity in highway maintenance and rehabilitation programming: A quantitative approach. *Sustainable Cities and Society, 48*, 101526.

Gardoni, P., & Murphy, C. (2018). Society-based design: Promoting societal well-being by designing sustainable and resilient infrastructure. *Sustainable and Resilient Infrastructure,* 1–16.

González, A. D., Dueñas-Osorio, L., Sánchez-Silva, M., & Medaglia, A. L. (2016). The interdependent network design problem for optimal infrastructure system restoration. *Computer-Aided Civil and Infrastructure Engineering, 31*(5), 334–350.

Graham, S. (2000). Constructing premium network spaces: Reflections on infrastructure networks and contemporary urban development. *International Journal of Urban and Regional Research, 24*(1), 183–200.

Gralla, E., Goentzel, J., & Fine, C. (2014). Assessing trade-offs among multiple objectives for humanitarian aid delivery using expert preferences. *Production and Operations Management, 23*(6), 978–989.

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

Guikema, S. D., Davidson, R. A., & Liu, H. (2006). Statistical models of the effects of tree trimming on power system outages. *IEEE Transactions on Power Delivery, 21*(3), 1549–1557.

Henry, D., & Ramirez-Marquez, J. E. (2012). Generic metrics and quantitative approaches for system resilience as a function of time. *Reliability Engineering & System Safety, 99*(1), 114–122.

Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research, 202*(1), 16–24.

Holland, S. M. (2008). *Principal components analysis (PCA)*. Athens, GA: Department of Geology, University of Georgia30602–32501.

Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. *Reliability Engineering & System Safety, 145*, 47–61.

Huang, M., Smilowitz, K., & Balcik, B. (2012). Models for relief routing: Equity, efficiency and efficacy. *Transportation Research Part E, 48*(1), 2–18.

Hwang, C.-L., & Yoon, K. (1981). *Methods for multiple attribute decision making. Multiple attribute decision making.* Berlin, Heidelberg: Springer58–191.

Johansson, J., & Hassel, H. (2010). An approach for modelling interdependent infrastructures in the context of vulnerability analysis. *Reliability Engineering & System Safety, 95*(12), 1335–1344.

Johnson, R. A., & Wichern, D. W. (1982). *Applied multivariate statistics.* Englewood Cliffs, NJ: Prentice Hall.

Jönsson, H., Johansson, J., & Johansson, H. (2008). Identifying critical components in technical infrastructure networks. *Journal of Risk and Reliability, 222*(2), 235–243.

Joseph, K. T., Rice, K., & Li, C. (2016). Integrating equity in a public health funding strategy. *Journal of Public Health Management and Practice, 22*(1), 68–76.

Kammouh, O., Zamani, A. N., Cimellaro, P. G., & Mahin, S. A. (2019). Resilience assessment of urban communities. *Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 5*(1) 04019002.A.

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

Kolesárová, A., Gaspar, M., & Radko, M. (2007). Weighted ordinal means. *Information Sciences, 177*(18), 3822–3830.

Koliou, M., van de Lindt, J. W., McAllister, T. P., Ellingwood, B. R., Dillard, M., & Cutler, H. (2018). State of the research in community resilience: Progress and challenges. *Sustainable and Resilient Infrastructure,* 1–21.

Kontokosta, C. E., & Malik, A. (2018). The resilience to emergencies and disasters index: Applying big data to benchmark and validate neighborhood resilience capacity. *Sustainable Cities and Society, 36*, 272–285.

Li, Y., & Lence, B. J. (2007). Estimating resilience of water resources systems. *Water Resources Research, 43*(7), W07422.

Lootsma, F. A. (1999). *Multi-criteria decision analysis via ratio and difference judgement.* Norwell, MA: Kluwer Academic Publishers29.

Manaugh, K., & El-Geneidy, A. (2012). Who benefits from new transportation infrastructure? Using accessibility measures to evaluate social equity in public transport provision. *Chapters,* 211–227.

Manaugh, K., Badami, M. G., & El-Geneidy, A. M. (2015). Integrating social equity into urban transportation planning: A critical evaluation of equity objectives and measures in transportation plans in North America. *Transport Policy, 37*, 167–176.

Marana, P., Eden, C., Eriksson, H., Grimes, C., Hernantes, J., Howick, S., ... Pyrko, I. (2019). Towards a resilience management guideline—Cities as a starting point for societal resilience. *Sustainable Cities and Society, 48*, 101531.

Mehta, S., & Kalra, M. (2013). Information and communication technologies. *The International Information & Library Review, 38*(3), 147–160.

Mileti, D. (1999). *Disasters by Design: A reassessment of natural hazards in the United States. Natural hazards and disasters: Reducing loss and building sustainability in a hazardous world: A series.* Joseph Henry Press.

Morrow, B. H. (2002). Identifying and mapping community vulnerability. *Disaster, 23*(1), 1–18.

Muralidharan, C., Anantharaman, N., & Deshmukh, S. G. (2002). A multi-criteria group decision making model for supplier rating. *The Journal of Supply Chain Management, 38*(3), 22–33.

Nagurney, A., & Qiang, Q. (2009). *Fragile networks: Identifying vulnerabilities and synergies in an Uncertain world.* John Wiley & Sons.

Nan, C., & Sansavini, G. (2017). A quantitative method for assessing resilience of interdependent infrastructures. *Reliability Engineering & System Safety, 157*, 35–53.

National Research Council (2006). *Facing hazards and disasters: Understanding human dimensions.* National Academies Press.

Newman, M. E. J., Holme, P., & Leicht, E. A. (2006). Vertex similarity in networks. *Physical Review E, 73*(2), 026120.

Nicholson, C. D., Barker, K., & Ramirez-Marquez, J. E. (2016). Flow-based vulnerability measures for network component importance: Experimentation with preparedness planning. *Reliability Engineering & System Safety, 145*, 62–73.

Norris, F. H., Stevens, S. P., Pfefferbaum, B., Wyche, K. F., & Pfefferbaum, R. L. (2007). Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *American Journal of Community Psychology, 41*(1-2), 127–150.

Noyan, N., Balcik, B., & Atakan, S. (2015). A stochastic optimization model for designing last mile relief networks. *Transportation Science, 50*(3), 1092–1113.

Nurre, S. G., Cavdaroglu, B., Mitchell, J. E., & Sharkey, T. C. (2012). Restoring infrastructure systems: An integrated network design and scheduling (INDS) problem. *European Journal of Operational Research, 223*(3), 794–806.

Obama, B. H. (2013). *Critical infrastructure security and resilience.* Washington: The White House.

Ogryczak, W., Luss, H., Pióro, M., Nace, D., & Tomaszewski, A. (2014). Fair optimization and networks: A survey. *Journal of Applied Mathematics*612018.

Okabe, A., Satoh, T., Furuta, T., Suzuki, A., & Okano, K. (2008). Generalized network Voronoi diagrams: Concepts, computational methods, and applications. *International Journal of Geographical Information Science, 22*(9), 965–994.

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

Ouyang, M., & Dueñas-Osorio, L. (2012). Time-dependent resilience assessment and improvement of urban infrastructure systems. *Chaos an Interdisciplinary Journal of Nonlinear Science, 22*(3), 033122.

Ouyang, M., Dueñas-Osorio, L., & Min, X. (2012). A three-stage resilience analysis framework for urban infrastructure systems. *Structural Safety, 36*, 23–31.

Panteli, M., Trakas, D. N., Mancarella, P., & Hatziargyriou, N. D. (2017a). Power systems

resilience assessment: Hardening and smart operational enhancement strategies. *Proceedings of the IEEE, 105*(7), 1202–1213.
Panteli, M., Mancarella, P., Trakas, D. N., Kyriakides, E., & Hatziargyriou, N. D. (2017b). Metrics and quantification of operational and infrastructure resilience in power systems. *IEEE Transactions on Power Systems, 32*(6), 4732–4742.
Ribeiro, P. J. G., & Gonçalves, L. (2019). Urban resilience: A conceptual framework. *Sustainable Cities and Society*101625.
Rinaldi, S. M., Peerenboom, J. P., & Kelly, T. K. (2001). Identifying, understanding and analyzing critical infrastructure interdependencies. *IEEE Control Systems Magazine, 21*(6), 11–25.
Rocco, C. M., Ramirez-Marquez, J. E., Salazar, D. E., & Zio, E. (2010). A flow importance measure with application to an italian transmission power system. *International Journal of Performability Engineering, 6*(1), 53–61.
Rose, A. (2007). Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions. *Environmental Hazards, 7*(4), 383–398.
Rosenheim, N., Guidotti, R., & Gardoni, P. (2017). Integration of detailed household characteristic data with critical infrastructure and its implementation to post-hazard resilience modelling. *Resilience,* 164.
Rosenthal, R., & Rubin, D. B. (1979). A note on percent variance explained as a measure of the importance of effects. *Journal of Applied Social Psychology, 9*(5), 395–396.
Rotmans, J., Walker, W. E., Harremoës, P., van der Sluijs, J. P., van Asselt, M. B. A., Janssen, P., & von Krauss, M. P. K. (2003). Defining uncertainty: A conceptual basis for uncertainty management in model-based decision support. *Integrated Assessment, 4*(1), 5–17.
Sharkey, T. C., Cavdaroglu, B., Nguyen, H., Holman, J., Mitchell, J. E., & Wallace, W. A. (2015). Interdependent network restoration: On the value of information-sharing. *European Journal of Operational Research, 244*(1), 309–321.
Shlens, J. (2014). *A tutorial on principal component analysis. arXiv preprint arXiv:1404.1100*.
Silver, A., & Andrey, J. (2014). The influence of previous disaster experience and socio-demographics on protective behaviors during two successive tornado events. *Weather Climate and Society, 6*(1), 91–103.
Tabandeh, A., Gardoni, P., Murphy, C., & Myers, N. (2018). Societal risk and resilience analysis: Dynamic bayesian network formulation of a capability approach. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems Part A, Civil Engineering, 5*(1), 04018046.
Tahmasbi, B., Mansourianfar, M. H., Haghshenas, H., & Kim, I. (2019). Multimodal accessibility-based equity assessment of urban public facilities distribution. *Sustainable Cities and Society*101633.
The Infrastructure Security Partnership (2011). Regional disaster resilience guide for developing an action plan. *Technical report, American Society of Civil Engineers.*.
The Report of the President's Commission on Critical Infrastructure Protection (1997). *Critical foundation: Protecting America's infrastructure. USA*.
Thomopoulos, N., & Grant-Muller, S. (2012). Incorporating equity as part of the wider impacts in transport infrastructure assessment: An application of the SUMINI approach. *Transportation, 40*(2), 315–345.
Thomopoulos, N., Grant-Muller, S., & Tight, M. R. (2009). Incorporating equity considerations in transport infrastructure evaluation: Current practice and a proposed methodology. *Evaluation and Program Planning, 32*(4), 351–359.
Tierney, K. (2009). *Disaster response: Research findings and their implications for resilience measures*Oak Ridge, TN: CARRI Research Report6.
Tierney, K. (2006). Social inequality, hazards, and disasters. *On risk and disaster: Lessons from Hurricane Katrina,* 109–128.
Turnquist, M., & Vugrin, E. (2013). Design for resilience in infrastructure distribution networks. *Environment Systems & Decisions, 33*(1), 104–120.
US Census Bureau (2010). *Geographic terms and concepts*.
Vugrin, E. D., Turnquist, M. A., & Brown, N. J. (2014). Optimal recovery sequencing for enhanced resilience and service restoration in transportation networks. *International Journal of Critical Infrastructures, 10*(3-4), 218–246.
Wang, S., Hong, L., Ouyang, M., Zhang, J., & Chen, X. (2013). Vulnerability analysis of interdependent infrastructure systems under edge attack strategies. *Safety Science, 51*(1), 328–337.
White House (2013). *Critical infrastructure security and resilience*.
Whitson, J. C., & Ramirez-Marquez, J. E. (2009). Resiliency as a component importance measure in network reliability. *Reliability Engineering & System Safety, 94*(10), 1685–1693.
Yan, S., & Shih, Y. L. (2009). Optimal scheduling of emergency roadway repair and subsequent relief distribution. *Computers & Operations Research, 36*(6), 2049–2065.
Yang, Y., Ng, S. T., Zhou, S., Xu, F. J., Li, D., & Li, H. (2020). A federated pre-event community resilience approach for assessing physical and social sub-systems: An extreme rainfall case in Hong Kong. *Sustainable Cities and Society, 52,* 101859.
Zhou, H., He, S., Cai, Y., Wang, M., & Su, S. (2019). Social inequalities in neighborhood visual walkability: Using Street View imagery and deep learning technologies to facilitate healthy city planning. *Sustainable Cities and Society*101605.
Zolfaghari, M. R., & Peyghaleh, E. (2015). Implementation of equity in resource allocation for regional earthquake risk mitigation using two-stage stochastic programming. *Risk Analysis, 35*(3), 434–458.