Integrating Social Equity and Vulnerability with Infrastructure Resilience Assessment

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ABSTRACT

Resilient infrastructure, which better withstands, adapts, and recovers from disasters, plays an important role in mitigating the impacts of natural hazards to the communities. However, disparities exist in infrastructure damage and recovery across communities with different socioeconomic backgrounds. Socially vulnerable communities experience more severe infrastructure damage and require longer time to repair and resume infrastructure services. Thus, there is a need to systematically integrate social equity with infrastructure resilience assessment. To address this need, this paper proposes a social welfare-based infrastructure resilience assessment framework that accounts for (1) the unequal distribution of infrastructure damage and recovery across communities with different socioeconomic statuses and (2) the potentially higher infrastructure damage and longer recovery time in socially vulnerable communities. The proposed model can facilitate equitable resilience in infrastructure planning and recovery by allowing for a better understanding and assessment on how infrastructure in different communities is equally or unequally affected by disasters.

Keywords: Infrastructure resilience, Resilience assessment, Social welfare theory, Social equity, Disaster vulnerability

INTRODUCTION

Critical infrastructure plays an essential role in natural hazards. Sufficient and high-quality infrastructure, such as power, water, and transportation systems, can limit the impacts natural hazards cause in terms of loss of life and economic damage (Godschalk 2003). Over the last decade, significant efforts have been made for the development and maintenance of infrastructure to withstand, adapt, and quickly recover from disasters. However, disparities exist in the investment and maintenance of infrastructure across different communities. Such disparities potentially result in varying levels of infrastructure damage across different communities during disasters. Previous research shows that communities with higher socioeconomic status (e.g., higher income, better education, higher housing value) typically receive more investment in building new or rehabilitating existing infrastructure (Nexus 2017). As a result, these communities tend to recover faster from disasters with minimal loss of infrastructure services (Masozera et al. 2006). On the contrary, infrastructure in socially vulnerable communities is frequently of insufficient quality. Socially vulnerable communities are communities with high percentages of populations who are not able to withstand adverse impacts from various stressors. Some examples of vulnerable populations include the elderly, the disabled, the economically disadvantaged, and the racial and ethnic minorities (AJMC 2006). These communities typically experience more severe physical damage on their infrastructure and/or require a longer time to resume infrastructure services. Due to the unequal distribution of disaster impacts on infrastructure, there is a need to systematically integrate such inequality with infrastructure resilience assessment. This is especially important to large infrastructure systems that serve multiple communities, such as interstate highway systems, electric substation and transmission lines, and municipal water supply systems. A quantitative measure on the collective resilience of infrastructure systems may guide equitable disaster recovery and resilience planning for future infrastructure.

Despite the need for and importance of integrating social equity with infrastructure resilience assessment, a number of knowledge gaps are identified in the infrastructure resilience literature. Many studies (e.g., Cimellaro et al. 2010, Rehak et al. 2019, Mao and Li 2018, Makropoulos et al. 2018, Yang et al. 2018) have proposed different resilience assessment frameworks or methods to measure the resilience of different types of infrastructure systems. For example, Cimellaro et al. (2010) proposed a comprehensive model including a loss estimation model and a recovery model to quantify the resilience of the network of hospital systems. Rahek et al. (2019) presented an infrastructure resilience assessment method that involves assessment of robustness, capacity to adapt to, and ability to recover from disruptive events. Makropoulos et al. (2018) proposed a methodological framework to assess the resilience of urban water systems. Yang et al. (2018) developed a resilience assessment framework that quantitatively evaluates the resilience of power transmission systems considering the impacts of disruptive events. These studies offered valuable contributions to infrastructure resilience evaluation. They, however, did not account for the unequal distribution of disaster impacts on infrastructure systems that serve multiple communities. They also did not consider the severe impacts on socially vulnerable communities.

To address the gaps, this paper proposes a new model that measures the collective resilience of infrastructure serving multiple communities by integrating (1) unequal distribution of disaster impacts on infrastructure serving different communities, and (2) more severe disaster impacts on infrastructure in socially vulnerable communities. The proposed model is theoretically grounded in social welfare theory and social welfare functions. It also adapts the concept of resilience triangle proposed by Bruneau et al. (2003) and social vulnerability index introduced by Cutter et al. (2003). The paper focuses on presenting the functions of the proposed model. A preliminary hypothetical case study was conducted to illustrate the use of the model.

SOCIAL WELFARE THEORY AND SOCIAL WELFARE FUNCTION

Social welfare theory studies the aggregated or collective welfare of a society or a group of individuals (Clarke and Islam 2003, Zhang and Sanake 2020). A social welfare function is a function that analyzes and ranks the welfare states of the society (Arrow 1963). This function can be utilized by the governments to identify solutions that facilitate optimal resource distribution, thus allowing the whole society to achieve the maximum collective welfare. Over the last several decades, many social welfare functions (SWFs) were proposed to measure the welfare of a group or a society. There are two major approaches for determining the welfare of a society: Utilitarian approach and Rawlsian approach. In Utilitarian SWFs, the social welfare is calculated as the sum of welfare of individual members (Schneider and Kim 2020, Harsanyi 1955). With this approach, a growth in welfare of any individuals in a society would result in increased total welfare of the society. Rawlsian approach, on the other hand, focuses on distributing the resources to aid the least fortunate individuals of a society with the goal to increase the collective welfare of the society (Schneider and Kim 2020, Rawls 1971). In Rawlsian approach, the welfare of a society is defined based on the welfare of the worst-off individuals in the society. The distribution of welfare presented by Utilitarian SWF differs with the one presented by Rawlsian SWF. To account for inequality of welfare distribution in a society, Sen (1997) proposed a SWF that integrates an inequality index, Gini coefficient, to measure the unequal distribution of welfare in a society. To account for the individuals who receive the minimum welfare in a society, Atkinson and Brandolini (2010) proposed a SWF that integrates a poverty indicator. This indicator is crucial as it accounts for the welfare of the worst-off individuals for determining the collective welfare of a society.

In recent years, social welfare theory and functions have been adapted to solve problems in the architecture, engineering, and construction (AEC) domain. For example, Mostafa and El-Gohary (2014) proposed a sustainable construction SWF that analyses the collective environmental, social, and economic benefits that infrastructure project alternatives provide to the stakeholders. Zhang and Sanake (2020) proposed a social welfare-based comfort analysis model for measuring the comfort level of a group of occupants in the indoor environments.

PROPOSED INFRASTRUCTURE RESILIENCE EVALUATION FRAMEWORK

In our study, we propose to adapt social welfare theory and functions into the area of infrastructure resilience assessment. As discussed in the previous section, the social welfare function is generally defined as a measure of the aggregated welfare of a group based on the allocation of one or more well-being requisites among the individuals of that group. In the context of infrastructure resilience assessment, the collective resilience of an infrastructure system serving multiple communities can be defined based on the resilience of infrastructure in each individual community. In our proposed model, functional loss and recovery time of infrastructure were selected as two indicators of infrastructure resilience. Here, functional loss is defined as the loss of infrastructure services due to disaster damage, such as percentage of power outages, percentage of communication service outages, and percentage of road and highway closures. Recovery time is the amount of time required for the infrastructure to be recovered to its full functional level, such as time required to resume electric power services, and time required to resume road services. The data for both indicators can be collected directly from public or private sources, including but not limited to Department of Transportation, Department of Emergency Management, and electric power companies. To determine the collective resilience of infrastructure serving multiple communities, we account for both inequality and vulnerability in disaster impacts across different communities. The following paragraphs offer detailed explanation and discussion.

Inequality in Disaster Impacts. In a society with ideal social equity conditions, all communities are expected to experience similar level of damage during disasters and require similar length of time in recovery after disasters, if they are exposed to the same or similar disaster threat level (e.g., wind threat level, rainfall threat level). However, in reality, disparities exist in the distribution of infrastructure functional loss and recovery time across different communities even these communities are exposed to the same disaster threat level. The unequal distributions of functional loss and recovery time are analogous to welfare inequality in a society. Thus, we propose to adapt Gini coefficient to measure such unequal distribution. Gini coeffect is one of the most commonly used indicators to measure inequality of social welfare (Atkinson and Brandolini 2010). In our proposed model, Gini coefficient is a measure of the unequal distribution of functional loss and recovery time of infrastructure serving different communities. The value of Gini coefficient ranges from 0 to1. A Gini coefficient of 0 indicates complete equality in functional loss and recovery time – the infrastructure systems across all communities experience the same level of functional loss and require the same length of time for recovery. Gini coefficient of 1 indicates complete inequality in disaster impacts – the infrastructure of only one community experiences the maximum level of functional loss and requires the longest time in recovery. Graphically, Gini coefficient can be represented though a Lorenz curve (Figure 1).

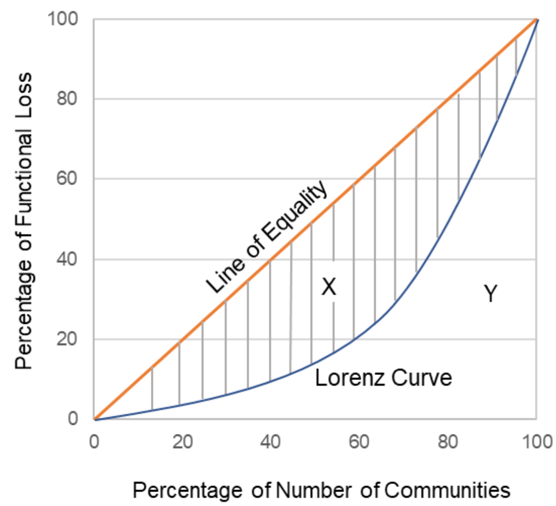


Figure 1. Lorenz Curve for distribution of infrastructure functional loss.

As per Figure 1, Gini coefficient can be measured by dividing the area between Lorenz curve and the line of complete equality (Area X) by the total area covered under the line of complete equality (Area X+Y). In our proposed model, Lorenz curve illustrates the percentage of cumulative infrastructure functional loss (or recovery time) experienced by the percentage of communities under consideration. The Lorenz curve being farther away from the line of complete equality indicates a higher level of inequality, and vice versa.

Vulnerability to Disaster Impacts. Vulnerability to disaster impacts is influenced by many socioeconomic and demographic factors, including age, income, and community characteristics (Flanagan et al. 2011). Socially vulnerable communities typically experience more severe damage to their infrastructure and often require longer time for recovering the infrastructure services to the pre-disaster level (Masozera et al. 2007). In mitigating the disaster impacts on vulnerable communities, it is necessary to identify and document those communities that suffer from the most severe infrastructure damage and spend the longest time in recovery. Thus, in our proposed model, we propose to define a "line of vulnerability" by adapting the work of Cutter et al. (2003) on social vulnerability. The "line of vulnerability" is a benchmark line that indicates the level of vulnerability. If the value of infrastructure functional loss and recovery time of a community is above this line, the community can be identified as one of the vulnerable communities. Mathematically, the line of vulnerability is defined as the sum of the mean and standard deviation of infrastructure functional loss (recovery time) experienced by all communities under consideration. Eq. (1) and Eq. (2) represent the equations for line of vulnerability for functional loss and recovery time, respectively:

$$lv_{FL} = \frac{1}{n} \sum_{i=1}^{n} FL_{ij} + S_n. \tag{1}$$

where lv_{FL} = line of vulnerability for functional loss; FL_{ij} = functional loss of an infrastructure that serves an individual community i of group j; n = total number of individual communities; S_n = standard deviation for the functional loss of infrastructure serving a group j of communities.

$$lv_{RT} = \frac{1}{n}\sum_{i=1}^{n} RT_{ij} + S_n \tag{2}$$

where lv_{RT} = line of vulnerability for recovery time; RT_{ij} = recovery time of an infrastructure that serves an individual community i of group j; n = total number of individual communities; S_n = standard deviation for the recovery time of infrastructure serving a group j of communities.

Defining such vulnerability line could be beneficial for socially vulnerable communities, as decision makers can pay special attention to these communities and facilitate the (re)development and (re)investment of infrastructure that leads to better equity outcomes.

Collective Disaster Impacts Measurement. In our study, collective disaster impacts refer to the aggregated disaster impacts on infrastructure serving a collection of multiple communities. Our proposed model measures the collective disaster impacts on infrastructure serving multiple communities by accounting for the inequality in and vulnerability to disaster impacts. The collective functional loss and collective recovery time for an infrastructure system are determined through two separate functions [Eq. (3) and Eq. (4), respectively] following a similar theoretical basis:

$$FL_j = \frac{1}{n}\sum_{i=1}^{n} FL_{ij} \times \left(1 + \gamma G_j\right) + \delta \frac{1}{n}\sum_{i=1}^{n} \max[0, (FL_{ij} - lv_{FL})] \tag{3}$$

where FL_j = the collective functional loss of an infrastructure system serving a group j of multiple communities; FL_{ij} = the functional loss of an infrastructure serving an individual community i of group j; n = total number of individual communities; G_j = the Gini coefficient for functional loss; lv_{FL} = the line of vulnerability for functional loss; γ = a coefficient that controls the degree of penalizing unequal distribution of functional loss, $0 \leq \gamma \leq 1$; and δ = a coefficient that controls the degree of penalizing extremely severe functional loss, $0 \leq \delta \leq 1$.

$$RT_j = \frac{1}{n}\sum_{i=1}^{n} R_{ij} \times \left(1 + \gamma G_j\right) + \delta \frac{1}{n}\sum_{i=1}^{n} \max[0, (RT_{ij} - lv_{RT})] \tag{4}$$

where RT_j= the collective recovery time of an infrastructure system serving a group j of multiple communities; RT_{ij} = the recovery time of an infrastructure serving an individual community i of group j; n = total number of individual communities; G_j = the Gini coefficient for recovery time; lv_{RT} = the line of vulnerability for recovery time; γ = a coefficient that controls the degree of penalizing unequal distribution of recovery time, $0 \leq \gamma \leq 1$; and δ = a coefficient that controls the degree of penalizing extremely long recovery time, $0 \leq \delta \leq 1$.

Each of the collective functional loss function and collective recovery time function consists of two main subfunctions: a subfunction for inequality and a subfunction for vulnerability. The inequality subfunction penalizes the unequal distribution of infrastructure functional loss and recovery time across different communities. This is based on the assumption that such inequality jeopardizes the achievement of overall resilience of the infrastructure system that serves multiple communities. A coefficient γ ranging between 0 and 1, is introduced to allow planners and decision makers to adjust the degree of penalization. The vulnerability subfunction penalizes the extremely severe infrastructure functional loss and long recovery time experienced by vulnerable communities. Similarly, this is based on the assumption that such vulnerability compromises the achievement of the overall resilience of infrastructure systems. To allow practitioners and decision makers to control the degree of penalization, a coefficient δ ranging between 0 and 1 is introduced to the vulnerability subfunction.

Infrastructure Resilience Assessment Function. The infrastructure resilience assessment function is used to measure the collective resilience of infrastructure systems that serve multiple communities. The theoretical foundation of the infrastructure resilience assessment function is grounded on the resilience triangle framework proposed by Bruneau et al. (2003). This approach is based on the fact that the quality of infrastructure varies with time (Figure 2).

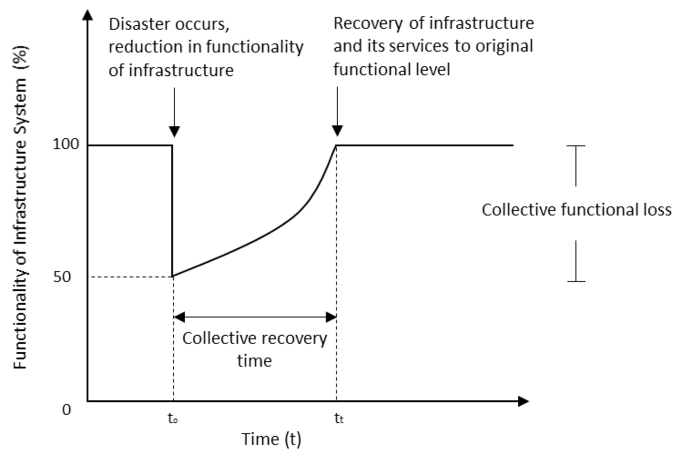


Figure 2. Collective Infrastructure resilience measurement (adapted from Bruneau et al. 2003)

Disasters could possibly cause severe damage and service outages, resulting in the reduction of the functionality of infrastructure systems. In general, the functionality of infrastructure is expected to be reduced after exposed to unexpected disruptive events (e.g., reduced from 100% to 60%). However, with the help of recovery efforts over a certain period of time (recovery time), the structure and service of infrastructure can be restored to a pre-disaster level. Based on Bruneau et al. (2003)'s resilience triangle framework, we define the collective loss of resilience of an infrastructure system in the equation below: Eq. (5).

$$LR_j = \int_{t_0}^{t_t} [FL_j\,]dt \tag{5}$$

where LR_j = collective loss of resilience in an infrastructure system serving a group j of multiple communities; FL_j = collective functional loss of an infrastructure system serving a group j of multiple communities; t_0 = time at which disaster occurs; and t_t = time at which the infrastructure system is fully recovered.

Assuming the infrastructure system is recovered with a constant speed, the functional loss and recovery time of the infrastructure system can be used to form a resilience triangle (Figure 3). Thus, the collective functional loss and collective recovery time of the infrastructure system can be represented as "height" and "base" of a right-angle triangle. Therefore, the collective loss of resilience of the infrastructure system can be simplified as Eq. (6).

$$LR_j = \frac{FL_j \times RT_j}{2} \tag{6}$$

where LR_j = collective loss of resilience in an infrastructure system serving a group j of multiple communities; FL_j = collective functional loss of an infrastructure system serving a group j of multiple communities; and RTj = collective recovery time of an infrastructure system serving a group j of multiple communities.

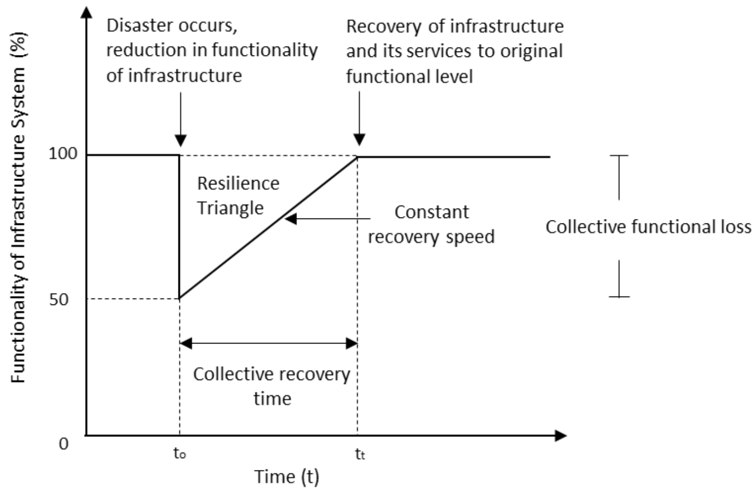


Figure 3. Concept of resilience triangle for the measurement of infrastructure resilience (adapted from Bruneau et al. 2003)

CASE STUDY

To apply our proposed model in analyzing collective infrastructure resilience, a hypothetical case study was conducted. Hypothetical case studies are widely used in multiple domains to test or illustrate the use and implementation of new models or methods (Balaei et al. 2018, Mosatafa and El-Gohary 2014). In our hypothetical case, Hurricane X caused major damage on a transportation infrastructure system that serves ten communities, numbered as Community A to Community J. The residents of these communities rely on the transportation infrastructure system (including highways, bridges, and local roads) to get access to goods, services, and amenities (e.g., school, restaurants, grocery stores, and health care facilities). After Hurricane X, the local roads and bridges were severely damaged in some communities, and the residents in these communities lost transportation accessibility for weeks. Some other communities had only minor damage on their road pavement, which caused traffic blockage for only a few days.

For our hypothetical case, we created a group of individual communities with different vulnerability levels. In our study, the vulnerability level indicates the state of being exposed to and the possibility of suffering from significant impacts on infrastructure systems from potential disasters. These ten communities have different levels of infrastructure damage and required different length of time in recovery. For example, Community A has low vulnerability level. Thus, it experienced a lower level of damage on its transportation infrastructure, and they resumed roadway and highway functions rapidly after the hurricane. On the other hand, Community J experienced a significant damage to their transportation infrastructure, and it took more than three weeks to repair and resume highway and roadway functions after the hurricane. The functional loss and recovery time of the transportation infrastructure in the ten communities are summarized in Table 1.

Based on the dataset in Table 1, five steps were taken to perform the resilience assessment. In Step 1, to ensure that the indicators in various scales and units are comparable (e.g., between 0 to1), normalization of the values of functional loss and recovery time was conducted. In Step 2, Gini coefficients were determined using the Lorenz curve. The Lorenz curves for functional loss and recovery time of transportation infrastructure in the ten communities are shown in Figures 4(a) and 4(b), respectively. The Gini coefficients for functional loss and recovery time were calculated as 0.47 and 0.45, respectively. In Step 3, the line of vulnerability was determined using Eq. (1) and Eq. (2). The lines of vulnerability for functional loss and recovery time were calculated to be 0.89 and 0.87, respectively. In Step 4, the collective functional loss and the collective recovery time of the transportation infrastructure system were calculated using Eq. (3) and Eq. (4), respectively. A value of 0.5 was chosen for the coefficients γ and δ, representing a medium level of penalization on (a) unequal distribution of functional loss and recovery time, and (b)extreme functional loss and recovery time in socially vulnerable communities, respectively. In Step 5, the collective resilience of the transportation infrastructure system was calculated using Eq. (5) and Eq. (6). In this case study, the recovery of the transportation infrastructure was assumed to follow a constant speed. Thus, the collective loss of resilience can be represented as the area of triangle with values ranging from 0 to 0.5. A lower value on collective loss of resilience indicates that the infrastructure system is more resilient to disruptive events, meaning the infrastructure system has less damage and is likely to resume normal operation in a short time. In our hypothetical case, the value of collective loss of resilience is equal to 0.17, which indicates the infrastructure system, overall, has a better than medium resilience performance.

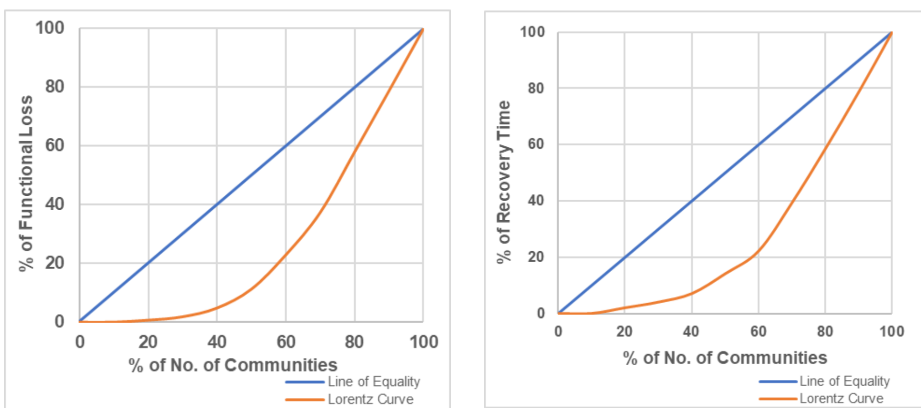
Table 1. Functional Loss and Recovery Time of a Transportation Infrastructure System Serving Multiple Communities

Community	Functional Loss (%)	Normalized Functional Loss	Recovery time (days)	Normalized Recovery Time	Vulnerability level
A	20	0.14	5	0.14	low
B	12	0.05	4	0.09	low
C	58	0.55	10	0.38	medium
D	70	0.68	19	0.81	medium
E	97	0.98	22	0.95	High
F	35	0.30	9	0.33	medium
G	7	0	2	0	low
H	10	0.03	4	0.09	low
I	98	0.99	21	0.9	high
J	99	1	23	1	high

CONCLUSIONS

This paper presents a new infrastructure resilience assessment model for measuring the collective resilience of infrastructure systems serving multiple communities. The proposed model accounts for the unequal distribution of disaster impacts on different communities and the potentially extreme impacts experienced by some socially vulnerable communities. The proposed model is theoretically grounded on social welfare theory and social welfare functions. It also adapts the concept of resilience triangle by Bruneau et al. (2003) and social vulnerability index proposed by Cutter et al. (2003). This study contributes to the body of knowledge by providing a new resilience assessment model that determines the collective resilience of infrastructure systems serving multiple communities. This study also provides a better understanding on how to quantify the unequal distribution of disaster impacts on infrastructure across different communities and the potentially severe impacts on the infrastructure of vulnerable communities.

In the ongoing and future work, the authors will conduct larger scale studies that compare the resilience of infrastructure across different groups of communities in various geographical conditions (e.g., different states) and further expand the current study to different types of infrastructure systems. The authors will conduct the studies based on real data collected in previous disasters (e.g., Hurricane Michael, Hurricane Irma). Furthermore, the proposed model will be implemented in a prototype system to allow decision makers to easily quantify and compare the collective resilience of infrastructure systems while accounting for social equity and vulnerability. The proposed model, together with the future work, may allow decision makers to better understand the interrelationships between infrastructure resilience and social equity, and it may also help decision makers prioritize infrastructure investment for socially vulnerable communities.



(a) (b)

Figure 4. Lorentz curves for (a) functional loss and (b) recovery time

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