Transition from Social Vulnerability to Resiliency vis-à-vis COVID-19

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Abstract

The COVID-19 pandemic has revealed systemic deficiencies in preparing and planning for disasters, with profound health, economic, social, political, and humanitarian consequences. When preparing for pandemics, social vulnerability needs to be assessed using vulnerability indices to identify which populations are at greater risk. In this context, we examined the possible association of social vulnerabilities in U.S. cities with COVID-19 case fatality ratios. Post-pandemic return to normalcy is fraught with uncertainty over the ability of different communities to recover with varying degrees of resilience. Towards this, we recommend use of a community resiliency planning framework, along with modeling and evaluation of the required measures, which may be useful for the Indian scenario.

Key words: Social vulnerability; Case fatality ratio; Community resilience; COVID-19; Pandemic; Socio-economic covariates.

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1. Introduction

The COVID-19 pandemic, which had its first reported case in Wuhan, China on 17 November 2019, has subsequently had profound global consequences on health, economic, social, political, and almost every major aspect of human life. It is unlike any other single phenomenon that has occurred in modern history since the end of World War II. The effects of the COVID-19 pandemic have spanned over a range that is so vast over space, and yet so condensed over time, that the dual blows of intensity and rapidity have exposed myriad systemic vulnerabilities in many societies around the world. Many countries with apparently robust systems have come under severe stress, and now expect to trudge a slow and painful path to recovery.

Evidently, such systemic deficiencies serve as a reminder of the complex interplay of anthropogenic factors that unfold daily in the form of a vast range of human activities that shape

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the world around us. By 2050, the average urbanization rate is expected to reach 86% in developed countries, and 64% in developing countries (Liu *et al.*, 2019). At the 2002 biennial meeting of the International Society for Ecosystem Health at Washington DC, a report titled, "Unhealthy Landscapes: How Land Use Changes Affect Health" was published (Patz *et al.*, 2004). We understand now how rapid and extensive land-use changes may activate cascades of risk factors involving deforestation, pollution, poverty, migration, and an alarming rise in new human-animal interfaces, which exacerbate the risk of emergence of novel communicable diseases, especially through zoonotic pathogens such as bat-borne coronaviruses (Pyne *et al.*, 2015).

A century after the 1918 "Spanish flu" pandemic, at a 2018 meeting in Geneva, the World Health Organization (WHO) warned us about the possibility of a zoonotic pandemic caused by a novel pathogen, which was enigmatically called, "Disease X" (WHO 2018 Annual review of diseases). In fact, Disease X was included in its "2018 list of diseases to be prioritized under the R&D Blueprint". Yet, as the COVID-19 crisis has clearly demonstrated, we have no choice but to identify, assess and address the systemic vulnerabilities not just at the level of select organizations, but indeed of entire societies.

2.   Social Vulnerability: The Place to Begin

There is a lack of consensus on the definition of vulnerability in scientific literature. In the context of a pandemic and other disease outbreaks, we assume that vulnerability is a property of a system, which upon interaction with a given hazard produces an outcome, including a disaster. A stress to the system that has a high potential to harm people and places is termed as a hazard. A disaster refers to a singular large-scale event to which a local community finds it difficult to effectively adapt or cope with. Risk is defined as the likelihood that certain loss or damage could result from a disaster (National Research Council, 2006).

In recent years, the field of vulnerability assessment has shifted from qualitative conceptualization to precise quantitative measures of vulnerability (Cutter SL, *et al.*, 2009). Index based measurement provides objectivity to analysis and allows assessment by integrating various indicators to represent different vulnerability scenarios. Known examples of vulnerability indices include the Environmental Sustainability Index (Esty *et al.*, 2005), and the Human Development Index (Burd-Sharps *et al.*, 2008). Vulnerability assessments need not aim for quantification of any absolute level of potential damage but rather attempt to assess objectively which populations, and the corresponding systems, are more vulnerable to a particular hazard.

While different frameworks of vulnerability assessment appear in literature, here we extend an earlier classification (Karmakar *et al.*, 2010) of human vulnerability with respect to pandemics to include the following types: (1) individual (age, education, nutrition, immune health, comorbidities, exposures, behavioral factors), (2) social (housing, household composition, minority status, community network), (3) economic (income and employment, health insurance, food security, ready government programs, monetary relief instruments designed for a lockdown), (4) infrastructure (regional level secure essential supply chains, energy and communication access, means of essential transport during a crisis, reserved medical stocks), (5) technological (platforms to monitor physical, cognitive and psychological well-being, dynamic information on available medical facilities, optimized diagnostic and vaccination strategies, protected healthcare personnel,

interactive apps and round-the-clock helplines, real-time data collection and visualization, digital connectivity), and (6) administrative (see below). The above list is, of course, not exhaustive.

In the context of a pandemic, useful administrative modes of action may consist of an assiduously data-driven apolitical style of leadership, dynamic and flexible decision-making, mandatory daily clear and accurate media updates on unfolding situations, active ongoing surveillance on the ground for both stationary and mobile populations, meticulous contact tracing with ethical protocols, recognizing sensitivity to key local needs, using empathy as a core criterion when dealing with minorities and vulnerable groups, taking swift steps to mitigate rumors and misinformation, meaningful engagement of communities to obtain regular feedback and respond accordingly and accountably, enact schemes of local and limited economic activity as equitably and cautiously as possible, and coordinate across a well-practiced disaster management plan.

To aid planning, comprehensive social vulnerability maps have been developed in many countries in North America and Europe, and also China. Recent studies have produced vulnerability indices for health risk (NITI Aayog, 2019) and hydro-climatic risk in India (Vittal H, *et al*, 2020). However, to the best of our knowledge, India lacks a comprehensive health risk atlas based on district-wise vulnerability indices that can lay out the key socioeconomic and environmental determinants of community-specific health. The recently published Vulnerability Atlas of India, Third Edition, 2019 includes hazard scenarios for natural disasters, should also be extended to address future epidemics or pandemics (Vulnerability Atlas of India, 2019). Such lacuna could undermine the capacity of an administration to confront a sudden pandemic situation as it might render any breakdown of its systemic responses unpredictable, and thus, result in confounding of priorities.

On quantitative assessment of vulnerability, we take the example of Social Vulnerability Index (SVI) developed by the Geospatial Research, Analysis, and Services Program (GRASP) within the United States Centers for Disease Control and Prevention (CDC) to help flag areas where residents will be in greatest need of support and recovery assistance in the case of a disaster or extreme weather event (CDC's Social Vulnerability Index). SVI provides four categories of vulnerability: socioeconomic status, household composition and disability, minority status and language, and housing and transportation based on data from the 2012-2016 American Community Survey. These four SVI indices along with an overall SVI score are available for different geographical units (e.g., all U.S. counties) at a national scale (CDC's Social Vulnerability Index).

3.   Does Social Vulnerability Impact COVID-19 Fatality?

Since the first reported case of COVID-19 in the U.S. in Washington State on January 31, 2020, there have been in the U.S. over 1.7 million cases as of May 27, 2020, when the number of related deaths crossed the mark of 100,000 (Coronavirus in the U.S., New York Times, 2020). In this study, we take a look at the early stages of the pandemic, from 29 February to 15 March, in the COVID-19 affected U.S. cities for possible association between their socioeconomic vulnerabilities and their case fatality ratio (CFR), which is given by the number of deaths by the disease divided by the number of confirmed cases of the same.

It is generally agreed that CFR of COVID-19 has varied between 4.5% and 16% globally, with the U.S. experiencing an overall 6% CFR. However, some U.S. cities have experienced a disproportionate number of deaths compared to others. Since precise calculation of CFR can be made only after an outbreak is over, which is not yet the case, we computed a crude version of CFR as the ratio of the cumulative number of deaths to the cumulative number of cases at a given city on a given date. This dynamic CFR value over a time-period starting from 29 February up to 15 March 2020, for 110 U.S. cities that had at least 500 cases of COVID-19 by that end date, are shown as a heatmap in Figure 1 (Annexure).

To identify the different common temporal patterns of CFR in an unsupervised manner, we used agglomerative hierarchical clustering with linkage by Ward's distance. It revealed 4 clusters of cities having (1) early and prolonged, (2) intermediate, (3) mild, and (4) weak CFR profiles. The names of the cities in the clusters (1) through (4) are depicted in Figure 1 in brown, red, orange, and yellow, respectively. Given the generally weak profiles in cluster 4, we exclude it from further analysis.

CFR is probably better suited than either absolute mortality figures or the COVID-19-specific mortality rate to provide insights into systemic deficiencies that may affect a community's response to the health and other challenges presented by the outbreak it faces. Upon grouping the cities according to the clustered CFR profiles, we compared the social vulnerability indices of these groups. We used SVI for Socioeconomic Status (SES), SVI for households, and overall SVI as computed by the U.S. CDC. Further, we also included some basic social and economic indicators from the latest U.S. Census Bureau data such as the percentages of black population (considered a minority group) and poor population of a city, and its Gini index as a known measure of overall wealth inequality. Figure 2 (Annexure) shows the boxplots for each of these indicators for the cities belonging to clusters 1 (brown), 2 (red) and 3 (orange).

We note that the 3 clusters, as well as their respective medians, differ significantly for each of these variables as per Kruskal-Wallis 3-group test (*p*-value < 0.1). Notably, cluster 1 with its early and prolonged CFR profile has higher median social vulnerability values compared to the other two clusters, on each of the stated indicators. While we want to avoid making any ecological fallacy in drawing inferences about individual disease outcomes based on city level socioeconomic conditions, it is nonetheless difficult to ignore the common pattern – of higher median vulnerability in cluster 1 – across the various indicators shown in Figure 2.

It is possible that pre-existing or chronic socioeconomic vulnerabilities could directly or indirectly contribute to the increased health risk in many of these cities when faced with the additional burden of a sudden and severe pandemic. The underlying pathways starting from one's exposure to death are often diverse, e.g., many of the young black casualties had little choice but to go out to work on jobs that could not be done remotely from the safety of home. According to the U.S. Bureau of Labor Statistics 2017-2018 report on job flexibilities, while more than 60% of the top quarter of salaried employees could work from home, that figure is less than 10% of those in the bottom quarter (Economic News Release, 2019). Intense research to shed light on this complex topic will no doubt be conducted over the coming years.

4.   Developing Community Resiliency to Pandemics

Post-pandemic return to normalcy is fraught with uncertainty over the ability of different communities to recover with varying degrees of resilience. Above, we discussed social vulnerability in the context of populations to determine who would be more impacted by a pandemic than others. Resiliency is a term related to vulnerability. While vulnerability focuses more on chronic stressors such as existing exposures and sensitivities, resiliency, by contrast, is a dynamic property of a population that involves transformative concepts such as learning, critical reflection, adaptation, and reorganization (Cimellaro *et al*., 2016). Rather than assessing the state of a system prior to a disaster, action-oriented questions such as how long it would take to respond, organize, incorporate the lessons learned, and resume normal activities, are asked to assess resiliency of a community.

To illustrate how to approach a community resilience planning process, we could take the example of the U.S. National Institute of Standards and Technology (NIST) Community Resilience Planning Guide (NIST Special Publication, 2016). It defines resilience as "the ability of a community to prepare for anticipated hazards, adapt to changing conditions, withstand, and recover rapidly from disruptions". Often, such ability relies on key components such as infrastructure, utilities, administration, and governance – each of which requires significant time and resources to re-build. Towards this, the NIST guide offers a template of community resilience measurement framework based on estimates of expected recovery times, especially for different communities and infrastructure sectors, which could now be adapted for pandemic resiliency. The expression of resiliency in terms of recovery of system functionality over time following disruption by a disaster event can be seen in the concept diagram [Figure 3 (Annexure)] adapted from NIST Community Resilience Planning Guide, 2016.

Community resiliency planning for a pandemic would require a population to adapt to the post-pandemic realities on the ground, allow backup measures and redundancies in the system, even at the cost of some efficiency, to halt cascades of avoidable losses and despair, restore supply chains for food and energy security, include built-in safety nets such as insurance plans, easy access to loans, medical reserves to limit avoidable losses of life and livelihood, activating new projects to generate economic vitality, resist various sources of rumors and misinformation, and support socializing activities as well as a variety of community-specific and locally relevant constructive measures.

While the technical experts and policy makers may want to develop such resiliency measures by proposing interventions, it is, however, challenging to conduct real-life testing and benchmarking of their impact, particularly among high-density urban populations. In this regard, agent-based modeling (ABM) offers a promising solution based on a computational simulation approach. (Willensky and Rand, 2015) ABM is modeled as a collection of autonomous, decision-making, and interacting entities called agents. An agent could represent an individual, an organization or, for that matter, any entity that can follow certain rules of behavior, and thus, interact with other agents and also the environment. As a result, we can observe macroscopic systemic behaviors – resulting from a large number of micro-level interactions among the agents – as bottom-up "emergent" properties. In an ABM, the stochastic behavior of each agent introduces a certain degree of randomness, which is compensated by conducting a large number of

simulations and aggregating the system responses at the end. By altering an input intervention for a fixed population that is subject to a fixed environment and disease conditions, and running over a given time-period, ABM can help in evaluating the impacts of different interventions.

Despite its ability to allow uncertainty in the model, the micro-level design of an ABM makes it difficult to include in model specification the large degree of detail required to accurately reproduce real-world phenomena. However, an investigation of underlying principles and basic mechanisms is still quite possible, and indeed, most valuable (Brudermann *et al.*, 2016). For example, measles outbreaks were modeled with FRED, an ABM platform, under different rates of vaccine coverage vis-à-vis anti-vaccination stigma among selected communities (Sinclair *et al.*, 2019). An ABM was combined with the application of optimal control theories in order to assess resilience of complex systems during extreme events (Cimellaro *et al.*, 2016). A post-epidemic (Ebola) society was modeled with ABM to show how the original structure of the social network, severity of the disaster, and individual beliefs may affect the resilience of the community (Michel S, et al 2015). The emBRACE project used interdisciplinary, socially inclusive, and collaborative methods to develop an ABM based resiliency framework for Europe (Deeming *et al.*, 2019). Another ABM study observed that relationship among the individuals of a community is so vital that a community with less population and more empathy may be more resilient to a disaster than one with more population and less empathy (Valinejad *et al.*, 2020).

Land use and land cover change often exhibit specific community dynamics, which have been modeled by several ABMs. (Guzy *et al.*, 2008; Robinson, *et al.* 2007; Schwarz *et al.*, 2012). This includes modeling of a cooperative approach to mitigate severe risk trade-offs resulting from increase in forest land at the cost of agricultural land (Guzy *et al.*, 2008). The scenario closely resembles real-life in which trade-offs are negotiated between competing risks. Cooperation setting and establishing common grounds demonstrated better outcomes in the model. Such strategies need to be modeled to compare the faced risks and benefits during pandemics to determine policies that ultimately build resilience among the affected communities.

Finally, we arrive at the problem of how to calibrate a model with community-specific characteristics. This is important as conditions prior to a disaster determine the degree of damage and lost functionality, which, in turn, impact resiliency of a community to withstand and recover. Therefore, when assessing resiliency, an ABM should be calibrated with pre-disaster conditions with community-specific real or estimated data and vulnerability indicators. For instance, a model for earthquake evacuation of pedestrians was based on the behavioral rules of the agents derived from real earthquake evacuations (Bernardini *et al.*, 2014). Since local level estimates are not often available, small-area estimates may be used to quantify community-specific health outcomes (Das *et al.*, 2019; Kong *et al.*, 2020). For instance, such estimates for 500 U.S. cities were computed using 27 chronic health and behavioral risk factors (COVID-19 Pandemic Vulnerability Index, NIEHS of NIH). In India, data from national scale surveys such as the National Family Health Survey, Annual Health Survey, Comprehensive National Nutrition Survey, etc., (Dandona *et al.*, 2016) may be harnessed to compute suitable small area estimates for calibrating reliable models of community resiliency.

We believe that the full potential of ABMs for modeling resiliency to disasters is yet to be realized. ABMs could be used for modeling complex administrative cascades, including obstacles,

trade-offs, dogmas, etc. Human emotions such as stigma or empathy can provide us key insights in testing of resilience. Examples of different ABM models were demonstrated in India at 2016 and 2018 'Health Analytics and Disease Modeling' workshops conducted by Health Analytics Network, and the Public Health Dynamics Laboratory of University of Pittsburgh (International Symposium on Health Analytics & Disease Modeling, 2016, 2018; Raghav and Verma, 2018).

5.   The Post-Pandemic Way Forward for India

Incidentally, when a super cyclone named Amphan hit parts of the eastern coast of India and Bangladesh on 20 May 2020, right in the midst of the pandemic, despite the significant damage to local infrastructure, a relatively small number of human lives were lost thanks to administrative preparedness and efficient action (Cyclone Amphan bears down on India and Bangladesh – New York Times, 2020) that had to balance the competing risks of mass evacuation against the ongoing lockdown. With climate change and various recurring and seasonal disasters, new multi-hazard indices may prove to be useful for assessing possible vulnerability to the emerging reality of multiple concurrent disasters of different types (Locusts, COVID-19, Flooding pose "Triple Threat" in Africa – New York Times, 2020).

As a model of a system that could be designed to perform like "well-oiled machinery" during a massive disaster, let us take the example of the 2004 tsunami in the Indian Ocean. WHO observed that despite the magnitude of the disaster that killed around 18,000 people in India, there was no significant disease outbreak. We can give credit for this to the state of Tamil Nadu (TN), which has, since 1922, legislated for an independent Directorate of Public Health with an administrative authority board and its own budget. Unlike other Indian states, TN keeps the delivery of public health and medical services distinct (Gupta *et al.*, 2010). Importantly, it maintains a dedicated cadre of professionals who are trained in different public health activities, allowing TN to conduct annual "anticipatory planning" to prepare for recurring disasters such as floods, endemic diseases, and other public health emergencies (Krishnan and Patnaik, 2020). Thus, even if badly affected by the pandemic, TN is likely to rebound with its resilient system.

Indeed, the central importance of the human component in the design of any critical system, however technologically enhanced, cannot be over-emphasized, especially if such a system is expected to have its "ear on the ground". The Global Public Health Intelligence Network (GPHIN), developed by Health Canada in collaboration with WHO, is a secure Internet-based multilingual early-warning digital tool that continuously searches global media sources to identify information about disease outbreaks and other events of potential international public health concern. Interestingly, more than 60% of the initial outbreak reports in GPHIN come from unofficial informal sources, including non-electronic media, which are then verified by human experts (WHO Epidemic Intelligence).

We conclude with mentioning the "Sendai Framework for Disaster Risk Reduction 2015-2030" (Sendai Framework for Disaster Reduction, 2015), which was adopted at the Third UN World Conference in Sendai, Japan, on 18 March 2015, and is supported by the United Nations Office for Disaster Risk Reduction. This framework aims to reduce disaster risk and losses over the next 15 years based on its 4 priorities: (1) understanding disaster risk, (2) strengthening disaster risk governance to manage disaster risk, (3) investing in disaster risk reduction for resilience, and

(4) enhancing disaster preparedness for effective response and to "Build Back Better" in recovery, rehabilitation and reconstruction. However, in its current form, it does not explicitly address the disaster of a pandemic. In India, the National Health Mission publishes the Indian Public Health Standards that incorporate many disasters but also lack explicit planning for pandemics (Krishnan and Patnaik, 2018). Likewise, the National Disaster Management Authority formed in 2005 addresses most natural and human-made disasters except for pandemics (Krishnan and Patnaik, 2020). Clearly, this is a gap that India needs to fill in its national planning efforts in the wake of COVID-19 pandemic.

It is not commonly known that during the 1918 Spanish flu pandemic, more than half of all deaths worldwide took place in (then British) India – as many as 17 million deaths from the disease (Schoenbaum, 2001). The high risks of zoonotic and other emerging infectious disease outbreaks for this region is well understood (Jones *et al.*, 2008; Allen *et al.*, 2017). Yet, at the same time, India has the advantage of having many strong institutions including its civilian services, research labs, vibrant media, and well-knit communities. We believe that by adopting the formal structure and priorities (such as those of the Sendai framework) to fortify its systems, India can emerge as a global leader in setting response and recovery standards that are specific to pandemic disasters and cognizant of the strengths and vulnerabilities of its unique and diverse communities, and thus, become more resilient to the complex crises of the future.

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ANNEXURE
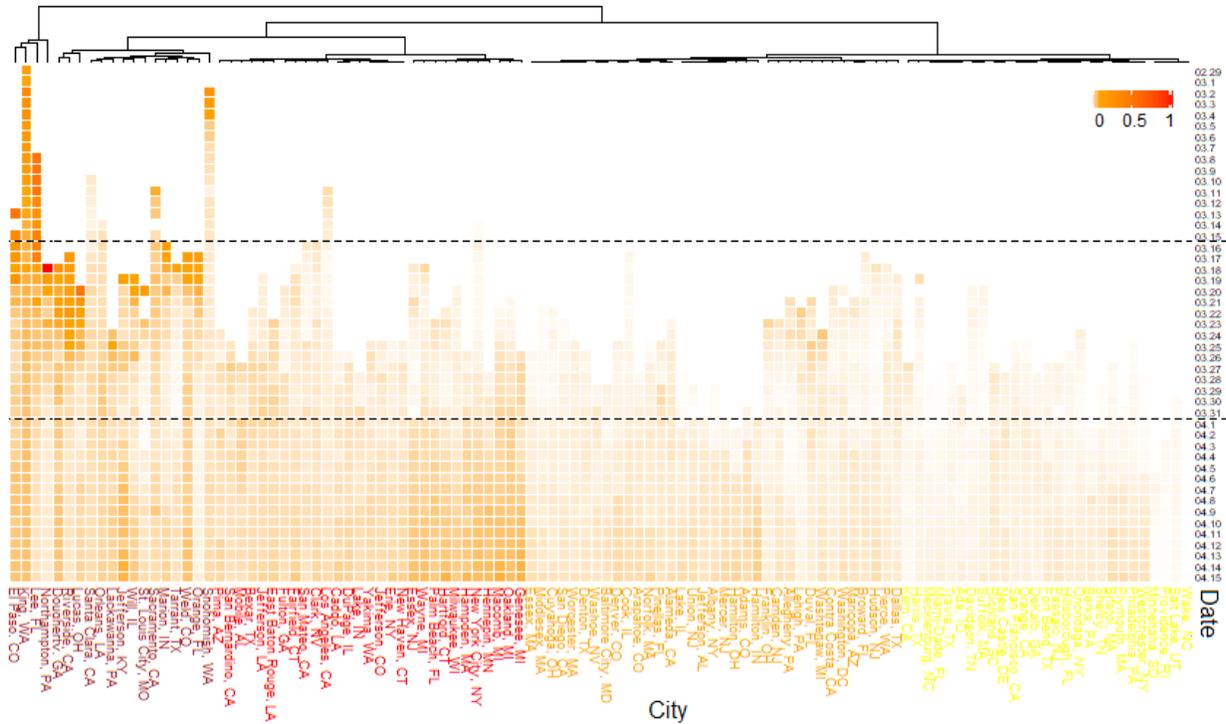
Figure 1: Clusters of COVID-19 affected U.S. cities. Unsupervised hierarchical clustering of dynamic CFR time series, shown in heatmap, of 110 U.S. cities (*x*-axis) revealed 4 clusters of cities, as named in 4 different colors. The dashed lines mark 15-day intervals over the time-period (*y*-axis) of February 29 to April 15, 2020. On top is a dendrogram showing the linkage among the clusters based on Ward's distance.
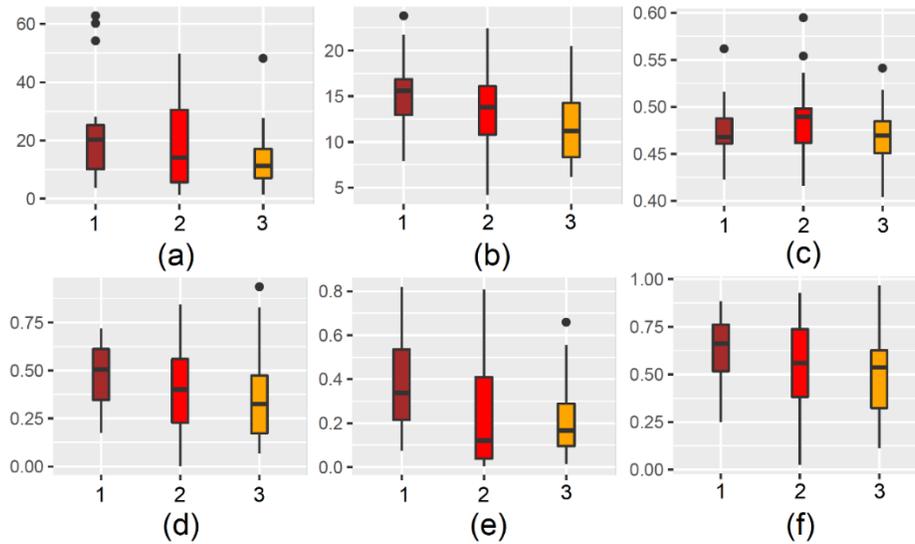
Figure 2: Comparison of socioeconomic covariates. For clusters 1, 2, and 3 of U.S. cities, the boxplots show (a) the percentage of black population, (b) the percentage of poor population, (c) Gini index, (d) SVI for SES, (e) SVI for households, and (f) overall SVI.
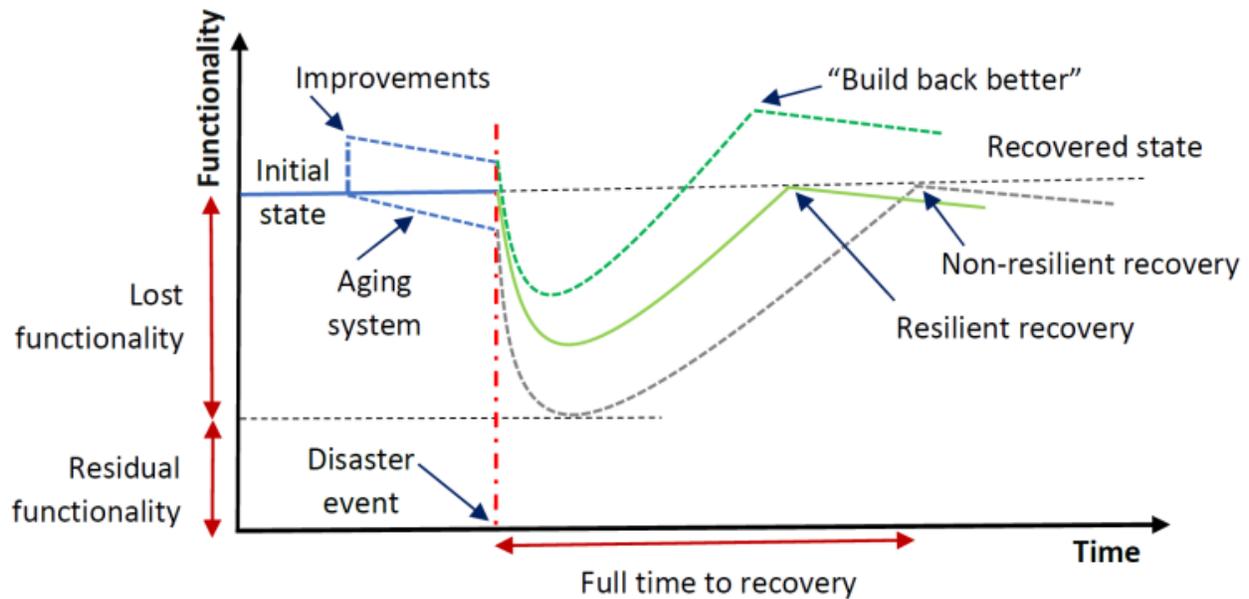

Figure 3: A Functional Concept of Resiliency. Resiliency can be expressed in terms of recovery of system functionality over time following disruption by a disaster event (adapted from NIST Community Resilience Planning Guide, 2016).