# Measuring the Impact of Transportation Diversity on Disaster Resilience in Urban Communities: Case Study of Hurricane Harvey in Houston, TX

Yan Wang, Ph.D., A.M.ASCE[1]; Armin Rahimi-Golkhandan, A.M.ASCE[2]; Changjie Chen[3]; John E. Taylor, Ph.D., M.ASCE[4]; and Michael J. Garvin, Ph.D., M.ASCE[5]

[1]Assistant Professor, Dept. of Urban and Regional Planning and Florida Institute for Built Environment Resilience, Univ. of Florida, PO Box 115706, Gainesville, FL 32611, U.S.A. (corresponding author). E-mail: yanw@ufl.edu
[2]Ph.D. Candidate, Via Dept. of Civil and Environmental Engineering, Virginia Tech, 121 Patton Hall, Blacksburg, VA 24061. E-mail: armin@vt.edu
[3]Ph.D. Candidate, College of Design, Construction and Planning, Univ. of Florida, PO Box 115706, Gainesville, FL 32611-5701. E-mail: chj.chen@ufl.edu
[4]Professor, School of Civil and Environmental Engineering, Georgia Institute of Technology, Mason 4140c, Atlanta, GA 30332, U.S.A. E-mail: jet@gatech.edu
[5]Associate Professor, Via Dept. of Civil and Environmental Engineering, Virginia Tech, 116 Patton, Blacksburg, VA 24061, U.S.A. E-mail: garvin@vt.edu

## ABSTRACT

The transportation system in urban areas plays a critical role in evacuation and resource supply during disasters. Transportation diversity, i.e., the availability and distribution of transportation modes across a community, impacts the mode complementarity, which can affect population movements and connectivity among spatial units—especially during extreme events when a failure in one mode can be compensated by other modes. However, few quantitative efforts have explored the impact of physical infrastructure configurations, and more specifically transportation diversity, on urban mobility and connectivity in an actual disaster context. In this paper, we measure transportation diversity with two factors—functional richness and functional evenness translated from the concept of diversity in ecological systems. Disaster resilience is regarded as a dynamic process pre, during, and post disaster in distinct communities and is tracked and quantified based on geospatial Twitter data of population cross-ZIP code tabulation areas movements with an ecology-inspired method—Fisher information—over time. Specifically, we compared the resilience of different neighborhoods in the city of Houston in Hurricane Harvey and found that neighborhoods with a higher level of transportation diversity demonstrated higher resiliency in their mobility during and after the hurricane. This study contributes to understanding how the availability and distribution of transportation infrastructure can impact the disaster resilience of human-infrastructure systems in urban areas. The results can improve transportation design and future urban planning, especially in the context of climate change and natural hazards.

## INTRODUCTION

Measuring resilience of the human-infrastructure system is the first step to operationalize the concept of resilience. Although an array of efforts have focused on defining and measuring resilience, very few have tried to understand how the distribution of transportation system modal options influences urban resilience at both spatial and temporal scales. Thus, it is still unknown how the availability and distribution of transportation modes across a community impact urban communities' capacity for preparing, absorbing, and recovery to disasters. Empirical studies on examining transportation physical configurations on resilience are still lacking. Most studies on transportation resilience that analyzed transportation modes focused on a single mode of transportation predominately (e.g., Omer et al., 2013; Kermanshah & Derrible, 2017; Amin et al., 2018) rather than considering multiple modes and their complementarity. While analyzing individual modes is beneficial in identifying the weaknesses of each mode separately, this approach fails to capture the capacity of the whole transportation system.

Therefore, a comprehensive analysis of a transportation system's resilience should encompass all available modes. Diversity is recognized as one of the properties of a resilient transportation system, and it is defined as having multiple elements with different functionality (Murray-Tuite, 2006). Characterizing the transportation diversity of an urban community can identify areas that are likely more vulnerable during a natural disaster. The measurements include functional richness and functional evenness of transportation modes (explained further in the next section) which are translated from the concept of biodiversity in ecological systems. Characterizing transportation diversity in different parts of an urban community enables us to investigate the impact of this factor on the resiliency of human mobility after a natural disaster.

Fortunately, the availability of crowdsourced data provides the opportunity to examine urban dynamics (e.g. human mobility) over time, especially, during disasters. Geographical and semantic data from a streaming API of Twitter (Wang & Taylor, 2018) have enabled the measurement of the dynamic process of urban resilience (Wang & Taylor, 2017). Therefore, taking advantage of the static geospatial data of the infrastructure system as well as the dynamic data of human movements, this research initiates the exploration of urban physical configuration's influence on resilience. Specifically, we examined how transportation diversity (quantified as functional richness and functional evenness) influences the dynamic process of resilience and explored if a case study community of higher transportation diversity would be more resilient to a disaster (i.e. hurricane and the following flood).

## LITERATURE REVIEW

**Ecology-inspired measurement of transportation systems:** In ecological systems, diversity is a key factor for the functionality of ecological communities and their resilience to disturbances (see, e.g., Tilman, 2014). Biodiversity is the number or composition of genotypes, species, or functional groups and how this composition is distributed in the functional space (Hooper et al., 2005). A group of species which are ecologically equivalent form a functional group (Naeem & Li, 1997). The existence and resilience of functional groups are more important than the abundance of individual species (Brokaw et al., 2012). Functional diversity in an ecological community has been characterized by (1) *functional richness* the abundance of functional groups, and (2) *functional evenness* the distribution of functional groups in the functional space (Mason et al., 2005; Mouillot et al., 2005, 2013). We translate these factors to transportation systems to characterize this resilience property of infrastructure.

**Ecology-inspired measurement of resilience:** Network analysis and Fisher information (FI) have been effectively used to assess vulnerability and measure resilience in ecology. Network analysis has been proven to be a useful quantitative tool for representing complex spatial structure (Bergsten & Zetterberg, 2013), describing the connectivity among fragmented landscapes (Fu et al., 2010), characterizing the spatially structured population in these landscapes (Bodin & Norberg, 2007), and disentangling the complexity within the spatiotemporal interactions between individuals and their environment (Jacoby & Freeman, 2016). Additionally, FI has been effectively used in measuring resilience in ecological systems by assessing changes in variables that characterize the condition of the system (e.g. Eason et al., 2016). This information-based method can detect the swift and subtle changes in system dynamics (Eason et al., 2016), and process a wide range of variables of different types and volumes (Eason & Cabezas, 2012). Urban communities are also characterized by dynamics and complexity. In this paper, we take advantage of network analysis in characterizing a population's movements and the underlying spatial structure and utilize FI to track the process of resilience to disasters.

## METHODOLOGY

Inspired by quantitative ecological approaches, we propose a research framework that comparatively examines how communities of different transportation diversity influence the process of resilience. We use Zip Code Tabulation Areas (ZCTA) as the basic spatial unit for the analysis of both transportation diversity and population movements. This is described in the following subsections.

**Transportation diversity:** Transportation diversity is characterized by (a) transportation functional richness: the abundance of alternative means (modes) for functionality (connectivity and mobility) in a community, and (b) transportation functional evenness: the homogeneity of the distribution of transportation modes across a community. The metrics for measuring these factors in each mode are provided in Table 1. Since the purpose of the richness metrics is to capture the availability of the physical structure of each mode in a ZCTA, the functionality and properties of these modes are not considered here. In the evenness metrics, the standard deviation of the shortest distance of census blocks within a ZCTA to an access point for a mode (i.e. a bus stop) indicates how a mode is distributed in that ZCTA, which is scaled by the square root of the ZCTA area for consistency. Richness and evenness metrics of all transportation modes in a ZCTA were combined using data envelopment analysis to indicate its diversity (Charnes et al., 1978).

**Table 1. Metrics of transportation functional richness and evenness**

| Mode | Functional Richness | Functional Evenness |
|---|---|---|
| ***1. Road Network (RN)*** | $R_{RN} = \frac{Total\ roadway\ mileage}{A}$ | $E_{RN} = \left(\frac{\sigma_{d_R}}{\sqrt{A}}\right)$ |
| ***2. Bus System (BS)*** | $R_{BS} = \left(\frac{n_s}{N_S^T \cdot A}\right)\left(\frac{n_l}{N_L^T}\right)$ | $E_{BS} = \left(\frac{\sigma_{d_B}}{\sqrt{A}}\right)$ |
| ***3. Rail Transit (RT)*** | $R_{RT} = \left(\frac{n_s}{N_S^T \cdot A}\right)\left(\frac{n_l}{N_L^T}\right)$ | $E_{RT} = \left(\frac{\sigma_{d_{RT}}}{\sqrt{A}}\right)$ |
| ***4. Bicycle Routes (BR)*** | $R_{BR} = \frac{Total\ bicycle\ routes\ mileage}{A}$ | $E_{BR} = \left(\frac{\sigma_{d_{BR}}}{\sqrt{A}}\right)$ |
| ***5. Walkways (WW)*** | $R_{WW} = \frac{Total\ walkway\ mileage}{A}$ | $E_{WW} = \left(\frac{\sigma_{d_W}}{\sqrt{A}}\right)$ |

$R$: richness
$n_s$: number of stops (stations)
$N_S^T$: the total number of bus (metro) stops (stations)
$\sigma_d$: SD of the shortest distance of census block centers in a ZCTA to transportation modes
$E$: evenness
$n_l$: number of bus (metro) lines
$N_L^T$: the total number of bus (metro) lines
$A$: area of the ZCTA

**Human movement-based resilience measurement:** We filtered geolocations into disaster-affected communities and aggregated the filtered data into the ZCTAs on a daily basis following methods proposed in Wang & Taylor (2015). An individual's movement from one ZCTA to another was regarded as a connection between the two areas. The choice of temporal scale (i.e. day) for forming one network can measure variations in network metrics and detect nuanced changes in the daily movement network over time. The spatial network formed in this study is a weighted undirected network, where nodes are distinct geographical areas, edges are movements between the two areas, and the number of movements is the weight of the edge regardless of direction. We then utilized system-wide network metrics (i.e. number of vertices, number of edges, average degree, density, diameter, average path length, giant component, transitivity, and modularity) (Newman, 2003) to measure the human-spatial system over time, and FI to assess the process of perturbation and resilience in the spatial networks of distinct urban communities. Details on FI calculation are available in Mayer et al. (2007).

## CASE STUDY AND RESULTS

**Case description:** Hurricane Harvey was a category *four* hurricane on the Saffir-Simpson Hurricane Wind Scale when it made landfall along the Texas coast on August 25, 2017. At least 68 people in Texas died during the storm and over half of the deaths (36) were in the Houston metropolitan area (National Hurricane Center, 2017). The hurricane warning was issued for most of the Texas coast on August 24 and ended on August 30 (National Hurricane Center, 2017), which also defines our studied disaster period. The city of Houston and the surrounding areas experienced unprecedented flooding with more than 80,000 homes affected (NOAA, 2017). The water in this area reached levels that have never been recorded and excessive rainfall caused widespread flooding on August 27th, and, in some areas, water levels remained elevated for a period of days to weeks.

**Data description:** The communities studied were formed by grouping individual ZCTAs with K-means clustering, which is an unsupervised clustering technique. We segmented 118 ZCTAs in the Houston metropolitan area into distinct subgroups and split them into k groups so that the variation within each group is as small as possible. Specifically, we considered both spatial contiguity and transportation diversity in the clustering analysis. Spatial contiguity was captured by the Euclidean distances between centroids of different ZCTAs. Both features were standardized before the K-means clustering. The Houston metropolitan area was partitioned into four subgroups, and we selected two subgroups as the comparative communities (Figure 1). One community (i.e. purple area) is in the downtown area of the City of Houston and contains 30 ZCTAs (area: 163 $mi^2$); the other is comprised of 21 ZCTAs in the southeast of Houston (area: 233 $mi^2$). The GIS data of transportation modes were derived from TxDOT and GIS databases of the City of Houston. Additionally, the cross-ZCTAs movements were generated based on Twitter geolocations over 42 days (i.e. August 10 to September 20, 2017). We used *spatial join* to filter geolocations in distinct ZCTAs within two communities. The two communities have a different number of cross-ZCTA movements: A total number of 14,724 movements were identified within the downtown community, whereas only 467 movements were found within the southeast community. This leads to, on average, approximately 350 and 11 daily cross-ZCTA movements in each community, respectively. The difference can be caused by population density, distinct cross-ZCTA movements inside selected communities, and data limitation.

**Results:** We measured the average diversity score of ZCTAs in the two communities in Houston: the score in the downtown community and the southeast community was 0.89 and 0.55, respectively. Figure 2 illustrates the diversity score in all ZCTAs of Houston. Subsequently, we computed network metrics of the two selected communities over the studied period and conducted FI analysis with all network metrics (due to page limitations, we omit the results of the network analysis over time). Figure 3 plots how FI values of the two selected communities changed pre, during, and post Hurricane Harvey. Both communities have experienced a decreasing dynamic order during the hurricane and the severe flooding and experienced additional dynamics after the perturbation. The downtown community shows more resistance to the disturbance due to the more stable FI pattern; while the southeast community continuously lost dynamic order over the two weeks during the disaster and started to bounce back with fluctuations over the last three weeks during our studied period.

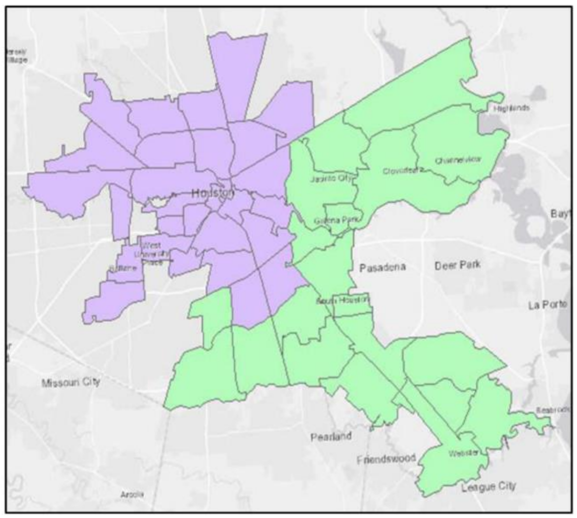


**Figure 1. Downtown community and southeast community in Houston**

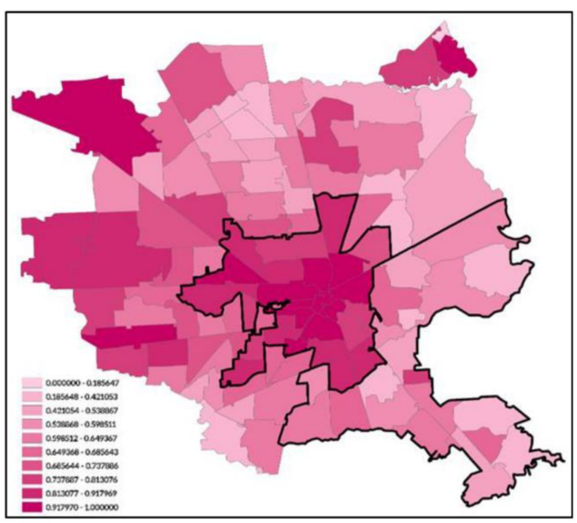

**Figure 2. Transportation diversity of ZCTAs in Houston**

## DISCUSSION

This preliminary study compares communities of different transportation diversity and their resilience to a disaster assessed by the process of absorption and recovery. The urban community characterized by a higher level of transportation diversity demonstrates more resilience. This can be caused by the fact that people in the downtown area have more selections of transportation modes and more accesses to different modes. Particularly, when a failure occurs in one or more modes due to a disaster, other modes can compensate for the failed ones in order to maintain the level of performance of the transportation system. To improve the diversity of transportation infrastructure in low-diversity ZCTAs in Houston, individual areas can be explored in more detail to identify whether modal availability (richness), distribution (evenness), or both need enhancement.

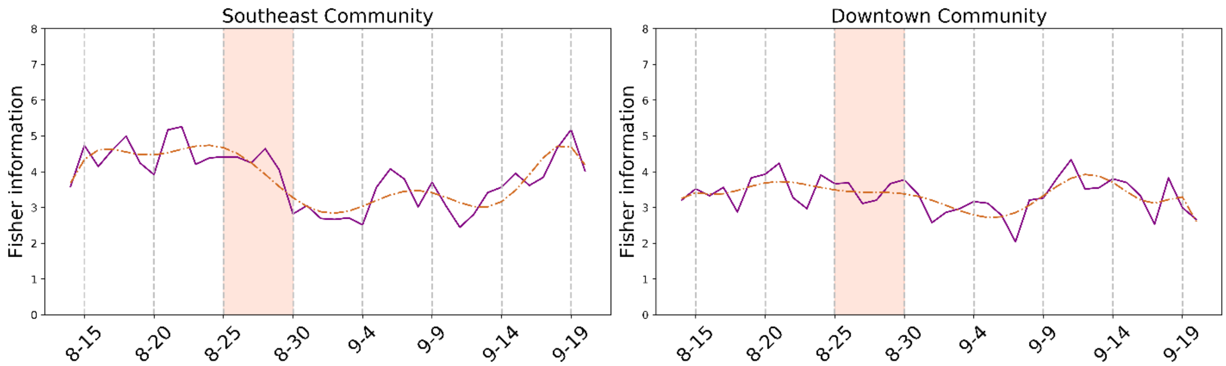


**Figure 3. Fisher information of the two communities**

There are some limitations that need to be addressed in our future work. Firstly, the calculation of evenness in ZCTAs only considers the direct distance of census block centers to a transportation mode which is an approximation of the actual distance. For more accurate calculation of distance, future studies can use Google Distance or Bing Map Distance from their APIs. Additionally, the number of daily average vertices in the spatial network retrieved from social networking platform at the community scale is not enough to make generalizations about the network of all locations in a city. However, the results show the perturbation on the human-spatial system caused by the hurricane and flood, as well as the recovery. With more geo-temporal data of higher resolution, a directed and weighted spatial network can be built to explore the system dynamics in distinct geographical contexts. Further, different selections of comparative communities may lead to differences in research results. Communities of distinct spatial scale in various urban contexts may suggest more underlying factors that contribute to resilience. Our selective communities are of a similar spatial scale and vulnerability level to flood hazard. The main difference between the two communities lies in transportation diversity, which makes them comparable. Our future research will extend this study by comparing urban communities of different scales.

## CONCLUSION

Ecology-inspired methods bridge the gap in engineering for quantitatively examining resilience with urban data and enable comparison between different communities. The case study presented in this paper takes a step towards understanding resilience as a unified concept across disciplines and explores the underlying physical factors of urban resilience. Our preliminary case study shows that an urban community characterized by a higher level of transportation diversity demonstrates more resilience during a disaster. We hope to extend this examination to more types of infrastructure systems (e.g. water, sewage, and electricity), different scales of urban communities, and other disaster cases. This study and the proposed future work will provide evidence-based design suggestions for civil engineers and urban planners to enable more resilience in the built environment.

## REFERENCES

Amin, M. S. R., Tamima, U., & Amador, L. (2018). Towards resilient roads to storm-surge flooding: case study of Bangladesh. *International Journal of Pavement Engineering*, 1-11.

Bergsten, A., & Zetterberg, A. (2013). To model the landscape as a network: A practitioner's perspective. *Landscape and Urban Planning*, 119, 35-43.

Bodin, Ö., & Norberg, J. (2007). A network approach for analyzing spatially structured populations in fragmented landscape. *Landscape Ecology*, 22(1), 31-44.

Brokaw, N., Zimmerman, J. K., Willig, M. R., Camilo, G. R., Covich, A. P., Crowl, T. A., ... & Myster, R. W. (2012). Response to disturbance. *A Caribbean Forest Tapestry: The Multidimensional Nature of Disturbance and Response*, 201-271.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429-444.

Derrible, S., & Kennedy, C. (2010). Characterizing metro networks: state, form, and structure. *Transportation*, 37(2), 275-297.

Díaz, S., & Cabido, M. (2001). Vive la difference: plant functional diversity matters to ecosystem processes. *Trends in Ecology & Evolution*, 16(11), 646-655.

Eason, T., & Cabezas, H. (2012). Evaluating the sustainability of a regional system using Fisher information in the San Luis Basin, Colorado. *Journal of Environmental Management*, 94(1), 41-49.

Eason, T., Garmestani, A. S., Stow, C. A., Rojo, C., Alvarez-Cobelas, M., & Cabezas, H. (2016). Managing for resilience: an information theory-based approach to assessing ecosystems. *Journal of Applied Ecology*.

Fu, W., Liu, S., Degloria, S. D., Dong, S., & Beazley, R. (2010). Characterizing the “fragmentation–barrier” effect of road networks on landscape connectivity: A case study in Xishuangbanna, Southwest China. *Landscape and Urban Planning*, 95(3), 122-129.

Hooper, D. U., Chapin, F. S., Ewel, J. J., Hector, A., Inchausti, P., Lavorel, S., ... & Schmid, B. (2005). Effects of biodiversity on ecosystem functioning: a consensus of current knowledge. *Ecological Monographs*, 75(1), 3-35.

Jacoby, D. M., & Freeman, R. (2016). Emerging network-based tools in movement ecology. *Trends in Ecology & Evolution, 31*(4), 301-314.

Jonkman, S.N., Godfroy, M., Sebastian, A. and Kolen, B. (2018). Brief communication: Loss of life due to Hurricane Harvey. *Natural Hazards and Earth System Sciences*, 18(4), pp.1073-1078.

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.

Mason, N. W., Mouillot, D., Lee, W. G., & Wilson, J. B. (2005). Functional richness, functional evenness and functional divergence: the primary components of functional diversity. *Oikos*, 111(1), 112-118.

Mayer, A. L., Pawlowski, C., Fath, B. D., & Cabezas, H. (2007). Applications of Fisher Information to the management of sustainable environmental systems Exploratory Data Analysis Using Fisher Information (pp. 217-244): *Springer*.

Mishra, S., Welch, T. F., & Jha, M. K. (2012). Performance indicators for public transit connectivity in multi-modal transportation networks. *Transportation Research Part A: Policy and Practice*, 46(7), 1066-1085.

Mouillot, D., Graham, N. A., Villéger, S., Mason, N. W., & Bellwood, D. R. (2013). A functional approach reveals community responses to disturbances. *Trends in Ecology & Evolution*, 28(3), 167-177.

Mouillot, D., Mason, W. N., Dumay, O., & Wilson, J. B. (2005). Functional regularity: a neglected aspect of functional diversity. *Oecologia*, 142(3), 353-359.

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

Naeem, S., & Li, S. (1997). Biodiversity enhances ecosystem reliability. Nature, 390(6659), 507-509.

National Hurricane Center. (2017). Hurricane HARVEY Advisory Archive. Retrieved from http://www.nhc.noaa.gov/archive/2017/HARVEY.shtml.

Newman, M. E. (2003). Mixing patterns in networks. *Physical Review E, 67*(2), 026126.

NOAA. (2017). Hurricane Harvey & Its Impacts on Southeast Texas from August 25th to 29th, 2017. Retrieved from http://www.weather.gov/hgx/hurricaneharvey.

Omer, M., Mostashari, A., & Nilchiani, R. (2013). Assessing resilience in a regional road-based transportation network. *International Journal of Industrial and Systems Engineering*, 13(4), 389-408.

Tilman, D., Isbell, F., & Cowles, J. M. (2014). Biodiversity and ecosystem functioning. Annual Review of Ecology, *Evolution, and Systematics*, 45.

Villéger, S., Mason, N. W., & Mouillot, D. (2008). New multidimensional functional diversity indices for a multifaceted framework in functional ecology. *Ecology*, 89(8), 2290-2301.

Wang, Q. and Taylor, J. (2015). "Process Map for Urban Human Mobility and Civil Infrastructure Data Collection Using Geo-Social Networking Platforms," *ASCE Journal of Computing in Civil Engineering*, 10.1061/(ASCE)CP.1943-5487.0000469, 04015004.

Wang, Y. & Taylor, J.E., (2017). Tracking urban resilience to disasters: a mobility network-based approach. In *Proceedings of the 14th International Conference on Information Systems for Crisis Response and Management* (ISCRAM 2017) (pp. 97–109). Albi, France.

Wang, Y., & Taylor, J. E. (2018). Coupling Sentiment and Human Mobility in Natural Disasters: A Twitter-based Study of the 2014 South Napa Earthquake. *Natural Hazards*, 1-19.