Transportation Infrastructure in Disaster Resilience Assessment

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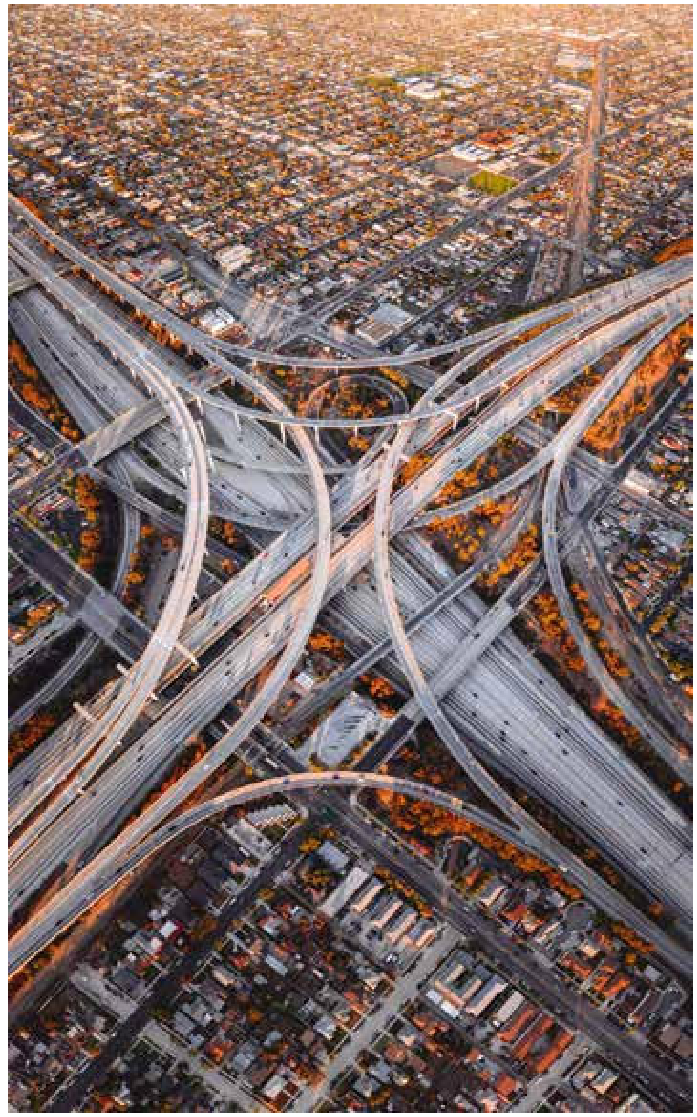
The first of several upcoming articles that are contributions from subject matter experts speaking on various components of resiliency and GIS – from URISA's Community Resiliency Task Force.

Disaster resilience refers to the ability of a system to respond to and recover from a disaster without significant outside assistance [1]. Because enhanced resilience can help significantly reduce social and economic losses resulting from disasters, disaster resilience assessment has become a major research focus across disciplines [2]. Given the dependency of resilience on various physical, social, political and economic factors, resilience assessment can be undertaken at different spatial scales ranging from the local to the global [2-4]. Many resilience assessment models (e.g., the disaster resilience of place (DROP) model [5], the baseline resilience index for communities (BRIC) model [4]) typically develop composite indicators based on different factors (e.g., social, economic, institutional, infrastructure, and community capital) [2]. For example, the BRIC model is based upon county-level indicators (e.g., percent population with a vehicle) and can be used for regional or national resilience assessments [4]. Most of the indicators used in the BRIC model rely on data available from various nationally consistent datasets developed by agencies such as the U.S. Census, the Federal Emergency Management Agency (FEMA), and U.S. Department of Agriculture [6]. However, the U.S. government is decentralized, and most of the spatial data are managed locally (within a municipality or a county), which poses a challenge to incorporate some more detailed indicators into the BRIC model for regional or national resilience assessment. As for resilience assessment at the local level (e.g., within a county), it is a common practice to select a set of indicators based on the ones used in the BRIC model and data availability in the study area. For example, Frazier et al. [3] developed a model based on the indicators in the BRIC model and some locally available data to assess community resilience in Sarasota County, Florida. Furthermore, this model also takes into account the spatial and temporal variability of resilience and uses focus groups to derive place-specific, differentially weighted indicators. Thus, this model could represent the best practice to develop local resilience assessment models, and resilience researchers and practitioners could employ the techniques used in this model to develop finer-grain models tailored for a specific place to further enhance community resilience.

Among all the components of resilience as per the URISA definition of community resilience, transportation infrastructure plays a significant role as it impacts the ability to move personnel, resources, and assets before, during, and after a hazard event. Resilient transportation systems can help enhance disaster preparedness, improve evacuation effectiveness and efficiency, and facilitate the recovery and reconstruction process after a disaster. In addition to the key components of transportation (e.g., roads, bridges, waterways, airports [3,4]), other evacuation-related factors such as household vehicle ownership, access to vehicles, the spatial distribution of shelters and other lifelines also play an important role in assessing transportation infrastructure resilience. The data sets available to represent these factors differ from one scale to another. For example, the principle arterial miles per square mile variable is used to represent access/evacuation potential in the BRIC model [4], while the detailed evacuation routes and many other fine-grain place-specific indicators (e.g., tourism, people's access to the evacuation routes) can be used to evaluate resilience at the local level [3]. Generally, the models used for regional or national resilience assessment employ coarse-grain variables due to limited data availability. However, with the rapid development of computing technologies and the advent of the big data era [7-9], it has become possible to use various high-resolution big data to develop relevant indicators and create finer-grain assessment models for larger study areas. For example, Cova et al. [10] used the critical cluster model (CCM), the national road layer from ESRI StreetMap, and the fire-hazard map from the LANDFIRE project [11] to evaluate wildfire evacuation potential for the communities in the American west. In the past, it used to be time-consuming to create and use fine-grain wildfire evacuation traffic simulation models due to limited data availability and computing power [12,13]. In recent years, there are many new high-resolution national datasets such as the national address database (NAD) developed by the U.S. Department of Transportation (DOT) [14-16], the Microsoft building footprint database [17], and the national shelter database from the American Red Cross [18], which enables the development of fine-grain transportation indicators for resilience assessment for a region or the entire nation. However, researchers and practitioners still need to solve many potential issues such as data inconsistency and availability so that different data sets including big data obtained from citizens and remote sensors can be integrated across scales to assess resilience effectively and efficiently.

Another challenge in building better resilience assessment models lies in interdisciplinary collaboration. Researchers and practitioners in different disciplines often have different interpretations of disaster resilience and have developed varying variables or metrics to measure resilience [2]. For example, engineers have developed a set of different metrics for resilience measurements [19], and many of them have not been included in those resilience assessment models developed by geographers or planners. The past few decades' hazards research has proved the necessity of interdisciplinary collaboration [20,21]. Ideally, the best practice in transportation resilience assessment is to consider the physical, human, and built environments and use big data to better measure those transportation infrastructure indicators that are related to community resilience. For example, we can integrate hazard simulations models and people's evacuation behaviors derived from relevant studies into evacuation modeling to derive more accurate evacuation time estimates and better measure the evacuation potential in the study area. The interdisciplinary nature of disaster research requires that researchers and practitioners from different disciplines collaborate more closely to develop assessment models to better measure the resilience of transportation infrastructure to build more resilient communities.



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