Sustainable and Resilient Infrastructure

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tsri20

# Resilience in multilayer transportation infrastructure networks: a review and conceptual framework for equity-based assessment

Mahsa Arabi, Simos Gerasimidis, Camille Barchers & Jimi Oke

SUSTAINABLE AND RESILIENT INFRASTRUCTURE
https://doi.org/10.1080/23789689.2024.2344909



# Resilience in multilayer transportation infrastructure networks: a review and conceptual framework for equity-based assessment

Mahsa Arabi[a], Simos Gerasimidis[a], Camille Barchers[b] and Jimi Oke[a]

[a]Department of Civil and Environmental Engineering, University of Massachusetts Amherst, Amherst, MA, USA; [b]Department of Landscape Architecture and Regional Planning, University of Massachusetts Amherst, Amherst, MA, USA

**ABSTRACT**
This paper presents a comprehensive review of resilience concepts, methodologies, metrics, and modeling techniques, and identifies key research gaps. These include the lack of multilayer network representations of transportation infrastructures when quantifying resilience, and insufficient metrics for assessing equitable outcomes. To address these gaps, we propose a conceptual multilayer framework for transporttaion infrastructure networks and develop equitable resilience metrics that incorporate socioeconomic and demographic variables. Using Pioneer Valley as a case study, we apply our framework to assess the resilience of transportation networks and demonstrate its utility in guiding resource allocation to enhance both the physical robustness and social equity of infrastructure. Our findings show that this approach significantly contributes to more informed and inclusive decision-making, fostering the development of resilient and equitable urban environments.

**ARTICLE HISTORY**
Received 23 August 2021
Accepted 15 April 2024

**KEYWORDS**
Equity; transportation infrastructure system; multilayer network; resilience

## 1. Introduction

The frequency and magnitude of extreme events have significantly increased across the globe over the past two decades (Kermanshah & Derrible, 2017). These events can severely impact the performance of infrastructure networks, such as transportation, telecommunications, and electric power systems, among others (Ilbeigi, 2019; Ouyang, 2014). Notably, the 2021 Winter Storm Uri caused extended power and water outages in over 25 states with Texas being the hardest hit (Nejat, Solitare, Pettitt, et al., 2022). Winter Storm Uri resulted in power outages for 11 million Texans, widespread disruptions in water services, and inflicted damages worth billions of dollars (Potts, Tiedmann, Stephens, et al., 2024). Additionally, the February 2023 twin earthquakes in southern Turkey and near the Syrian border significantly highlight the vulnerability of infrastructure to natural disasters, affecting estimated 14 million people and causing over 50,000 deaths, further underlining the critical need for resilient infrastructure systems (Mavrouli, Mavroulis, Lekkas, et al., 2023).

Transportation systems, in particular, are vulnerable to a wide range of natural events and disruptions such as hurricanes, tornadoes, and earthquakes, among others (Bhavathrathan & Patil, 2018). An extreme event that underscores this vulnerability was Hurricane Irene, which caused $65 million worth of damage to the US state of Vermont's transportation network in 2011 (Ghorbanzadeh, Koloushani, Ozguven, et al., 2022). The resilience of critical infrastructure, especially transportation, is thus one of the increasing concerns for national governments, infrastructure managers, and local authorities (Dvořák, Sventeková, Řehák, et al., 2017).

Robust resilience assessments for mobility infrastructure require a consideration of the interconnections among its various components, such as roads, bridges, and buildings. Socioeconomic and demographic factors are also important in accounting for the vulnerability of individuals and communities to hazards (Bolin & Kurtz, 2018; Cutter, 1995). Transportation infrastructure serves as a foundation for security, economy, and public welfare and thus plays a critical role in addressing equity concerns and ensuring fair access to essential services and opportunities (Qiang & Xu, 2019). Yet, there remains a gap in comprehensive resilience modeling frameworks that explicitly incorporate equity considerations.

This paper addresses these challenges by first synthesizing current and relevant work in quantifying the resilience of transportation infrastructure (Section 2). We critically analyze extant resilience concepts, approaches, metrics, and modeling methods (Section 3). Importantly, we introduce a conceptual multilayer framework for transportation networks that incorporates roads, bridges, public transportation, and

**CONTACT** Mahsa Arabi marabi@umass.edu

buildings (Section 4). We then develop equitable resilience metrics for resilience in multilayer transportation infrastructure and demonstrate them in a case study transportation network in the US state of Massachusetts (Section 5).

## 2. Resilience concepts in transportation infrastructure: a background

### 2.1. Evolution of transportation resilience research

Research on transportation system resilience began in the 1990s (Ahmed & Dey, 2020). Since the concept of resilience engineering emerged, a significant portion of research has initially centered on roadway-based transportation systems, reflecting early priorities and available data (Ahmed & Dey, 2020). This initial focus paved the way for broader investigations as the field matured.

Earlier efforts concentrated on a qualitative treatment of resilience (Baroud, Barker, Ramirez-Marquez, et al., 2014; Bhatia, Kumar, Kodra, et al., 2015). In recent years, however, quantitative resilience methods have attracted more attention. This interest has resulted in a substantial number of frameworks for quantifying transportation network resilience, such as (Adjetey-Bahun, Birregah, Chatelet, et al., 2014; Bhatia, Kumar, Kodra, et al., 2015; Cavallaro, Asprone, Latora, et al., 2014; Donovan & Work, 2017), marking a significant advancement in how resilience is understood and applied. As a result of the developments in resilience engineering studies, the definition of system resilience has shifted from a system's ability to deal with threats to its ability to adjust its functionality (Hollnagel, Pariès, Woods, et al., 2010). Based on this new definition, a system is resilient when it can respond to what happens, monitor significant developments, anticipate future threats, and sustain required functions (Hollnagel, Pariès, Woods, et al., 2010). Reflecting on these developments, it is evident that resilience, though variably defined, is universally acknowledged as time-phased, dynamic, multifaceted, and comprehensive (Wang, Wu, & Yuen, 2023). These attributes are crucial for transportation systems, which must continuously adapt to changing conditions and emerging threats.

### 2.2. Dimensions and phases of resilience

There are three different aspects associated with the concept of resilience (Weilant, Strong, & Miller, 2019):

- Decreasing the probability of a disaster and increasing the ability of a community to resist it.
- Increasing the adaptability of a system while maintaining functions in the presence of disasters.
- Decreasing the time needed for the system to recover to normal functioning.

Building on these principles, Weilant, Strong, and Miller (2019) outlines resilience in four essential dimensions that cover technical, organizational, social, and economic aspects. This broad perspective sets the stage for a more detailed examination of the transportation sector. Specifically, Ahmed and Dey (2020) and Murray-Tuite (2006) present a framework of ten critical dimensions for transportation resilience, including redundancy, diversity, efficiency, components' dependency, strength, stakeholders' collaboration, adaptability, transportation performance, safety performance, and the ability to recover quickly. In a similar approach, Nipa, Kermanshachi, and Pamidimukkala (2023) offers a refined model that includes redundancy, efficiency, diversity, strength, adaptability, autonomous components, collaboration, mobility, safety, and rapidity (Nipa, Kermanshachi, & Pamidimukkala, 2023). Despite their similarities, this latter framework shifts focus towards autonomous operations and mobility, reflecting evolving priorities within the field of transportation resilience.

Some approaches divide the post-disaster phase into two sub-phases: the immediate response and the subsequent restoration (Tingting & Yu, 2020). The response phase is shortly after the disruptive event, while the restoration phase follows the response phase. During the restoration phase, the infrastructure is awaiting repair, but daily travel demand has recovered to a relatively normal level. However, the degraded infrastructure network cannot satisfy some demands (Tingting & Yu, 2020). Other studies add complexity to this view. Chang, Elnashai, and Spencer (2012) and Kilanitis and Sextos (2019) demonstrate that post-disaster travel demand and network performance can vary significantly, with seismic events leading to increased travel times and trip cancellations due to bridge and road network damages. Wu and Chen (2023c) further elaborates on transportation resilience, suggesting that bridge reconstruction and recovery planning must consider time-evolving travel demand to accurately model post-earthquake resilience.

### 2.3. Infrastructure deterioration

When considering an existing network system, the real structural condition of the main infrastructure assets is rarely pristine. Studies in the last few decades have revealed that the condition of main infrastructure assets has been deteriorating for many years, thus rendering part of the existing infrastructure structurally deficient (Lin, Yuan, & Tovilla, 2019; Rashedi & Hegazy, 2016; Uddin, Hudson, & Haas, 2013). Within a transportation network, bridges are widely recognized as the most critical yet vulnerable components (Alipour & Shafei, 2016b). An example of this vulnerability was seen in the collapse of the Morandi Bridge in Genoa, Italy in 2018. The failure of this single bridge disrupted local and also national and international transportation, leading to significant economic and social impacts (Pirlone, Spadaro, & Candia, 2020). In the US highway system, 39% of 614,387 bridges have been in service for more than five decades (ASCE, 2017). In a recent study, about 55,000 of these bridges are considered structurally deficient, with the backlog of bridge repair needs estimated at US$123 billion (ASCE, 2017; Federal Highway Administration, 2017). Although this cost is considered monumental, it is also uncertain how these bridges will respond to a disastrous event. Recent efforts have focused on the deterioration of bridges and the accumulation of natural damage to the structural system (Tzortzinis, Knickle, Bardow, et al., 2021). Some studies modified resilience measures considering the impact of aging mechanisms to better estimate the functionality of transportation networks after a disruptive event (Alipour & Shafei, 2016b). A commonly used method to assess the damages caused by catastrophic events in deteriorating networks is to estimate travel time before and after the occurrence of the event (Alipour & Shafei, 2016a). This helps evaluate the losses incurred due to disruptions, such as earthquakes.

In the last few decades, several efforts have focused on assessing the remaining capacity of existing infrastructure, aiming at providing critical information first for potential repair and replacement decisions and second for describing the onset of resilience models (Morcous, Rivard, & Hanna, 2002; Rashedi & Hegazy, 2016; Stewart, Wang, & Nguyen, 2011). These efforts include new techniques for inspections (Hamida & Goulet, 2020), monitoring, analyzing, and predicting the phenomenon of deterioration and how it affects the structural capacity of major infrastructure assets (Jeong, Kim, Kim, et al., 2017; Kobayashi, Kaito, & Lethanh, 2012; Medina, González, & Todisco, 2022; Wu, Lin, Liang, et al., 2023). Recent advancements in infrastructure monitoring have been highlighted by a study that integrates visual inspections with a nonlinear deterioration model to more accurately predict the lifespan and necessary maintenance of concrete bridges, particularly in response to environmental stressors like corrosion (Bah, Sanchez, Zhang, et al., 2024). Additionally, the combination of satellite remote sensing and ground-based non-destructive testing methods has been identified as a transformative approach for the comprehensive monitoring of transport infrastructure, enhancing early detection and maintenance planning (Gagliardi, Tosti, Bianchini Ciampoli, et al., 2023). Generally, the implication for resilience modeling, which aims to quantify resilience in the communities, is that infrastructure deterioration will also need to be taken into account, at least for the main infrastructure assets such as bridges in a transportation network. Inspection records and experimental testing data can be harnessed to predict the condition of bridges (and other infrastructure) over time under various disasters.

### 2.4. Equity considerations

Equity represents an extensive concept aimed at systematically addressing and diminishing disparities across different sectors and communities (Bruzzone, Cavallaro, & Nocera, 2023). Communities need to plan for, respond to, and recover from disasters. Across these three phases of decision-making, communities require an enormous amount of data to understand vulnerabilities and allocate resources effectively. In the post-disaster context, short-term needs encompass rapidly identifying vulnerable populations, providing evacuation plans, and ensuring the allocation of essential resources such as healthcare, food, and energy. Long-term strategies focus on enhancing the resilience of infrastructure networks and guiding future developments to safer locations (Tamima & Chouinard, 2016; Wu & Chen, 2023a, 2023b). These strategies underscore the necessity for models that support informed decision-making and policy development aimed at mitigating the effects of natural hazards on communities, as outlined by Boakye, Guidotti, Gardoni, et al. (2022).

Incorporating equity into urban planning and resilience measures, particularly within the domain of mobility infrastructure, is critical for effective disaster recovery and sustainable community development. The study by Boakye, Guidotti, Gardoni, et al. (2022) highlights the critical need to link transportation functionality with individual capabilities, such as health and mobility, essential for both immediate response and long-term disaster recovery. Similarly, recent studies on urban logistics systems, particularly during the COVID-19 pandemic disruptions, emphasize the need for equity in emergency response strategies to maintain service capabilities (Li & Zhou, 2024). This approach extends to ensuring access to essential services – medical facilities, food sources, and shelters, which is fundamental for community support during crises (Logan &

Guikema, 2020). Further illustrating the interconnectedness of resilience and equity, research utilizing smartphone-location data shows that reducing access inequality can significantly enhance urban resilience by optimizing facility distribution and reducing travel costs (Fan, Jiang, Lee, et al., 2022). These studies collectively underscore the importance of integrating equity into urban planning to build more resilient and inclusive communities.

Equitable resilience can be considered as a form of human-environmental resilience that includes social vulnerability issues and differentiated access to power, knowledge, and resources (Matin, Forrester, & Ensor, 2018). However, achieving equitable resilience is not without its challenges. A comprehensive review of 38 resilience plans from US cities found that, while equity is recognized in both explicit and implicit ways, its translation into practical actions within these plans is infrequent (Lambrou & Loukaitou-Sideris, 2021). This suggests that there is a gap between acknowledging the importance of equity and implementing it in resilience strategies. Furthermore, there is variability in the attention paid to equity in urban resilience planning. A comparative study on urban resiliency planning has revealed the need for aligning different interpretations of resiliency, particularly in the domains of transportation and Green Infrastructure, to ensure comprehensive and equitable urban planning (Applegate & Tilt, 2023). A study highlighted the need for improvement, particularly in addressing the recognitional and procedural dimensions of equity (Meerow, Pajouhesh, & Miller, 2019). In an attempt to address this challenge, a novel subjective approach was proposed by another study, which involved conducting household interviews and using participatory methods. This approach underscored the necessity of incorporating diverse perspectives and taking into account contextual factors when assessing resilience. The researchers argued that such a comprehensive approach is crucial for shaping better policy and practice (Ensor, Mohan, Forrester, et al., 2021). In Seoul, enhancing flood resilience through institutional adaptive capacity has been shown to effectively involve local communities, emphasizing the necessity of equitable resilience strategies that empower all urban residents (Ro & Garfin, 2023).

While many studies have emphasized the importance of integrating equity into resilience research, they often remain theoretical and neglect to measure equity effectively. This underscores the urgency for tangible, quantifiable methods in assessing equity within the sphere of resilience, particularly in mobility infrastructure. Thus, it is important to explore the potential consequences of disasters on the most vulnerable populations, including low-income individuals, the elderly, and those with disabilities.

## 3. Resilience methods and metrics

Various methods have been applied in studying the resilience of a transportation system. Ahmed and Dey (2020) categorized modeling frameworks for quantifying transportation resilience into step-wise assessments, which include qualitative analyses and simulations, alongside optimization approaches. Similarly (Hosseini, Barker, & Ramirez-Marquez, 2016) have categorized resilience models into optimization, simulation, and fuzzy logic. This paper provides a comprehensive review of quantitative resilience modeling techniques and multilayer network representations and proposes a classification approach for resilience metrics.

### *3.1. Quantitative approaches*

Fuzzy logic has emerged as a pivotal tool in this field. The flexibility of fuzzy logic allows for handling uncertainties inherent in real-world data, making it indispensable for interpreting ambiguous or incomplete information. This approach, as detailed by (Serulle, Heaslip, Brady, et al., 2011), enables decision-makers to develop more adaptable and responsive resilience frameworks. Furthermore, recent applications of fuzzy logic have broadened its scope in urban resilience studies. A notable example is a study examining Rio de Janeiro's public transport system, where fuzzy logic was used to evaluate resilience against economic threats, such as the end of fare subsidies. This approach highlighted disparities in resilience among different districts, demonstrating fuzzy logic's potential in addressing socio-economic challenges beyond natural or technical disturbances (Santos, Fernandes, Cardoso, et al., 2023).

Optimization techniques also play a critical role in measuring resilience. These methods are crucial for formulating strategies that optimize resource allocation and system recovery post-disruption. The bi-objective bi-level optimization framework developed by Tingting and Yu (2020) illustrates the application's breadth, focusing on the restoration of transportation systems by balancing unmet demand and travel time. Moreover, optimization has facilitated the identification of critical infrastructure components, as demonstrated by Ip and Wang (2011), who evaluated passageways between cities to enhance network resilience. Recent advancements have integrated equity and efficiency considerations, as seen in (Li & Zhou, 2024) resilience-oriented capacity reallocation models for urban logistics systems.

Simulation methods stand out for their ability to replicate complex systems and forecast recovery strategies. Aydin, Duzgun, Heinimann, et al. (2018) employed topology-based simulations and the Monte Carlo method to analyze rural road recovery post-earthquakes, showcasing the simulation's capability to quantify resilience and uncertainty. Furthermore, simulation techniques have been applied to assess the resilience of mass railway and waterway transportation systems by Adjetey-Bahun, Birregah, Châtelet, et al. (2016) and Wang and Yuen (2022), respectively, focusing on metrics such as passenger delay and system recovery cost.

In recent years, complex network analysis and machine learning have gained traction as innovative approaches to studying resilience. Network analysis provides a structured method to evaluate the interconnectivity and robustness of transportation systems, effectively applied by Leu, Abbass, and Curtis (2010) in assessing Melbourne's ground transportation network.

Machine learning and statistical modeling are closely linked approaches that enhance the understanding and prediction of transportation system resilience, combining data analysis with computational techniques. Statistical modeling has been leveraged to establish robust quantitative foundations for resilience analysis, demonstrated by a study on New York City's post-hurricane transportation recovery which used logistic models and Moran's I test on taxi and subway data to highlight the impact of geographical factors on resilience (Zhu, Xie, Ozbay, et al., 2017). As another example, Chandramouleeswaran and Tran (2018) applied statistical methods to assess the resilience of air transportation networks, highlighting the technique's effectiveness and versatility. The utility of statistical models extends beyond traditional applications, allowing for the integration of diverse data types and resolutions, a feature exemplified in the work by (Ilbeigi, 2019). Machine learning, on the other hand, offers powerful predictive capabilities, as evidenced by Soleimani and Hajializadeh (2022), who utilized bagging and boosting methods for the resilience assessment of highway bridges.

A summary of the most common modeling approaches in quantifying resilience in transportation infrastructure is shown in Table 1:

### 3.2. Network representations

Network analysis has long been considered an effective method to study the behavior of complex systems, such as social, biological, and transportation systems. Representing these networks as graphs is one of the primary steps in assessing resilience in them. There are different approaches to modeling transportation networks, including representing cities as nodes and traffic roads as edges (Ip & Wang, 2009), considering potential traffic bottlenecks in a city as nodes and streets as edges (Das, 2020), and modeling intersections and state bridges as nodes and interstates, highways or spurs as edges (Antony, 2017).

Complex systems such as transportation infrastructure are not isolated. The functioning of nodes in one system often promotes or suppresses the functioning of nodes in another (Danziger, Bonamassa, Boccaletti, et al., 2019). Given the complexity and heterogeneity of transportation infrastructure, monoplex networks may not always satisfy the requirements for robust resilience assessments in real-world systems. This highlights the need for modeling interactions between various elements of the system. Traditional studies of networks however generally assume that nodes are connected by a single type of static edge that reflects all connections between them. This is almost always an oversimplification. Thus, traditional network analyses fail to provide a comprehensive overview of a complex system, as they ignore multiple types of edges in which entities have a different neighborhood in each layer (Domenico, Solé-Ribalta, Cozzo, et al., 2013). Although focusing on analyzing network interconnections has become a trending topic in recent years (Almoghathawi & Barker, 2019; Danziger, Bonamassa, Boccaletti, et al., 2019; Ouyang, 2014; Sediek, El-Tawil, & McCormick, 2022), there still is a significant gap in modeling a transportation infrastructure system with its

**Table 1.** Classic approaches for quantifying resilience in transportation networks.

| Category | Approach | Key Studies |
|---|---|---|
| Data interpretation | Fuzzy logic | (Santos, Fernandes, Cardoso, et al., 2023; Serulle, Heaslip, Brady, et al., 2011) |
| System optimization | Optimization techniques | Tingting and Yu (2020), Ip and Wang (2011) (Li & Zhou, 2024), Leu, Abbass, and Curtis (2010) |
| | Network analysis | |
| System simulation | Simulation methods | Aydin, Duzgun, Heinimann, et al. (2018), Adjetey-Bahun, Birregah, Châtelet, et al. (2016), Wang and Yuen (2022), (Gao, Hu, & Wang, 2024) |
| Predictive analysis | Machine learning | Soleimani and Hajializadeh (2022) |
| | Advanced statistical methods | (Zhu, Xie, Ozbay, et al., 2017), Ilbeigi (2019), Chandramouleeswaran and Tran (2018) |

key elements, including roads, bridges, public transportation, and buildings, as a multilayer complex system.

#### 3.2.1. Multilayer networks

Multilayer networks contain at least two types of nodes or two types of edges (Škrlj, Kralj, & Lavrač, 2019). These networks are widespread in real-world systems such as communication systems, social systems, biological systems, and transportation systems (Wu, Pu, Li, et al., 2020). Studying the resilience of transportation infrastructure by representing them as multilayer networks is an effective approach that can reveal more complex inter-dependencies compared to a single-layer representation (Wu, Pu, Li, et al., 2020). This thus yields important insights for better decision-making. Various studies have considered multiple components in modeling transportation infrastructure as multilayer networks, as illustrated in Table 2.

There are two typical multilayer network models (Wu, Pu, Li, et al., 2020): multilayer model with a logical layer and a physical layer, and multilayer model with the abstraction of real multilayer networks, in which entities can travel across multiple network layers (for example, a high-speed layer and a low-speed layer). Kurant and Thiran (2006) proposed a generalized multilayer network model in which the lower layer represents the physical infrastructure and the upper layer represents the traffic flows. Ip and Wang (2011) represented transportation networks by an indirect graph, where the nodes are cities and edges are traffic roads. González, DueñDueñAs-Osorio, Sánchez-Silva, et al. (2016) defined a multilayer framework of critical infrastructure including electrical, water, and telecommunication. Tabassum, Chinthavali, Chen, et al. (2018) presented a dynamic modeling approach to capture the inter-dependencies of critical infrastructure including the electric grid and transportation systems.

**Table 2.** Multilayer network components.

| Multilayer network component | References |
|---|---|
| Bike paths | Antony (2017) |
| Bridges | Antony (2017); Zhang, Wang, and Nicholson (2017) |
| Cities | (Ip & Wang, 2009) |
| Passenger and freight systems | Ahmed and Dey (2020) |
| Public and private roads | Antony (2017); Aleta, Meloni, and Moreno (2017); Zhang, Wang, and Nicholson (2017); Baggag, Abbar, Zanouda, et al. (2018) |
| Public transit (bus, tramway, metro) | Ahmed and Dey (2020); Aleta, Meloni, and Moreno (2017) |
| Railways | Bhatia, Kumar, Kodra, et al. (2015) |
| Traffic bottlenecks | (Das, 2020) |
| Walkways | Antony (2017) |

Various approaches have been used to define layers for developing a multilayer transportation network. However, in most cases, each transportation mode is treated as a distinct layer within the multilayer network. Further exploring the complexities of urban transportation, a comprehensive study has been conducted on the integration of various transport modes in metropolitan areas, emphasizing the importance of viewing these systems through the lens of multilayer networks to enhance urban mobility and sustainability (Alessandretti, Natera Orozco, Saberi, et al., 2023). For example, Baggag, Abbar, Zanouda, et al. (2018) developed a multiplex network system that accounted for different modes of transportation as different layers to evaluate the resilience of the transportation system against any failure by analyzing the coverage in the network. Similar to that work, Asgari, Sultan, Xiong, et al. (2016) developed an unsupervised mapping algorithm to map sparse cellular trajectories and modeled a transportation network as a large multilayer graph, with distinct layers for trains, subways, and roads. In a more advanced approach, Aleta, Meloni, and Moreno (2017) introduced a new layer to represent walking and included it in their multilayer model to allow for the possibility of pedestrian movement within the city. This model represents the transportation system of an entire city, with each line of each mode of transport (bus, metro, and tram) treated as a distinct layer and each stop represented as a node. Following a different approach to analyzing transportation systems as a multilayer network, Li, Dong, Mostafavi, et al. (2019) simulated the network dynamics of inter-organizational coordination among interdependent infrastructure systems, including transportation, flood control, emergency response, community development, and environmental conservation. Furthermore, Solé-Ribalta, Gómez, and Arenas (2016) employed a multiplex representation to characterize congestion, wherein the same nodes are present in each layer. Focusing on resilience (Cardillo, Zanin, Gómez-Gardeñes, et al., 2013), analyzed the vulnerability of the European air transport system by utilizing a multilayer network model. In this model, each airline company is represented as a separate layer. In the field of maritime transportation, recent research introduces a novel multilayer network modeling approach to identify versatile ports and understand their roles in global maritime logistics, thereby extending the application of multilayer networks beyond urban settings to international trade and transportation flows (Peng, Claramunt, Cheng, et al., 2023).

We provide an overview of the most relevant reviewed resilience research and compare them based on various aspects (Table 3). Many studies have focused on developing transportation systems as complex multilayer networks, but there is still a gap in studying the resilience of transportation infrastructure as an integrated system considering all key components of roads, public transportation, bridges, and buildings. To properly assess resilience in transportation infrastructure, it is necessary to consider interactions between these components, which are all necessary components of a functioning transportation system.

### 3.3. Taxonomy of resilience metrics

The initial step in developing a decision-making framework for assessing the resilience of transportation infrastructure is to define relevant resilience metrics. These metrics should be able to reflect the ability of transportation infrastructure, to respond to and recover from disasters. Various resilience metrics are used to analyze the resilience of the transportation networks, which are summarized in Table 4. From the literature, we identify five domains (level I metric) to organize existing network-based resilience metrics, which are shown in (Figure 1). These domains include:

- Accessibility: Refers to the important destinations that can be reached.
- Efficiency: Refers to the traffic, time, and cost efficiency of travel within the network.
- Connectivity: Refers to the degree to which nodes in a network are interconnected or related to other nodes by links.
- Reliability: Focuses on how consistently a network can perform or how likely it is to fail.
- Restoration: Quantifies how likely a failure is to happen and how easily the network can be reconstructed in the event of a failure.
- Equity: Highlights the importance of ensuring fair access to facilities among different socio-economic categories of people.

This taxonomy reveals the dearth of quantitative equity-based resilience metrics. In the following

**Table 3.** Overview of relevant resilience studies on transportation infrastructure.

| Reference | Resilience metric | Disaster | Number of layers | Layers | Case study |
|---|---|---|---|---|---|
| (González, DueñDueñAs-Osorio, Sánchez-Silva, et al., 2016) | Reconstruction cost and connectivity | Natural disasters | 3 | Water, gas, and power networks | - |
| (Tabassum, Chinthavali, Chen, et al., 2018) | Vulnerability | Natural disasters | 1 | Electric grid and transportation | - |
| (Bhavathrathan & Patil, 2018) | Travel time at an upper envelope of operable disruptions | - | 1 | Road | Anaheim city road network |
| (Antony, 2017) | Centrality measures | Natural or man-made disaster | 1 | Road and air | Saint-Louis, Missouri |
| (Aydin, Duzgun, Heinimann, et al., 2018) | Proximity to the main research center, time to recovery | Geohazards, especially earthquakes | 1 | Road | Sindhupalchok district in Nepal |
| (Tingting & Yu, 2020) | Unmet demand, total travel time | Hurricane, earthquake, flood | 1 | Road | Sioux Falls |
| (Serulle, Heaslip, Brady, et al., 2011) | Road available capacity, road density, alternate infrastructure proximity, level of intermodality, average delay, average speed reduction, personal transport cost, commercial—industrial transport cost, network management | Flood | 1 | Road | Santo Domingo, Dominican Republic |
| (Hong, Lam, & Nan, 2018) | Vulnerability | Man-made emergency events (labor strikes) | - | Port-hinterland | China's pre-hinterland container transportation network |
| (Baggag, Abbar, Zanouda, et al., 2018) | Network coverage | - | 3 | Bus, metro, and road | Transportation network of Paris, London, New York, and Chicago |
| (Aleta, Meloni, & Moreno, 2017) | Vulnerabilities | - | 4 | Bus, metro, tram and walking path | 9 different cities in Europe |
| (Ip & Wang, 2011) | Weighted average number of reliable passageways with all other city nodes in the network | - | 1 | Railway | Railway network within the Chinese mainland |
| (Asgari, Sultan, Xiong, et al., 2016) | - | - | 3 | Train, subway and road | Ile-de-France (Paris) metropolitan area |
| (Li & Zhou, 2024) | Equity and efficiency in capacity reallocation | Pandemic lockdowns | - | - | Shanghai |


**Figure 1.** Mind map of currently used network-based resilience metrics.

section, we propose a conceptual framework that explicitly demonstrates how equity-related measures, such as population density and income, can be incorporated into network resilience metrics for equitable decision-making.

## 4. Conceptual multilayer framework for equitable resilience

In this section, we introduce definitions of a multilayer network. Then, we present a toy example of a conceptual transportation network in the multilayer setting. To motivate the incorporation of equity considerations, we first provide examples of a few commonly used network resilience metrics. We then demonstrate how equity measures can be explicitly applied to derive equitable resilience metrics.

### 4.1. Multilayer network definitions

A multilayer network consists of connected layers of networks, each with its own sets of nodes and edges. Edges connecting nodes between a pair of layers are referred to as interlayer edges. Generally, a multilayer network $\mathcal{M}$ is given by:

$$\mathcal{M} = (\mathcal{Y}, \mathcal{G}) \tag{4.1}$$

where $\mathcal{Y}$ is the set of layers in the network (with $M$ the total number of layers).

$$\mathcal{Y} = \{\alpha | \alpha \in \{1, 2, \ldots, L\}\} \tag{4.2}$$

$G$ represents the ordered list of networks:

$$\mathcal{G} = (\mathcal{G}^1, \mathcal{G}^2, \ldots, \mathcal{G}^L), \tag{4.3}$$

Thus, each layer $\alpha$ in the network is given by

$$\mathcal{G}^\alpha = (\mathcal{V}^\alpha, \mathcal{E}^\alpha) \tag{4.4}$$

**Table 4.** Taxonomy of level I and level II resilience metrics synthesized from the literature.

| Level I metric | Level II metric | References | Description |
|---|---|---|---|
| Accessibility | Accessibility to resources | Ahmed and Dey (2020), Aydin, Duzgun, Heinimann, et al. (2018) | |
| | Directional reach | Pearce, Matsunaka, and Oba (2021) | The total network length that can be covered when walking in all directions from a specific origin up to a specified distance |
| | Loss of service cost | Baroud, Barker, Ramirez-Marquez, et al. (2014), Fang, Pedroni, and Zio (2016) | Maximum reaching value of inoperability before rebounding towards recovery |
| | Transportation | Field, Sutley, Naderpajouh, et al. (2022) | |
| | Pedestrian route directness | Pearce, Matsunaka, and Oba (2021) | The ratio of actual travel distance to straight-line |
| | Pedsheds | Pearce, Matsunaka, and Oba (2021) | Percentage of the corresponding Euclidean area accessible from a specific location via a network for a specified distance |
| | Shortest path | Ahmed and Dey (2020) | |
| | Unmet travel demand | Ahmed and Dey (2020), Bhatia, Kumar, Kodra, et al. (2015), Jenelius, Petersen, and Mattsson (2006), Kermanshah and Derrible (2017), Tingting and Yu (2020) | |
| Efficiency | Traffic efficiency | Y. Wu, Hou, and Chen (2021) | |
| | Travel cost | Jenelius, Petersen, and Mattsson (2006), Zou and Chen (2021) | |
| | Travel time | Ahmed and Dey (2020), Aleta, Meloni, and Moreno (2017), Jenelius, Petersen, and Mattsson (2006), Tingting and Yu (2020), Y. Wu, Hou, and Chen (2021), Wu, Pu, Li, et al. (2020) | |
| Connectivity | Betweenness centrality | Pearce, Matsunaka, and Oba (2021) | Number of shortest paths passing through a node |
| | Closeness centrality | Pearce, Matsunaka, and Oba (2021) | Pairwise similarity |
| | Components' dependency | Ahmed and Dey (2020), Bhatia, Kumar, Kodra, et al. (2015), Jenelius, Petersen, and Mattsson (2006), Mattsson and Jenelius (2015) | |
| | Connected node ratio | Pearce, Matsunaka, and Oba (2021) | Shows mutual dependence of nodes to each other |
| | Interdependence | Du, Zhou, Lordan, et al. (2016) | |
| | Link-Node Ratio | Pearce, Matsunaka, and Oba (2021) | |
| | Weighted degree centrality | Henry, Furno, and Faouzi (2021) | |
| Reliability | Max loss of functionality | Pant, Barker, and Zobel (2014) | |
| | Network capacity | Ahmed and Dey (2020), Jenelius, Petersen, and Mattsson (2006), Wu, Pu, Li, et al. (2020), | |
| | Redundancy | Guo, Zhu, Liu, et al. (2021) | |
| | Robustness | Ahmed and Dey (2020), Almoghathawi and Barker (2019), Aydin, Duzgun, Heinimann, et al. (2018), Guo, Zhu, Liu, et al. (2021), Jenelius, Petersen, and Mattsson (2006), Zhang and Wang (2016) | |
| | Safety | Ahmed and Dey (2020), Field, Sutley, Naderpajouh, et al. (2022), Y. Wu, Hou, and Chen (2021) | |
| | Vulnerability | Ahmed and Dey (2020), Almoghathawi and Barker (2019), Ansari Esfeh, Kattan, Lam, et al. (2022), Aydin, Duzgun, Heinimann, et al. (2018), Jenelius, Petersen, and Mattsson (2006), Zhang and Wang (2016) | |
| Restoration | Average time of operability | Pant, Barker, and Zobel (2014) | |
| | Bridge functionality | Kameshwar, Misra, and Padgett (2020) Traffic restrictions on bridges | |
| | Recovery efficiency | Aydin, Duzgun, Heinimann, et al. (2018), Zhang, Wang, and Nicholson (2017) | |
| | Restoration costs | Ahmed and Dey (2020), Aydin, Duzgun, Heinimann, et al. (2018), Baroud, Barker, Ramirez-Marquez, et al. (2014) | |
| | Recovery time | Ahmed and Dey (2020), Almoghathawi and Barker (2019), Aydin, Duzgun, Heinimann, et al. (2018), Baroud, Barker, Ramirez-Marquez, et al. (2014), Fang, Pedroni, and Zio (2016), Ilbeigi (2019), Pant, Barker, and Zobel (2014), Zhang, Wang, and Nicholson (2017), Taghizadeh, Mahsuli, and Poorzahedy (2023) | |
| Equity | Affected population | Aydin, Duzgun, Heinimann, et al. (2018) | |
| | Health and well-being | Field, Sutley, Naderpajouh, et al. (2022) | |
| | Prosperity | Field, Sutley, Naderpajouh, et al. (2022) | |

where $\mathcal{V}^\alpha$ is the set of nodes and $\mathcal{E}^\alpha$ the set of edges (intralinks) in layer $\alpha$.

### 4.2. Multilayer transportation network: toy example

We develop a toy example of a multilayer transportation network to illustrate the framework and the computation of equitable resilience metrics (Figure 2). There are four different layers: roads, public transportation, bridges, and buildings. This four-layer multilayer network $\mathcal{M}$ is given by:

$$\mathcal{M} = (\mathcal{Y} = \{\alpha\}, \mathcal{G} = \{\mathcal{G}^\alpha\} : \alpha \in \{1,2,3,4\}) \tag{4.5}$$

In layer 1 (buildings), all important residential and commercial buildings and essential service providers such as health care, fire stations, etc. will be represented as nodes. Layer 1 has five nodes and no intra-layer edges. To consider the possibility of moving by walking to nodes in the building layer, we considered

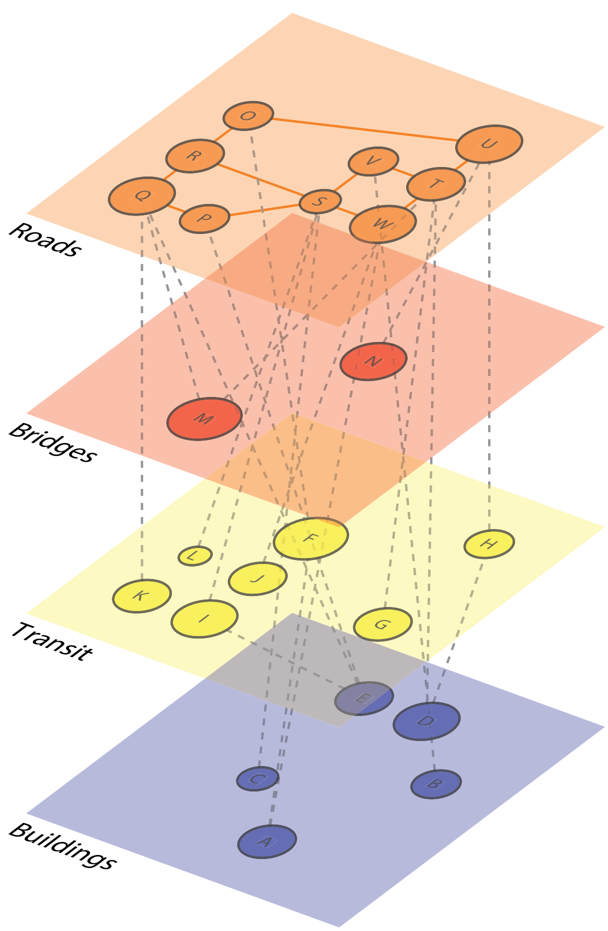



Figure 2. Example interconnected multilayer network diagram of critical mobility infrastructure. Inter-layer connections are shown using dashed lines, while intra-layer connections are indicated via solid lines.

400 m distance which is a walkable distance in 5 minutes (Pearce, Matsunaka, & Oba, 2021). If the walking distance from nodes in the public transportation layer and nodes or edges in the roads and bridges layer to the nodes in the building layer is less than 400 m, there will be an inter-layer edge between them. It means there is a connection between nodes in roads, bridges, and public transportation layers with the building layer if the distance between nodes in these three layers and nodes in the building layers is less than 400 m. This way, we guarantee a walkable distance to the buildings through nodes in roads, bridges, and public transportation layers.

In layer 2 (public transportation layer), all transit stops are represented as nodes, while an edge connects them if a path exists in the road network. In the example network, layer 2 has seven nodes. In layer 3 (bridges), each bridge is modeled as a single node. An edge will exist between two bridges if there is a road between them. Layer 3 has two nodes and one intra-layer edge.

In layer 4 (road layer), all main and secondary road intersections are represented as nodes, and roads are represented as connecting paths. Layer 4 has nine nodes and eleven intra-layer edges. The network also has some inter-layer connections between various layers.

### 4.3. Selected network resilience metrics

Decision-makers and planners take advantage of a large variety of metrics to quantify networks in terms of connectivity, interdependence, accessibility, and coverage. We define a few examples of these below.

#### 4.3.1. Degree

The degree $k$ of node $i$ in layer $\alpha$ of a multilayer network is the number of edges incident to that node. It is given by:

$$k_i^\alpha = \sum_{j \in V_\alpha} \mathbb{I}\,(\exists e_{ij}^\alpha), \tag{4.6}$$

where $V_\alpha$ is the set of nodes in layer $\alpha$ and $\mathbb{I}\,(\exists e_{ij}^\alpha)$ is an indicator function that returns 1 if there is an edge between nodes $i$ and $j$ in layer $\alpha$. To evaluate the resilience of a network, we can conduct site percolation by systematically eliminating nodes from the network using a high-degree or low-degree selection method.

#### 4.3.2. Overlapping degree

Interdependence is another important aspect of network resilience, which can be measured using the overlapping degree metric. In a multilayer network, the overlapping degree of a node is defined as the number of unique neighbors of that node across all layers (Du, Zhou, Lordan, et al., 2016). The overlapping degree of a node ($o_i$), is then calculated as follows:

$$o_i = \sum_{k=1}^{L}\sum_{\alpha=1}^{L}\sum_{j=1}^{N} \mathbb{I}\,(k \neq \alpha)\mathbb{I}\,(j \in \mathcal{N}_i^{\alpha} \cap \mathcal{N}_i^{k})\mathbb{I}\,(\exists e_{ij}^{k}), \tag{4.7}$$

where $\mathcal{N}_i^{\alpha}$ is the neighborhood of node $i$ in layer $\alpha$. The indicator function $\mathbb{I}\,(\exists e_{ij}^{k})$ is 1 if there is an edge between nodes $i$ and $j$ in layer $k$. $j$ denotes neighbor nodes, $\alpha$ and $k$ are layers, and $L$ is the total number of layers in the network. To calculate the overlapping degree of a node, two summations are taken. The first summation excludes the current layer $\alpha$ and includes all other layers, while the second summation includes all common neighbors $j$ of node $i$ in both layer $\alpha$ and layer $k$.

### 4.3.3. Shortest path

One important aspect of a resilient network is accessibility. Various metrics can be used to assess accessibility in a network, such as the shortest path, betweenness centrality, and eigen centrality. The shortest path is the minimum distance needed to travel between two nodes in a network and can be calculated using Dijkstra's algorithm. In order to calculate the shortest path in a multilayer network, we need to take into account the paths that traverse multiple layers of the network (Brodka, Stawiak, & Kazienko, 2011). The shortest multilayer path between nodes $i$ and $j$ ($s_{ij}$), can be calculated as follows:

$$s_{ij} = \min_{p \in \mathcal{P}_{ij}} \sum_{(\alpha \in p)} s_{ij}^{\alpha}, \tag{4.8}$$

where $\mathcal{P}_{ij}$ is the set of all inter-layer paths between nodes $i$ and $j$, and $s_{ij}^{\alpha}$ is the shortest path length between nodes $i$ and $j$ in layer $\alpha$.

### 4.3.4. Eigen centrality

An alternative approach to measuring accessibility in a network is through eigen centrality. This metric assigns higher scores to nodes that are connected to other highly central nodes and are based on the concept of eigenvectors and eigenvalues of the network's adjacency matrix (De Domenico, Porter, & Arenas, 2015). The eigen centrality $c_i^{\alpha}$ of node $i$ in layer $\alpha$ can then be calculated as:

$$c_i^{\alpha} = \frac{1}{\lambda^{\alpha}} \sum_{j=1}^{N}\sum_{k=1}^{N} \boldsymbol{T}_{ijk}^{\alpha}\boldsymbol{a}_k^{\alpha}, \tag{4.9}$$

where $\boldsymbol{T}^{\alpha}$ is the adjacency tensor of the multilayer network in layer $\alpha$, $\boldsymbol{a}^{\alpha}$ is the eigenvector corresponding to the largest eigenvalue $\lambda^{\alpha}$ of $T^{\alpha}$. Nodes that are directly and indirectly connected to nodes $i$, are represented by $j$ and $k$ respectively.

### 4.3.5. Betweenness centrality

Betweenness centrality measures the extent to which a node acts as a bridge along the shortest paths between other nodes (Freeman, 1977). High betweenness centrality indicates that a node has a large influence on the information flow across the network. The betweenness centrality of node $i$ in layer $\alpha$ for a multilayer network ($b_i^{\alpha}$) can be calculated as:

$$b_i^{\alpha} = \sum_{j=1}^{N}\sum_{k=1}^{N} \mathbb{I}\,(i \neq j)\mathbb{I}\,(i \neq k)\frac{|\mathcal{S}_{ijk}^{\alpha}|}{|\mathcal{S}_{jk}^{\alpha}|}, \tag{4.10}$$

where $|\mathcal{S}_{jk}^{\alpha}|$ is the number of shortest paths from node $j$ to node $k$ in layer $\alpha$, while $|\mathcal{S}_{ijk}^{\alpha}|$ denotes the number of those paths that involve node $i$.

### 4.3.6. PageRank

PageRank is a metric that represents the importance of nodes in the network and can be an indicator of accessibility. The technique of PageRank was initially created by Google to assess the significance of web pages based on their link structure. Nevertheless, the mathematical principles that underlie PageRank are broadly applicable and can be used to evaluate any network or graph in any field. As a result, PageRank has become a commonly used method Gleich (2015). To calculate a node PageRank score, the scores of the nodes that link to it are considered along with the number of links they have. This calculation is done repeatedly until the scores are accurate. PageRank score of node $i$ in a multilayer network ($p_i^{\alpha}$), calculate as:

$$p_i^{\alpha} = \frac{1}{N}(1-d) + d\sum_{j \in \mathcal{N}_i} \frac{p_j^{\alpha}}{m_j^{\alpha}} \tag{4.11}$$

where $N$ is the total number of nodes in the network, $(1-d)$ represents the probability that a user randomly goes to any node in the network, and $m_j$ is the number of outgoing links from node $j$. Set $\mathcal{N}_i$ is the neighborhood of node $i$ in the network, which includes all nodes that link to node $i$.

However, we note that none of these metrics directly address equity considerations. In order to develop equitable resilience metrics for analyzing the multilayer network performance, we can go further by expanding the approach to change these metrics to equitable ones that ensure providing fair access for different socio-economic classes.

### 4.4. Equity weighting

To account for potential disparities in resilience metrics, we propose a method to apply equity weights to resilience metrics based on population density and income level. The equity weighting incorporates demographic and socioeconomic factors into resilience metrics, providing a more equitable representation of the resilience of a given network.

As an example, we propose three equity weights ($w_e$), where $e \in \{inc, popd, edu\}$ and $inc$, $popd$, and $edu$ denote income, population density, and education equity measures respectively. For a given node $i$, population density-based weight ($w_{popd,i}$), income-based weight ($w_{inc,i}$), and education-based weight ($w_{edu,i}$) are calculated as follows:

$$w_{popd,i} = \frac{popd_i}{A_i} \tag{4.12}$$

$$w_{inc,i} = \frac{1}{inc_i} \tag{4.13}$$

$$w_{edu,i} = \frac{1}{edu_i} \tag{4.14}$$

where $popd_i$ and $A_i$ are the numbers of people per square kilometer and the area (in square kilometers) in the zone in which node $i$ is located, $inc_i$ indicates the median income (in \$), and $edu_i$ shows the number of people with educational attainment for the population aged 25 years and over in that zone. The equity weights are then normalized using the min-max normalization method to have the same scale.

Let $r_i$ denote a generic resilience metric for node $i$. The equity-weighted resilience metric $r_{e,i}$ for equity measure $e$ at node $i$ is then given by:

$$r_{e,i} = w_{e,i} \cdot r_i \tag{4.15}$$

where $r_i$ is the unweighted metric.

By incorporating equity weights into resilience metrics, we can better capture the varying needs and vulnerabilities of different demographic and socioeconomic groups in the network. We summarize the equity-weighted metrics in Table 5.

**Table 5.** Overview of proposed equity-weighted metrics.

| Measure | Metric | Equity weight |
|---|---|---|
| Connectivity and accessibility | Node degree | Population density, inverse income |
| | Shortest path | |
| | Eigen centrality | |
| | Betweenness centrality | |
| | PageRank | |
| Interdependence | Overlapping degree | |

### 4.5. Equitable resilience framework

We further extend our framework by introducing a composite equitable resilience index, $HR_i$, for each node $i$ in the network. This metric aggregates the individual equity-weighted resilience metrics to provide a comprehensive measure of a node's resilience, reflecting both its structural role in the network and its socio-economic significance. Formally, the composite equitable resilience index is defined as follows:

$$HR_i = \alpha \cdot w_{popd,i} \cdot k_i + \beta \cdot w_{inc,i} \cdot o_i + \gamma \cdot w_{edu,i} \cdot p_i \tag{4.16}$$

where $\alpha$, $\beta$, and $\gamma$ are coefficients that reflect the relative importance of degree, overlapping degree, and pagerank in holistic resilience assessment, respectively. These coefficients can be adjusted based on specific study needs or policy priorities. The composite equitable resilience index $HR_i$ thus combines the adjusted resilience metrics across all considered equity dimensions, offering a nuanced perspective on resilience that accounts for both infrastructural and community-level considerations.

This formulation allows for an integrated view of resilience that takes into account various factors and their impact on different demographic and socioeconomic groups within the network. Ultimately, these equitable resilience metrics would be used for robust decision-making. We present a flowchart of the envisioned framework in Figure 3.

## 5. Case study

In this study, we evaluate and scrutinize two resilience indicators within the context of a multilayer network analysis of the Pioneer Valley region in Massachusetts, U.S.A.. This investigation aims to illustrate certain facets of our proposed multilayer framework by examining and assessing equitable resilience metrics within this specific network. The Pioneer Valley comprises three counties: Franklin, Hampshire, and Hampden, which includes the Springfield Metropolitan Statistical Area (MSA), with the City of Springfield as its urban center. Due to its geographical constraints, limited alternatives

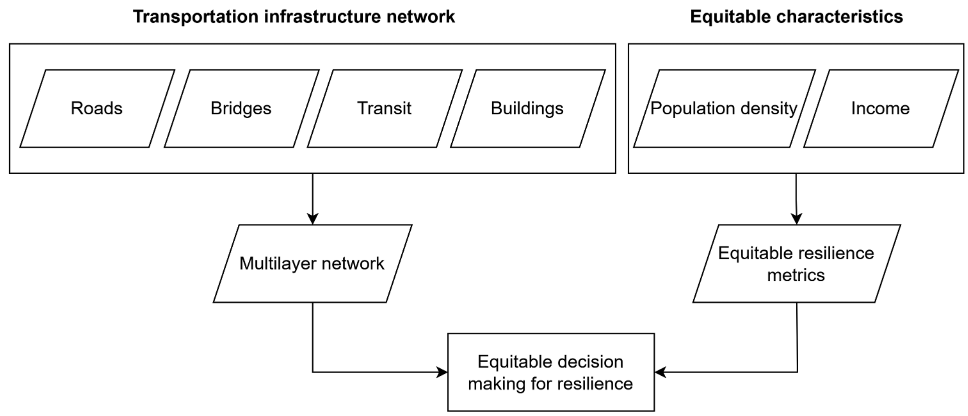



Figure 3. Flowchart of the proposed framework for equitable multilayer network modeling (Parallelograms indicate data inputs and outputs, while rectangles indicate processes).

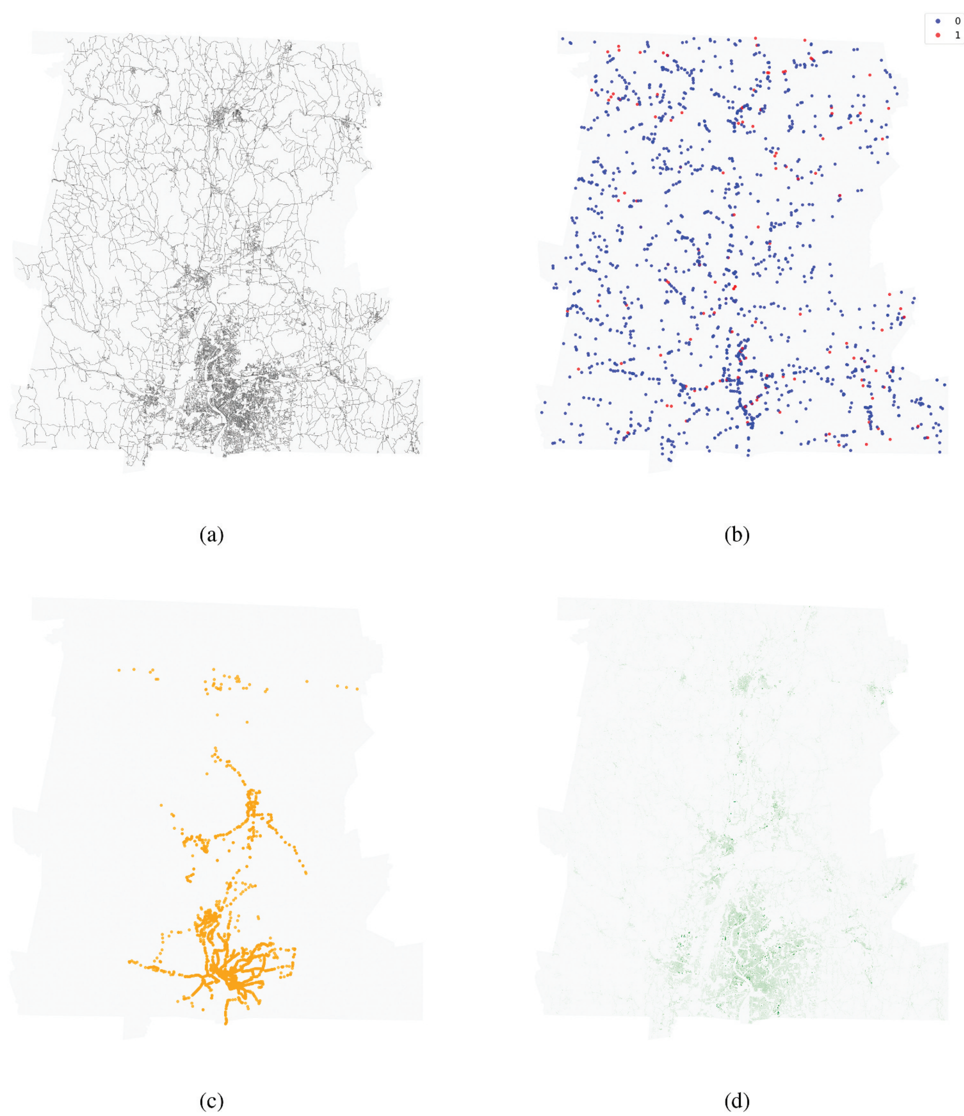



Figure 4. Components of the proposed multilayer network in the study area: (a) roads, (b) bridges (“1” indicates structural deficiency), (c) public transportation (bus stops), and (d) buildings.

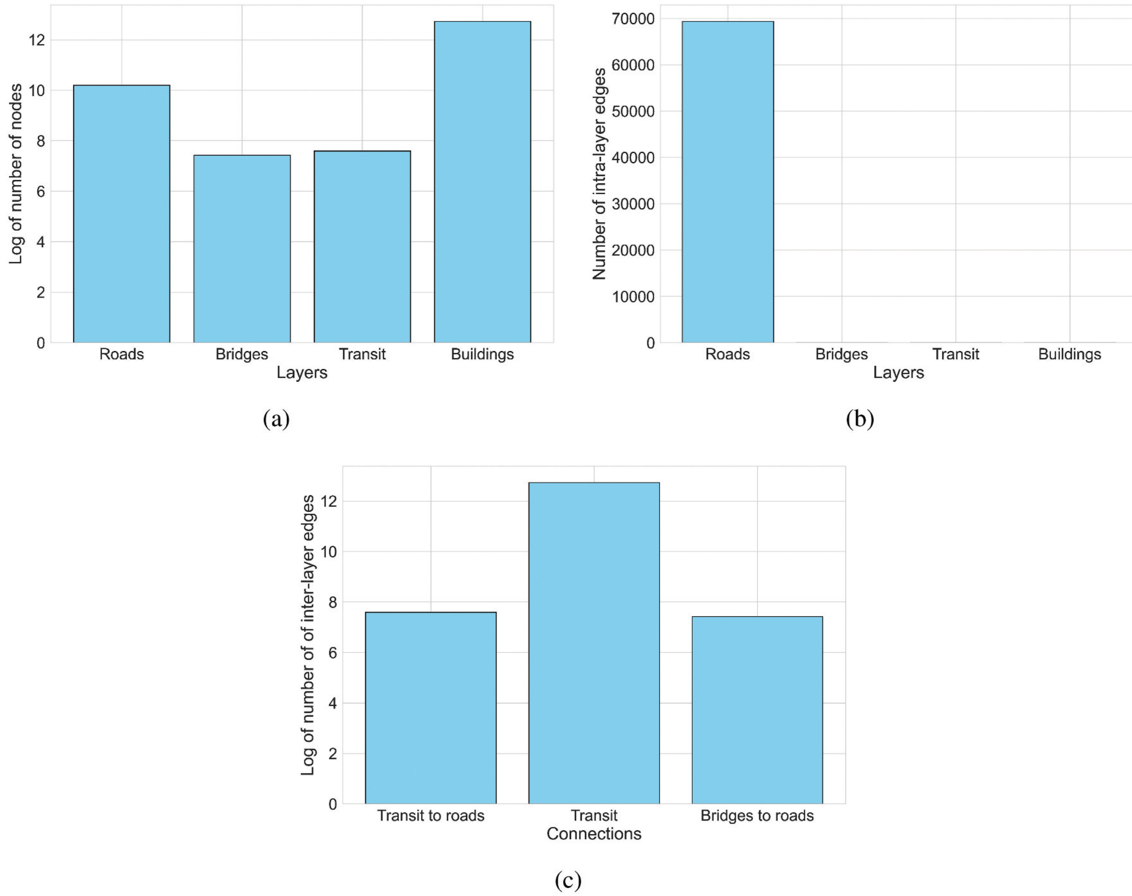



**Figure 5.** Distribution of (a) log of number of nodes and (b) intra-layer edges and (c) log of number of inter-layer edges across components of the created multilayer network.

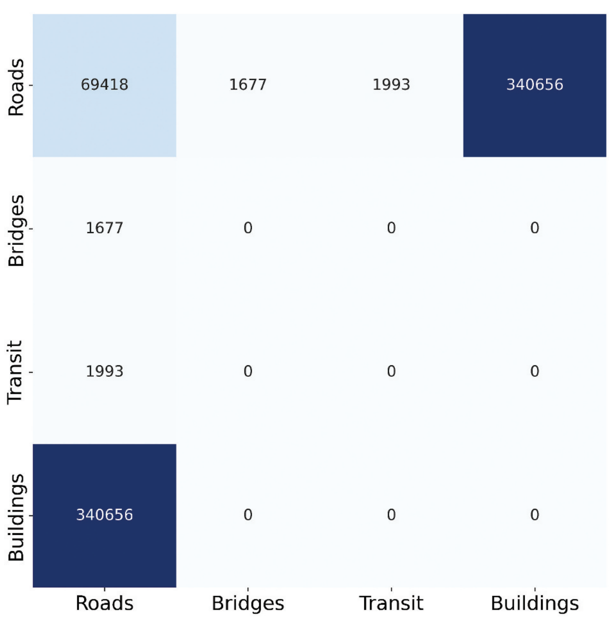



**Figure 6.** Adjacency matrix.

to automobile transportation, and predominantly rural character, the region's transportation infrastructure – encompassing roads, public transport systems, buildings, and bridges – plays a vital role in determining the resilience of its communities. Ongoing efforts for the region have prioritized resilience planning, requiring a decision-making framework to identify detailed policy priorities for adapting to climate-change-related disruptions (Commission, 2018).

### 5.1. *Equitable resilience assessment of the Pioneer Valley transportation network*

The proposed multilayer framework consists of four key elements: roads, bridges, public transportation, and buildings, as illustrated in Figure 4. The road layer contains 22,036 intersections. Bridges in the study area, including those that are deficient, were mapped using information obtained from inspection records (Tzortzinis, Knickle, Bardow, et al., 2021). Out of 1,455 bridges in the study area, 136 were found to be deficient. Additionally, there are 1,993 bus stops and 339,201 buildings in the study area.

Using the OSMNX and NetworkX Python packages, we developed a multilayer network model for the

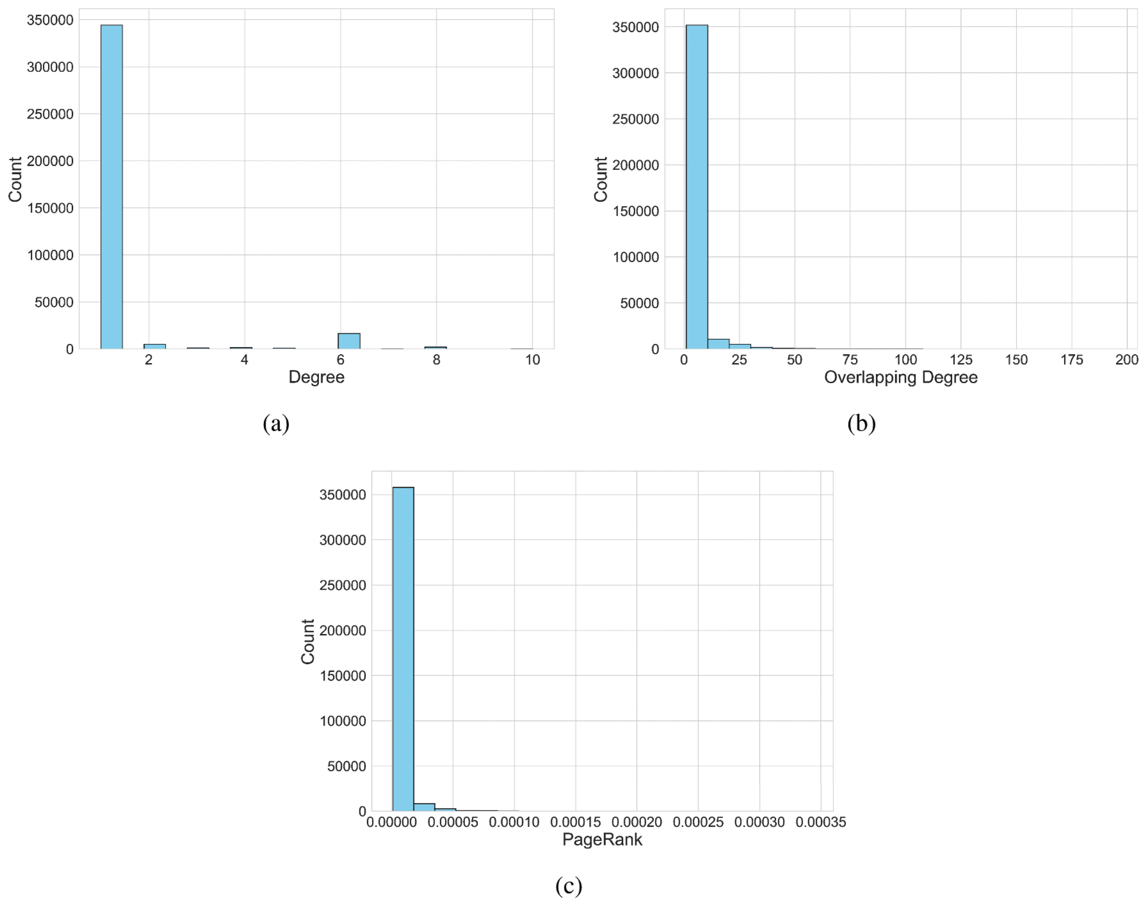



**Figure 7.** Histogram of (a) nodes' degree (b) nodes' overlapping degree and (c) PageRank.

Pioneer Valley area. This model includes various elements of mobility, such as roads, bridges, public transportation, and buildings. In our analysis, we calculated resilience metrics, specifically the degree and PageRank.

The network overviewed in Figure 5(a) displays the distribution of nodes across different layers, reflecting the structural characteristics of each. Additionally, Figure 5(b) presents the distribution of intra-layer edges, illustrating the internal connectivity within each layer. Figure 5(c) exhibits the inter-layer edge distribution, highlighting the interconnectivity between layers. The matrix in Figure 6, represents the interconnections among different mobility elements within the Pioneer Valley network. This matrix plot shows the number of connections between roads, bridges, transit, and buildings. Notably, it highlights a significant number of connections between roads and bridges, demonstrating the dense interconnectivity within these layers of the network.

we evaluated the network's resilience by calculating three critical metrics: the degree of nodes, their overlapping degree, and their PageRank values. The distribution of these metrics across the network is depicted in histograms (Figure 7). Furthermore, spatial visualizations of these metrics (Figure 8) provide an overview of the network's structure, highlighting clusters of high resilience and areas of potential vulnerability.

We obtained demographic and socioeconomic variables (Figure 9), namely population, population density, household income, and age in the study area, obtained from the American Community Survey (Bureau, 2017). The heterogeneity across the variables – population (Figure 9(a)), population density (Figure 9(b)), aggregated household income in 2016 (Figure 9(c)), and median age (Figure 9(d)) – reveals the necessity of their incorporation to ensure fair access to transportation facilities for different socioeconomic categories of people.

We then apply equity weights to these variables to compute equitable resilience metrics for the study area's transportation network. To calculate equity weights, we used population density (per sq.km),

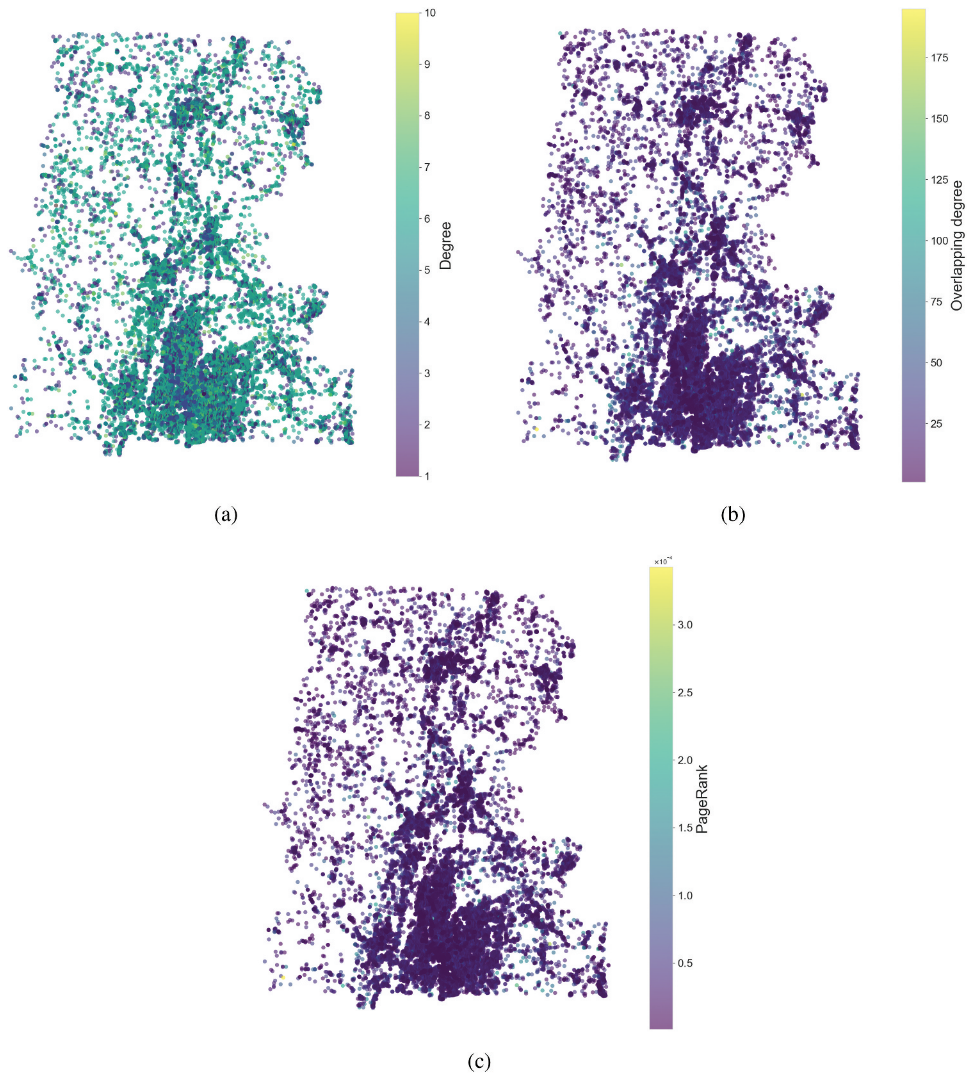



Figure 8. The spatial presentation of (a) nodes' degree (b) nodes' overlapping degree and (c) PageRank.

median income ($), and educational attainment for the population 25 years and over data from the American Community Survey (ASCE, 2017). Visualization of the computed resilience metrics is shown in Figures 10, 11 and Figure 12.

The computation of the construction of the multilayer mobility network and the computing of 4 resilience metrics were completed in approximately 318.82 seconds. This evaluation was performed on a machine equipped with an Intel Core i7 -10,610 U CPU at 1.80 GHz, 32 GB of RAM, running Windows 11 Pro. The analysis was carried out on a network comprising 371,095 nodes and 413,744 edges, demonstrating that the proposed framework is computationally efficient and feasible for real-world applications, even on moderately equipped computer systems. This efficiency underscores the practicality of this approach for analyzing and enhancing the resilience of urban transportation networks.

### 5.2. Expected outcomes

A highlight of this review – concept paper is the development of a conceptual framework for quantifying resilience using equity-based metrics in multilayer mobility networks. Most of the previous research studies focused on analyzing resilience in the network just by considering common network metrics related to analyzing networks from centrality, connectivity, accessibility, and other performance metrics. This paper provides a novel approach by including equity-based metrics using equity-related weights acquired based on data on population density, income level, and education attainment. This way, the framework ensures fair and equitable

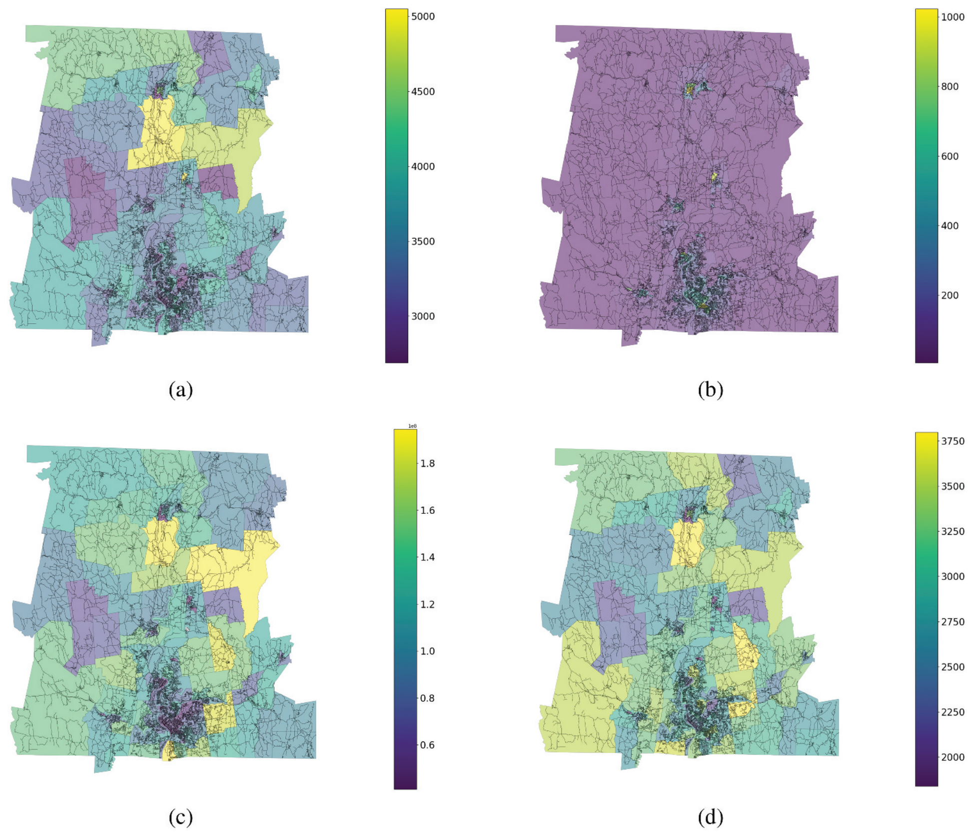



**Figure 9.** Demographic and socioeconomic variables in the study area: (a) population, (b) population density (per sq. km), (c) aggregate household income in the past year ($), and (d) educational attainment for the population 25 years and over.

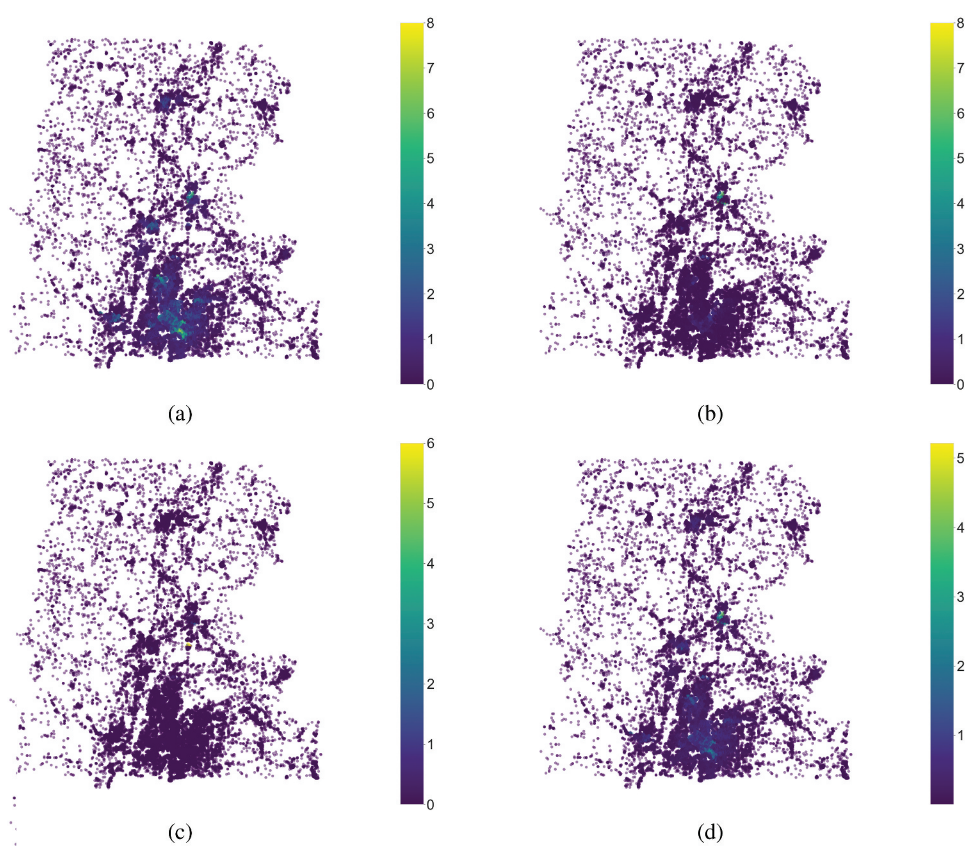



**Figure 10.** Equity-weighted node degree in the study area: (a) Population density-weighted; (b) Inverse income-weighted; (c) Inverse educated-weighted; and (d) Population density, inverse income, and inverse educated-weighted.

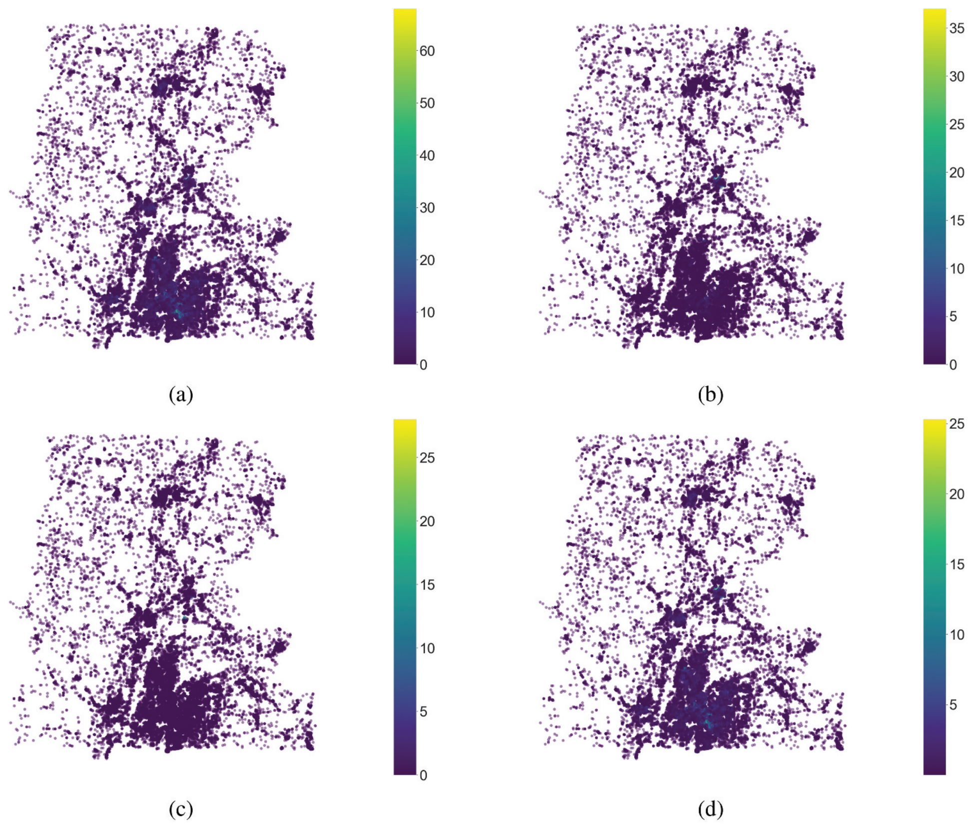



**Figure 11.** Equity-weighted node overlapping degree in the study area: (a) Population density-weighted; (b) Inverse income-weighted; (c) Inverse educated-weighted; and (d) Population density, inverse income, and inverse educated-weighted.

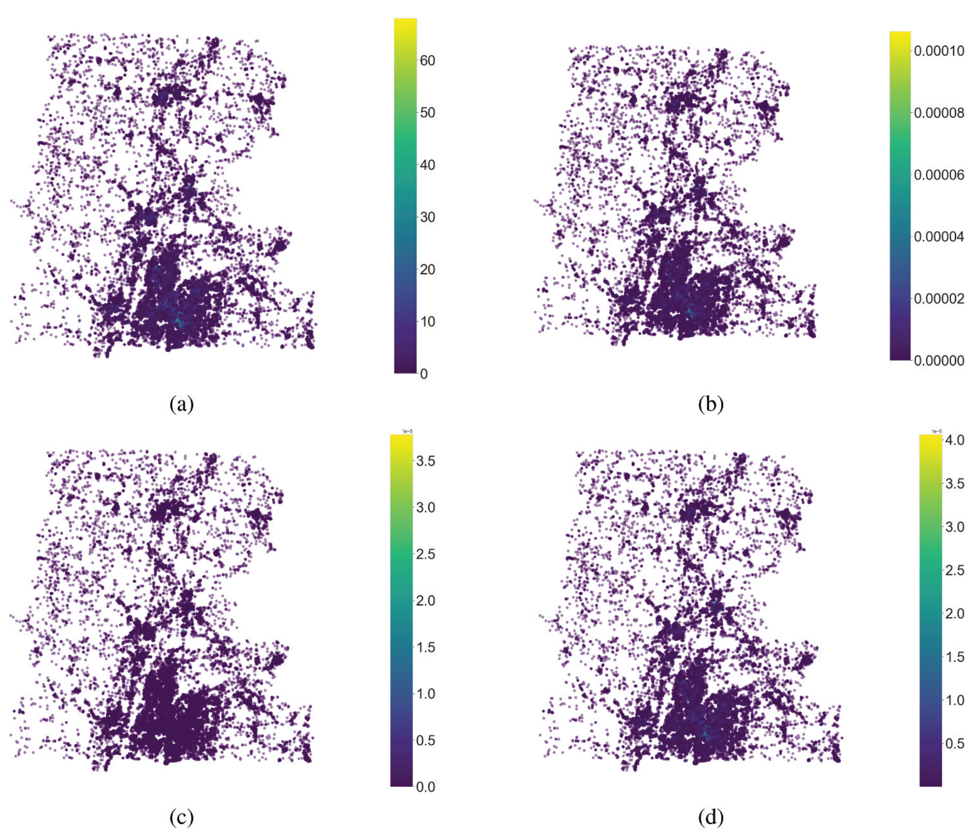
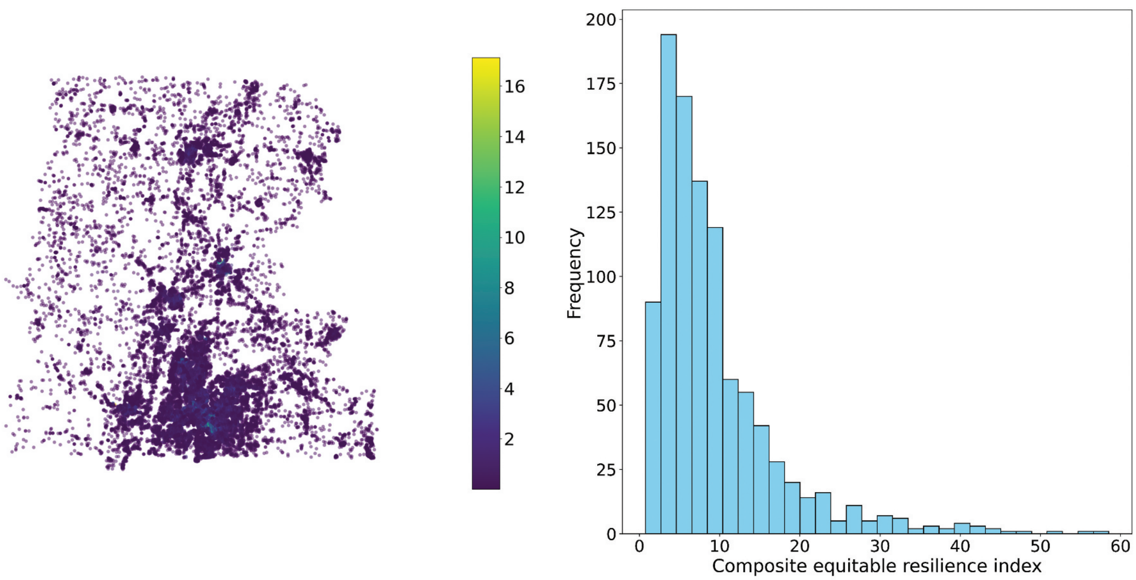



**Figure 12.** Equity-weighted node PageRank in the study area: (a) Population density-weighted; (b) Inverse income-weighted; (c) Inverse educated-weighted; and (d) Population density, inverse income, and inverse educated-weighted.




(a) (b)

**Figure 13.** Equity-weighted composite equitable resilience index, combining degree, overlapping degree, and PageRank: (a) spatial distribution, (b) histogram.

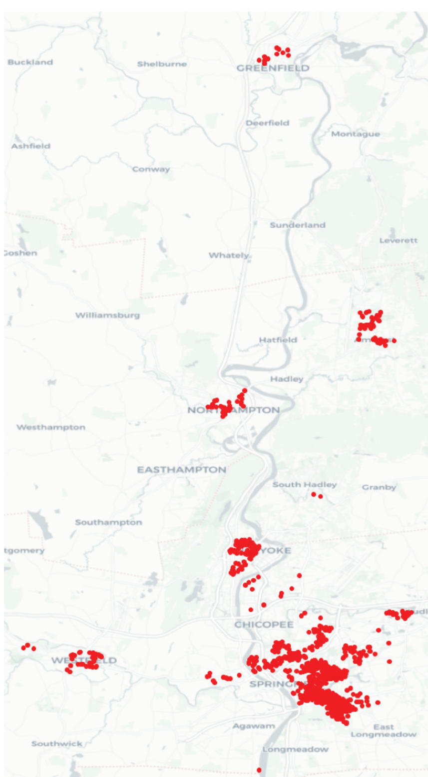



**Figure 14.** Visualization of the 1000 most critical nodes identified using a composite equitable resilience index, highlighting areas for targeted network enhancement.

access to critical infrastructure for different social and economic classes, which is crucial in the event of a crisis.

We expect that the proposed framework will yield the following outcomes:

- Multilayer network modeling that takes into account the interconnections between various layers in a mobility infrastructure network, including roads, bridges, public transportation, and buildings.
- Enable decision-makers to consider critical interactions between different elements in a transportation infrastructure network by treating it as a multilayer network.
- Incorporating socioeconomic and demographic variables, such as population density, income, and educational attainment into resilience metrics to ensure equitable decision-making.

In this study, we introduce a composite equitable resilience index designed to guide decision-makers in prioritizing infrastructure improvements, thereby optimizing resource allocation and enhancing urban resilience. This metric represents a weighted average of three distinct equitable resilience metrics: degree, overlapping degree, and PageRank. Figure 13 illustrates the visualization of this comprehensive metric across the Pioneer Valley network, highlighting its utility in identifying critical areas for resilience enhancement.

By applying this integrated approach within a specific decision-making scenario, we have been able to identify the 1000 most critical nodes within the network. These nodes, crucial for targeted investment, play a significant role in bolstering overall equitable network resilience. The prioritization of these nodes allows for a focused and strategic approach to infrastructure development, particularly beneficial for urban planners and policymakers aiming to fortify urban transportation networks against disruptions. The visualization of these critical nodes is presented in Figure 14, with an emphasis on regions such as Springfield, Amherst, Holyoke, Northampton, Greenfield, and Westfield. This strategic identification and visualization enable more informed decision-making processes, directly contributing to the enhancement of urban resilience through targeted efforts.

## 6. Conclusion

In light of the uncertainties posed by disasters such as earthquakes, floods, or hurricanes, it is crucial to develop a comprehensive framework to quantify resilience in a multilayer transportation network. Using this quantifying framework, we can assess effective mitigation, response strategies, and optimal recovery actions considering interactions between all key components of a transportation system. Additionally, by incorporating equity into the quantification of resilience, we can achieve improved outcomes for the most vulnerable segments of society.

In this paper, we provide a comprehensive review of resilience metrics and modeling approaches in quantifying transportation infrastructure resilience. First, we highlight the lack of equity-related metrics when evaluating resilience within transportation infrastructure. Then, we propose a novel strategy for the integration of equity-based considerations into the assessment of resilience. We introduce a framework designed for multilayer transportation infrastructure networks. This framework treats roads, public transportation, bridges, and buildings as components of a multilayer network and incorporates equity aspects into resilience assessment. By considering the interactions between various components within the transportation infrastructure and incorporating equity, this comprehensive resilience framework aims to support decision-makers in formulating equitable responses to disruptive events within their communities. This methodology ensures equitable access to vital resources such as rescue operations, emergency services, and food across diverse demographic and socio-economic strata during crises.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Notes on contributors

*Mahsa Arabi* is a Ph.D. candidate in the Department of Civil and Environmental Engineering at the University of Massachusetts Amherst. She works as a graduate research assistant in the Networks for Accessibility, Resilience, and Sustainability (NARS) Laboratory.

*Simos Gerasimidis* is an Associate Professor of Civil and Environmental Engineering at the University of Massachusetts Amherst working on bridge engineering, infrastructure resilience, additive manufacturing, structural stability, and new architected metamaterials.

*Camille Barchers* is an Assistant Professor in the Department of Landscape Architecture and Regional Planning at the University of Massachusetts Amherst where she runs the graduate planning studio.

*Jimi Oke* is an Assistant Professor in the Department of Civil and Environmental Engineering at the University of Massachusetts Amherst where he directs the Networks for Accessibility, Resilience and Sustainability (NARS) Laboratory

## ORCID

Mahsa Arabi http://orcid.org/0000-0003-1784-0906

## Data availability statement

Data used in this study are publicly available. Network data were obtained from OSMnx, acces- sible via their GitHub repository. Demographic information was sourced from the U.S. Census Bureau. These datasets are open for academic use, adhering to the original providers' terms. All the code used in generating the results and figures in this paper are publicly available at https://github.com/narslab/equi-resnet.

## References

Adjetey-Bahun, K., Birregah, B., Chatelet, E., & Laurens-Fonseca, E. (2014). A simulation-based approach to quantifying resilience indicators in a mass transportation system. *11th International Conference on Information Systems for Crisis Response and Management*. Pennsylvania, USA.

Adjetey-Bahun, K., Birregah, B., Châtelet, E., & Planchet, J.-L. (2016). A model to quantify the resilience of mass railway transportation systems. *Reliability Engineering & System Safety*, *153*, 1–14. https://doi.org/10.1016/j.ress.2016.03.015

Ahmed, S., & Dey, K. (2020). Resilience modeling concepts in transportation systems: A compre- hensive review based on mode, and modeling techniques. *Journal of Infrastructure Preservation and Resilience*, *8*(1). https://doi.org/10.1186/s43065-020-00008-9

Alessandretti, L., Natera Orozco, L. G., Saberi, M., Szell, M., & Battiston, F. (2023). Multimodal urban mobility and multilayer transport networks. *Environment and Planning B:*

*Urban Analytics and City Science*, *50*(8), 2038–2070. https://doi.org/10.1177/23998083221108190

Aleta, A., Meloni, S., & Moreno, Y. (2017). A multilayer perspective for the analysis of urban transportation systems. *Scientific Reports*, *7*(1), 1–9. https://doi.org/10.1038/srep44359

Alipour, A., & Shafei, B. (2016a). Assessment of postearthquake losses in a network of aging bridges. *Journal of Infrastructure Systems*, *22*(2), 04015023. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000253

Alipour, A., & Shafei, B. (2016b). Seismic resilience of transportation networks with deteriorating components. *Journal of Structural Engineering*, *142*(8), C4015015. https://doi.org/10.1061/(ASCE)ST.1943-541X.0001399

Almoghathawi, Y., & Barker, K. (2019). Component importance measures for interdependent infrastructure network resilience. *Computers & Industrial Engineering*, *133*, 153–164. https://doi.org/10.1016/j.cie.2019.05.001

Ansari Esfeh, M., Kattan, L., Lam, W. H. K., Salari, M., & Ansari Esfe, R. (2022). Road network vulnerability analysis considering the probability and consequence of disruptive events: A spatiotemporal incident impact approach. *Transportation Research Part C: Emerging Technologies*, *136*, 103549. https://doi.org/10.1016/j.trc.2021.103549

Antony, E. (2017). Developing restoration schemes for a road transportation network in the event of a disaster. 56.

Applegate, J. D., & Tilt, J. H. (2023). Using content and comparative analysis to contextualize the criteria for urban resiliency planning from international and US cities perspectives. *Frontiers in Environmental Science*, *11*. https://doi.org/10.3389/fenvs.2023.1103115

ASCE. (2017). *American infrastructure report card*. American Society of Civil Engineers.

Asgari, F., Sultan, A., Xiong, H., Gauthier, V., & El-Yacoubi, M. A. (2016). CT-Mapper: Mapping sparse multimodal cellular trajectories using a multilayer transportation network. *Computer Communications*, *95*, 69–81. https://doi.org/10.1016/j.comcom.2016.04.014

Aydin, N. Y., Duzgun, H. S., Heinimann, H. R., Wenzel, F., & Gnyawali, K. R. (2018). Framework for improving the resilience and recovery of transportation networks under geohazard risks. *International Journal of Disaster Risk Reduction*, *31*, 832–843. https://doi.org/10.1016/j.ijdrr.2018.07.022

Baggag, A., Abbar, S., Zanouda, T., & Srivastava, J. (2018). Resilience analytics: Coverage and robustness in multi-modal transportation networks. *EPJ Data Science*, *7*(1), 14. https://doi.org/10.1140/epjds/s13688-018-0139-7

Bah, A. S., Sanchez, T., Zhang, Y., Sasai, K., Conciatori, D., Chouinard, L., Power, G.J., & Zufferey, N. (2024). Assessing the condition state of a concrete bridge combining visual inspection and nonlinear deterioration model. *Structure and Infrastructure Engineering*, *20*(2), 149–164. https://doi.org/10.1080/15732479.2022.2081987

Baroud, H., Barker, K., Ramirez-Marquez, J. E., & Rocco, C. M. (2014). Inherent costs and interdependent impacts of infrastructure network resilience. *Risk Analysis*, *35*(4), 642–662. https://doi.org/10.1111/risa.12223

Bhatia, U., Kumar, D., Kodra, E., Ganguly, A. R., & Linkov, I. (2015). Network science based quantification of resilience demonstrated on the indian railways network. *Public Library of Science ONE*, *10*(11), 10. https://doi.org/10.1371/journal.pone.0141890

Bhavathrathan, B. K., & Patil, G. R. (2018). Algorithm to compute urban road network resilience. *Transportation Research Record*, *2672*(48), 104–115. https://doi.org/10.1177/0361198118793329

Boakye, J., Guidotti, R., Gardoni, P., & Murphy, C. (2022). The role of transportation infrastructure on the impact of natural hazards on communities. *Reliability Engineering & System Safety*, *219*, 108184. https://doi.org/10.1016/j.ress.2021.108184

Bolin, B., & Kurtz, L. C. (2018). Race, class, ethnicity, and disaster vulnerability. In Rodríguez, H., Donner, W., & Trainor, J. (Eds.), *Handbook of disaster research* (pp. 181–203). Springer.

Brodka, P., Stawiak, P., & Kazienko, P. (2011). Shortest path discovery in the multi-layered social network. *2011 International Conference on Advances in Social Networks Analysis and Mining* (pp. 497–501). Kaohsiung, Taiwan.

Bruzzone, F., Cavallaro, F., & Nocera, S. (2023). The definition of equity in transport. *Transportation Research Procedia*, *69*, 440–447. https://doi.org/10.1016/j.trpro.2023.02.193

Bureau, U. S. C. (2017). *Data profiles*. Retrieved March 28, 2023, from https://www.census.gov/programs-surveys/acs/

Cardillo, A., Zanin, M., Gómez-Gardeñes, J., Romance, M., García Del Amo, A., & Boccaletti, S. (2013). Modeling the multi-layer nature of the European air transport network: Resilience and passengers Re-scheduling under random failures. *The European Physical Journal Special Topics*, *215*(1), 23–33. https://doi.org/10.1140/epjst/e2013-01712-8

Cavallaro, M., Asprone, D., Latora, V., Manfredi, G., & Nicosia, V. (2014). Assessment of urban ecosystem resilience through hybrid social–physical complex networks. *Computer-Aided Civil and Infrastructure Engineering*, *29*(8), 608–625. https://doi.org/10.1111/mice.12080

Chandramouleeswaran, K. R., & Tran, H. T. (2018). Data-driven resilience quantification of the US air transportation network. *2018 Annual IEEE International Systems Conference (SysCon)* (pp. 1–7). Vancouver, Canada.

Chang, L., Elnashai, A. S., & Spencer, B. F., Jr. (2012). Post-earthquake modelling of transportation networks. *Structure and Infrastructure Engineering*, *8*(10), 893–911.

Commission, P. V. P. (2018). *Community resilience in the Pioneer Valley*. Retrieved April 27, 2023, from https://pioneervalleydata.org/community-resilience-in-the-pioneer-valley-region/

Cutter, S. (1995). Race, class, and environmental justice. *Progress in Human Geography*, *19*(1), 111–122. https://doi.org/10.1177/030913259501900111

Danziger, M. M., Bonamassa, I., Boccaletti, S., & Havlin, S. (2019). Dynamic interdependence and competition in multilayer networks. *Nature Physics*, *15*(2), 178–185. https://doi.org/10.1038/s41567-018-0343-1

Das, R. (2020). Approach for measuring transportation network resiliency: A case study on Dhaka, Bangladesh. *Case Studies on Transport Policy*, *8*(2), 586–592. https://doi.org/10.1016/j.cstp.2020.04.001

De Domenico, M., Porter, M. A., & Arenas, A. (2015). MuxViz: A tool for multilayer analysis and visualization of networks. *Journal of Complex Networks*, *3*(2), 159–176. https://doi.org/10.1093/comnet/cnu038

Domenico, M. D., Solé-Ribalta, A., Cozzo, E., Kivelä, M., Moreno, Y., Porter, M. A., Gómez, S., & Arenas, A. (2013). Mathematical formulation of multilayer networks. *Physical Review X*, *3*(4), 041022. https://doi.org/10.1103/PhysRevX.3.041022

Donovan, B., & Work, D. B. (2017). Empirically quantifying city-scale transportation system resilience to extreme events. *Transportation Research Part C: Emerging Technologies*, *79*, 333–346. https://doi.org/10.1016/j.trc.2017.03.002

Du, W.-B., Zhou, X.-L., Lordan, O., Wang, Z., Zhao, C., & Zhu, Y.-B. (2016). Analysis of the Chinese airline network as multi-layer networks. *Transportation Research Part E: Logistics & Transportation Review*, *89*, 108–116. https://doi.org/10.1016/j.tre.2016.03.009

Dvořák, Z., Sventeková, E., Řehák, D., & Čekerevac, Z. (2017). Assessment of critical infrastructure elements in transport. *Procedia Engineering*, *187*, 548–555. https://doi.org/10.1016/j.proeng.2017.04.413

Ensor, J. E., Mohan, T., Forrester, J., Khisa, U. K., Karim, T., & Howley, P. (2021). Opening space for equity and justice in resilience: A subjective approach to household resilience assessment. *Global Environmental Change*, *68*, 102251. https://doi.org/10.1016/j.gloenvcha.2021.102251

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. https://doi.org/10.1109/TR.2016.2521761

Fan, C., Jiang, X., Lee, R., & Mostafavi, A. (2022). Equality of access and resilience in urban population-facility networks. *npj Urban Sustainability*, *2*(1), 1–12. https://doi.org/10.1038/s42949-022-00051-3

Federal Highway Administration. (2017). *National bridge inventory*. Retrieved August 12, 2021, from https://www.fhwa.dot.gov/bridge/nbi/ascii2017.cfm

Field, C., Sutley, E., Naderpajouh, N., van de Lindt, J. W., Butry, D., Keenan, J. M., Smith-Colin, J., & Koliou, M. (2022). Incorporating socioeconomic metrics in civil engineering projects: The resilience perspective. *Natural Hazards Review*, *23*(1), 04021064. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000537

Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry*, *40*(1), 35–41. https://doi.org/10.2307/3033543

Gagliardi, V., Tosti, F., Bianchini Ciampoli, L., Battagliere, M. L., D'Amato, L., Alani, A. M., & Benedetto, A. (2023). Satellite remote sensing and non-destructive testing methods for transport infrastructure monitoring: Advances, challenges and perspectives. *Remote Sensing*, *15*(2), 418. https://doi.org/10.3390/rs15020418

Gao, W., Hu, X., & Wang, N. (2024). Resilience analysis in road traffic systems to rainfall events: Road environment perspective. *Transportation Research Part D: Transport & Environment*, *126*, 104000. https://doi.org/10.1016/j.trd.2023.104000

Ghorbanzadeh, M., Koloushani, M., Ozguven, E. E., Vanli, A., & Arghandeh, R. (2022). City transportation network vulnerability to disasters: The case of hurricane hermine in Florida. *Environmental Hazards*, *21*(3), 199–217. https://doi.org/10.1080/17477891.2021.1933885

Gleich, D. F. (2015). PageRank beyond the web. *SIAM Review*, *57*(3), 321–363. https://doi.org/10.1137/140976649

González, A. D., DueñDueñAs-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. https://doi.org/10.1111/mice.12171

Guo, J., Zhu, X., Liu, C., Ge, S., & Rodino, L. (2021). Resilience modeling method of airport network affected by global public health events. *Mathematical Problems in Engineering*, *2021*, 1–13. https://doi.org/10.1155/2021/6622031

Hamida, Z., & Goulet, J.-A. (2020). Modeling infrastructure degradation from visual inspections using network-scale state-space models. *Structural Control and Health Monitoring*, *27*(9), e2582. https://doi.org/10.1002/stc.2582

Henry, E., Furno, A., & Faouzi, N.-E.-E. (2021). Approach to quantify the impact of disruptions on traffic conditions using dynamic weighted resilience metrics of transport networks. *Transportation Research Record*, *2675*(4), 61–78. https://doi.org/10.1177/0361198121998663

Hollnagel, E., Pariès, J., Woods, D., & Wreathall, J. (2010). *Resilience engineering in practice* (reprint). Ashgate Publishing, Ltd., 2012.

Hong, C., Lam, J. S. L., & Nan, L. (2018). Strategic investment in enhancing port–hinterland container transportation network resilience: A network game theory approach. *Transportation Research Part B: Methodological*, *111*, 83–112. https://doi.org/10.1016/j.trb.2018.03.004

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. https://doi.org/10.1016/j.ress.2015.08.006

Ilbeigi, M. (2019). Statistical process control for analyzing resilience of transportation networks. *International Journal of Disaster Risk Reduction*, *33*, 155–161. https://doi.org/10.1016/j.ijdrr.2018.10.002

Ip, W., & Wang, D. (2009). Resilience evaluation approach of transportation networks. *Proceedings of the International Joint Conference on Computational Sciences and Optimization* (Vol. 2. pp. 618–622). Sanya, China.

Ip, W. H., & Wang, D. (2011). Resilience and friability of transportation networks: Evaluation, analysis and optimization. *IEEE Systems Journal*, *5*(2), 189–198. https://doi.org/10.1109/JSYST.2010.2096670

Jenelius, E., Petersen, T., & Mattsson, L.-G. (2006). Importance and exposure in road network vulnerability analysis. *Transportation Research Part A: Policy and Practice*, *40*(7), 537–560. https://doi.org/10.1016/j.tra.2005.11.003

Jeong, H., Kim, H., Kim, K., & Kim, H. (2017). Prediction of flexible pavement deterioration in relation to climate change using fuzzy logic. *Journal of Infrastructure Systems*, *23*(4), 04017008. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000363

Kameshwar, S., Misra, S., & Padgett, J. E. (2020). Decision tree based bridge restoration models for extreme event performance assessment of regional road networks. *Structure and Infrastructure Engineering*, *16*(3), 431–451. https://doi.org/10.1080/15732479.2019.1668026

Kermanshah, A., & Derrible, S. (2017). Robustness of road systems to extreme flooding: Using elements of GIS, travel demand, and network science. *Natural Hazards*, *86*(1), 151–164. https://doi.org/10.1007/s11069-016-2678-1

Kilanitis, I., & Sextos, A. (2019). Impact of earthquake-induced bridge damage and time evolving traffic demand on the road network resilience. *Journal of Traffic & Transportation Engineering*, *6*(1), 35–48. https://doi.org/10.1016/j.jtte.2018.07.002

Kobayashi, K., Kaito, K., & Lethanh, N. (2012). A statistical deterioration forecasting method using hidden Markov model for infrastructure management. *Transportation Research Part B: Methodological*, *46*(4), 544–561. https://doi.org/10.1016/j.trb.2011.11.008

Kurant, M., & Thiran, P. (2006). Layered complex networks. *Physical Review Letters*, *96*(13), 138701. https://doi.org/10.1103/PhysRevLett.96.138701

Lambrou, N., & Loukaitou-Sideris, A. (2021). Resilience plans in the US: An evaluation. *Journal of Environmental Planning and Management*, *65*(5), 809–832. https://doi.org/10.1080/09640568.2021.1904849

Leu, G., Abbass, H., & Curtis, N. (2010). *Resilience of ground transportation networks: A case study on Melbourne*. World Transit Research.

Li, Q., Dong, S., Mostafavi, A., & Lozano, S. (2019). Modeling of inter-organizational coordination dynamics in resilience planning of infrastructure systems: A multilayer network simulation framework. *Public Library of Science ONE*, *14*(11), e0224522. https://doi.org/10.1371/journal.pone.0224522

Lin, P., Yuan, X.-X., & Tovilla, E. (2019). Integrative modeling of performance deterioration and maintenance effectiveness for infrastructure assets with missing condition data. *Computer- Aided Civil and Infrastructure Engineering*, *34*(8), 677–695. https://doi.org/10.1111/mice.12452

Li, S., & Zhou, Y. (2024). Integrating equity and efficiency into urban logistics resilience under emergency lockdowns. *Transportation Research Part E: Logistics & Transportation Review*, *183*, 103446. https://doi.org/10.1016/j.tre.2024.103446

Logan, T. M., & Guikema, S. D. (2020). Reframing resilience: Equitable access to essential services. *Risk Analysis*, *40*(8), 1538–1553. https://doi.org/10.1111/risa.13492

Matin, N., Forrester, J., & Ensor, J. (2018). What is equitable resilience? *World Development*, *109*, 197–205. https://doi.org/10.1016/j.worlddev.2018.04.020

Mattsson, L.-G., & Jenelius, E. (2015). Vulnerability and resilience of transport systems – a discussion of recent research. *Transportation Research Part A: Policy and Practice*, *81*, 16–34. https://doi.org/10.1016/j.tra.2015.06.002

Mavrouli, M., Mavroulis, S., Lekkas, E., & Tsakris, A. (2023). An emerging health crisis in Turkey and Syria after the earthquake disaster on 6 february 2023: Risk factors, prevention and management of infectious diseases. *Healthcare*, *11*(7), 1022. https://doi.org/10.3390/healthcare11071022

Medina, P. A., González, F. J. L., & Todisco, L. (2022). Data-driven prediction of long-term deterioration of RC bridges. *Construction and Building Materials*, *317*, 125790. https://doi.org/10.1016/j.conbuildmat.2021.125790

Meerow, S., Pajouhesh, P., & Miller, T. R. (2019). Social equity in urban resilience planning. *Local Environment*, *24*(9), 793–808. https://doi.org/10.1080/13549839.2019.1645103

Morcous, G., Rivard, H., & Hanna, A. M. (2002). Case-based reasoning system for modeling infrastructure deterioration. *Journal of Computing in Civil Engineering*, *16*(2), 104–114. https://doi.org/10.1061/(ASCE)0887-3801(2002)16:2(104)

Murray-Tuite, P. M. (2006). A comparison of transportation network resilience under simulated system optimum and user equilibrium conditions. *Proceedings of the 2006 Winter Simulation Conference* (pp. 1398–1405). Proceedings of the 2006 Winter Simulation Conference. Monterey, CA, USA.

Nejat, A., Solitare, L., Pettitt, E., & Mohsenian-Rad, H. (2022). Equitable community resilience: The case of winter storm Uri in Texas. *International Journal of Disaster Risk Reduction*, *77*, 103070. https://doi.org/10.1016/j.ijdrr.2022.103070

Nipa, T. J., Kermanshachi, S., & Pamidimukkala, A. (2023). Identification of resilience dimensions in critical transportation infrastructure networks. *Journal of Legal Affairs and Dispute Resolution in Engineering and Construction*, *15*(2), 03122001. https://doi.org/10.1061/JLADAH.LADR-870

Ouyang, M. (2014). Review on modeling and simulation of interdependent critical infrastructure systems. *Reliability Engineering & System Safety*, *121*, 43–60. https://doi.org/10.1016/j.ress.2013.06.040

Pant, R., Barker, K., & Zobel, C. W. (2014). Static and dynamic metrics of economic resilience for interdependent infrastructure and industry sectors. *Reliability Engineering & System Safety*, *125*, 92–102. https://doi.org/10.1016/j.ress.2013.09.007

Pearce, D. M., Matsunaka, R., & Oba, T. (2021). Comparing accessibility and connectivity metrics derived from dedicated pedestrian networks and street networks in the context of Asian cities. *Asian Transport Studies*, *7*, 100036. https://doi.org/10.1016/j.eastsj.2021.100036

Peng, P., Claramunt, C., Cheng, S., Yang, Y., & Lu, F. (2023). A multi-layer modelling approach for mining versatile ports of a global maritime transportation network. *International Journal of Digital Earth*, *16*(1), 2129–2151. https://doi.org/10.1080/17538947.2023.2220614

Pirlone, F., Spadaro, I., & Candia, S. (2020). More resilient cities to face higher risks. The case of Genoa. *Sustainability*, *12*(12), 1–21. https://doi.org/10.3390/su12124825

Potts, J., Tiedmann, H. R., Stephens, K. K., Faust, K. M., & Castellanos, S. (2024). Enhancing power system resilience to extreme weather events: A qualitative assessment of winter storm Uri. *International Journal of Disaster Risk Reduction*, *103*, 104309. https://doi.org/10.1016/j.ijdrr.2024.104309

Qiang, Y., & Xu, J. (2019). Empirical assessment of road network resilience in natural hazards using crowdsourced traffic data. *International Journal of Geographical Information Science*, *0*(0), 1–17.

Rashedi, R., & Hegazy, T. (2016). Holistic analysis of infrastructure deterioration and rehabilitation using system dynamics. *Journal of Infrastructure Systems*, *22*(1), 04015016. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000273

Ro, B., & Garfin, G. (2023). Building urban flood resilience through institutional adaptive capacity: A case study of Seoul, South Korea. *International Journal of Disaster Risk Reduction*, *85*, 103474. https://doi.org/10.1016/j.ijdrr.2022.103474

Santos, T., Fernandes, V. A., Cardoso, M., & da Silva, M. (2023). Resilience and vulnerability of urban mobility systems in developing countries: A case study of Rio De Janeiro's transportation fare policy.

Sediek, O. A., El-Tawil, S., & McCormick, J. (2022). Modeling interdependencies between the building portfolio, transportation network, and healthcare system in community resilience. *Natural Hazards Review*, *23*(1), 04021060. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000538

Serulle, N. U., Heaslip, K., Brady, B., Louisell, W. C., & Collura, J. (2011). Resiliency of transportation network of Santo Domingo, Dominican Republic: Case study. *Transportation Research Record*, *2234*(1), 22–30. https://doi.org/10.3141/2234-03

Škrlj, B., Kralj, J., & Lavrač, N. (2019). Py3plex toolkit for visualization and analysis of multilayer networks. *Applied Network Science*, *4*(1), 94. https://doi.org/10.1007/s41109-019-0203-7

Soleimani, F., & Hajializadeh, D. (2022). Bridge seismic hazard resilience assessment with ensemble machine learning. *Structures*, *38*, 719–732. https://doi.org/10.1016/j.istruc.2022.02.013

Solé-Ribalta, A., Gómez, S., & Arenas, A. (2016). Congestion induced by the structure of multiplex networks. *Physical Review Letters*, *116*(10), 108701. https://doi.org/10.1103/PhysRevLett.116.108701

Stewart, M. G., Wang, X., & Nguyen, M. N. (2011). Climate change impact and risks of concrete infrastructure deterioration. *Engineering Structures*, *33*(4), 1326–1337. https://doi.org/10.1016/j.engstruct.2011.01.010

Tabassum, A., Chinthavali, S., Chen, L., & Prakash, A. (2018). Data mining critical infrastructure systems: Models and tools. *IEEE Intelligent Informatics Bulletin*, *19*(2), 1727–5997. https://www.osti.gov/biblio/1503981

Taghizadeh, M., Mahsuli, M., & Poorzahedy, H. (2023). Probabilistic framework for evaluating the seismic resilience of transportation systems during emergency medical response. *Reliability Engineering & System Safety*, *236*, 109255. https://doi.org/10.1016/j.ress.2023.109255

Tamima, U., & Chouinard, L. (2016). Development of evacuation models for moderate seismic zones: A case study of Montreal. *International Journal of Disaster Risk Reduction*, *16*, 167–179. https://doi.org/10.1016/j.ijdrr.2016.02.003

Tingting, Z., & Yu, Z. (2020). Transportation infrastructure restoration optimization considering mobility and accessibility in resilience measures. *Transportation Research Part C: Emerging Technologies*, *117*, 102700. https://doi.org/10.1016/j.trc.2020.102700

Tzortzinis, G., Knickle, B. T., Bardow, A., Breña, S. F., & Gerasimidis, S. (2021). Strength evaluation of deteriorated girder ends. I: Experimental study on naturally corroded I-beams. *Thin-Walled Structures*, *159*, 107220. https://doi.org/10.1016/j.tws.2020.107220

Uddin, W., Hudson, W. R., & Haas, R. (2013). *Public Infrastructure Asset Management*. Retrieved April 25, 2023, from https://www.accessengineeringlibrary.com/content/book/9780071820110

Wang, N., Wu, M., & Yuen, K. F. (2023). A novel method to assess urban multimodal transportation system resilience considering passenger demand and infrastructure supply. *Reliability Engineering & System Safety*, *238*, 109478. https://doi.org/10.1016/j.ress.2023.109478

Wang, N., & Yuen, K. F. (2022). Resilience assessment of waterway transportation systems: Combining system performance and recovery cost. *Reliability Engineering & System Safety*, *226*, 108673. https://doi.org/10.1016/j.ress.2022.108673

Weilant, S., Strong, A., & Miller, B. M. (2019). *Incorporating resilience into transportation planning and assessment* (No. RR-3038-TRB). RAND.

Wu, Y., & Chen, S. (2023a). Resilience modeling and pre-hazard mitigation planning of transportation network to support post-earthquake emergency medical response. *Reliability Engineering & System Safety*, *230*, 108918. https://doi.org/10.1016/j.ress.2022.108918

Wu, Y., & Chen, S. (2023b). Traffic resilience modeling for post-earthquake emergency medical response and planning considering disrupted infrastructure and dislocated residents. *International Journal of Disaster Risk Reduction*, *93*, 103754. https://doi.org/10.1016/j.ijdrr.2023.103754

Wu, Y., & Chen, S. (2023c). Transportation resilience modeling and bridge reconstruction planning based on time-evolving travel demand during post-earthquake recovery period. *Sustainability*, *15*(17), 12751. https://doi.org/10.3390/su151712751

Wu, Y., Hou, G., & Chen, S. (2021). Post-earthquake resilience assessment and long-term restoration prioritization of transportation network. *Reliability Engineering & System Safety*, *211*, 107612. https://doi.org/10.1016/j.ress.2021.107612

Wu, B., Lin, Z., Liang, Y., Zhou, Z., & Lu, H. (2023). An effective prediction method for bridge long-gauge strain under moving trainloads with experimental verification. *Mechanical Systems and Signal Processing*, *186*, 109855. https://doi.org/10.1016/j.ymssp.2022.109855

Wu, J., Pu, C., Li, L., & Cao, G. (2020). Traffic dynamics on multilayer networks. *Digital Communications and Networks*, *6*(1), 58–63. https://doi.org/10.1016/j.dcan.2018.10.011

Zhang, W., & Wang, N. (2016). Resilience-based risk mitigation for road networks. *Structural Safety*, *62*, 57–65. https://doi.org/10.1016/j.strusafe.2016.06.003

Zhang, W., Wang, N., & Nicholson, C. (2017). Resilience-based post-disaster recovery strategies for road-bridge networks. *Structure and Infrastructure Engineering*, *13*(11), 1404–1413. https://doi.org/10.1080/15732479.2016.1271813

Zhu, Y., Xie, K., Ozbay, K., Zuo, F., & Yang, H. (2017). Data-driven spatial modeling for quantifying networkwide resilience in the aftermath of hurricanes Irene and Sandy. *Transportation Research Record*, *2604*(1), 9–18. https://doi.org/10.3141/2604-02

Zou, Q., & Chen, S. (2021). Resilience-based recovery scheduling of transportation network in mixed traffic environment: A deep-ensemble-assisted active learning approach. *Reliability Engineering & System Safety*, *215*, 107800. https://doi.org/10.1016/j.ress.2021.107800