January 11, 2024

Lyles School of Civil Engineering
Delon and Elizabeth Hampton Hall of Civil Engineering
550 Stadium Mall Drive
West Lafayette, IN 47907-2051

Dear Colleagues

I am pleased to apply for the open-rank faculty position in your department in the area of Construction and Engineering and Management with a focus on Engineering for Humanity. I am a Tenured Associate Professor in the Zachry Department of Civil and Environmental Engineering at Texas A&M University. I received my doctoral degree in Civil Engineering from Purdue University in August 2013. As a Purdue alumni, I am interested in pursuing this faculty position in your department because I believe that my qualifications and research program fit well with the position description, as well as the strategic plan of your school.

I have a proven record of developing a vibrant externally-funded research program. Since I joined the Zachry Department of Civil and Environmental Engineering at TAMU in 2016, I have established a strong externally-funded interdisciplinary research program focusing on urban infrastructure resilience and data science/AI and have built synergistic collaborations across various disciplines. I established a new lab, the *UrbanResilience.AI* Lab, to coalesce innovative methods and models for understanding and improving resilience in urban systems. During my time at TAMU, I have been awarded, as the *lead PI* on multiple interdisciplinary projects, grants totaling more than $8.2M, with my share exceeding $5M. I have received various competitive awards such as a the NSF CAREER Award, Early-Career Fellowship of the National Academies' Gulf Research Program, ASCE Halpin Award, AWS Machine Learning Award, ENR's Top 20 Under 40, College of Engineering Faculty Excellence Award, Dean of Engineering Excellence Award, and Research Impact Award of Civil Eng. Department, and Best Paper Awards in ASCE Computing in Civil Engineering and Construction Research Congress. This competitive level of funding allows me to support a large and growing research group and maintain a productive research program. I am currently supervising 2 post-docs, 12 Ph.D. students, 8 MS students, and six funded undergraduate researchers in my lab. I have published 145 journal papers in various high impact civil engineering, disaster management, and interdisciplinary journals.

My research program advance convergence research in four new interdisciplinary and interrelated discovery areas: (1) Resilience of Interdependent Infrastructure Networks, (2) Equitable and Human-Centric Resilience, (3) Urban AI for Integrated Urban Design, and (4) Disaster Data Science for Smart Resilience. In all these discovery areas, my team and I utilize simulation, data analytics, complex network modeling, and machine learning to examine, understand, model, and improve resilience in urban systems through a better understanding of network dynamics in the Humans, Disasters, and Built Environment (HDBE) nexus. My research has a strong and direct impact on resiliency practice, and has attracted a lot of attention from industrial collaborators and stakeholders. For example, my research on resilience intelligence and disaster informatics is strongly supported by leading technology companies such as Waze, Facebook, INRIX, Microsoft, Cuebiq and AWS in terms of funding, datasets, as well as computational resources. Also, my research has received broad external media coverage. A key aspect of my research program is that I combine engineering, computing, and social sciences in ways that address resiliency issues more effectively through transcending disciplinary silos. During my time at TAMU, I have led multiple successful grants and projects with interdisciplinary teams from engineering, social, computer, and natural sciences. My commitment and contributions to interdisciplinary research has been recognized by me being named a Faculty/Research Fellow in the Institute for Disaster Resilient Texas (IDRT), Hazard Reduction and Recovery Center (HRRC), and the Institute for Sciences, Technology and Public Policy (ISTPP) at TAMU.

My time at TAMU has given me the opportunity to refine and demonstrate my effectiveness in teaching. I continually adopt innovative pedagogical methods, which has led me to consistently receive very positive student evaluations for my courses. I integrate my research into my teaching to provide high impact learning experiences for undergraduate students. I have consistently recruited undergraduate students in my lab and later recruited them for graduate studies. I have been a faculty mentor for Vertically Integrated Project (VIP) teams with more than 60 students from various departments over the past five years. My undergraduate and graduate research student

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mentees have received significant awards and scholarships. I have diverse expertise to develop and teach a variety of undergraduate and graduate courses related to urban infrastructure systems topics in your program.

I also have a strong record of external service and community engagement. In addition to membership in various professional committees and technical committees of top conferences in his field, I am a member of editorial boards of three ASCE journals. I get regularly invited to serve on NSF review panels. To broaden the impact of my research on communities, I closely collaborates with various regional organizations such as the Harris County Flood Control District, the Galveston District of the U.S. Army Corps of Engineers, and the City of Houston Office of Resiliency, as well as global organizations such as the World Bank's Disaster Risk Reduction and Recovery.

As an alumnus of Purdue, I am familiar with the level of excellence and interdisciplinary research and Purdue and I believe that my background, interdisciplinary research program, and technical expertise make me a unique fit for the posted position. I expect excellent opportunities for campus-wide collaborations (with different researchers in the School of Civil Engineering, College of Engineering, and other colleges) to create a hub for smart urban resilience research at Purdue.

I enclosed my curriculum vitae, statements for research, teaching, CV, and references in support of my application. If you require additional information, I will be happy to provide it.

Sincerely,

Ali Mostafavi

Associate Professor, Zachry Department of Civil and Environmental Engineering
Faculty Director, UrbanResilience.AI Lab
Early-Career Research Fellow, National Academies' Gulf Research Program
Faculty Fellow, Institute for Sustainable Communities
Fellow, Hazard Reduction and Recovery Center
Resilience Fellow, 4TU Resilience Engineering Center, TU Delft
Research Fellow, Institute for Science, Technology, and Public Policy
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Contact

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Website:
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Citizenship:
U.S. Citizen

Research Interests

Societal Challenges
Urban resilience, Disaster intelligence and informatics, Smart cities; Sustainable infrastructure.

Theory
Network dynamics; Complex adaptive systems; Urban science, Deep uncertainty decision-making.

Methods and Tools
Complex modeling; Dynamic network analysis; AI/Data analytics; Urban informatics; Agent-based modeling

Professional Experience, Affiliations, and License

Zachry Career Development Endowed Professorship
Zachry Department of Civil and Environmental Engineering
Texas A&M University
September 2021–present

Associate Professor
Zachry Department of Civil and Environmental Engineering
Texas A&M University - August 2020–Present

Assistant Professor
Zachry Department of Civil and Environmental Engineering
Texas A&M University - August 2016–August 2020

Texas Professional Engineer (PE) - 143521

Distinguished Partner
Institute for Disaster Resilient Texas, Texas A&M University
Jan 2023–present

Faculty Fellow
Hazard Reduction and Recovery Center, Texas A&M University
August 2018–present

Resilience Fellow
4TU Resilience Engineering Center, TU Delft, Netherlands
Oct 2020-present

Research Fellow
Institute for Science, Technology, and Public Policy,
Texas A&M University
November 2018–present

Associate Research Engineer
Texas Transportation Institute
August 2016–present

Assistant Professor
College of Engineering & Computing, Florida International University
August 2013–August 2016

Graduate Research/Teaching Assistant
School of Civil Engineering, Purdue University
May 2009–August 2013

Education

Ph.D., Civil Engineering
Purdue University, West Lafayette, Indiana, August 2013
Dissertation Title: Ex-Ante Assessment of Financial Innovation Policies in Infrastructure System-of-Systems

M.S., Industrial Administration
Purdue University, Krannert School of Management, August 2011
M.S., Industrial Administration

M.S., Civil Engineering
University of Tehran, August 2008
Thesis Title: Development of a Fuzzy Model for Appropriate Project Delivery System Selection

B.S., Civil Engineering
K.N. Toosi University of Technology, May 2006

Merit-based Awards, Honors, Fellowships, and Recognitions

- **2023 ASCE Daniel W. Halpin Award** for Scholarship in Construction from ASCE's Construction Institute for "exceptional leadership in establishing an outstanding research program that pioneer theories and practices of civil infrastructure resilience management to extreme weather events through advancing the state of the art in data-driven methods and computational modeling techniques."
- **Dean of Engineering Excellence Award – Associate Professor Level** (in recognition of excellence in all three major pillars of academia: teaching, research and service/engagement), College of Engineering, Texas A&M University, 2023.
- **Top 2% scientists in the world, 2021-2023:** in the subfields of Civil Engineering and AI, Reference: Ioannidis JPA (2023) Updated science-wide author databases of standardized citation indicators. https://elsevier.digitalcommonsdata.com/datasets/btchxktzyw/4
- **College of Engineering Excellence Faculty Award** (in recognition of excellence in contributions to the Engineering Program (scholarly activities, classroom instruction, and professional service)), College of Engineering, Texas A&M University, 2021.
- **Truman Jones Graduate Teaching Award (**In recognition of excellence in graduate teaching), Zachry Department of Civil and Environmental Engineering. Texas A&M University, 2021.
- **Best Paper Award,** Risk Analysis Journal, For the paper entitled: "Cultivating Metacognition In Each Of Us: Thinking About "Thinking" In Interdisciplinary Disaster Research", 2021**.**
- **Dean of Engineering Excellence Award – Assistant Professor Level** (in recognition of excellence in all three major pillars of academia: teaching, research and service/engagement), College of Engineering, Texas A&M University, 2020.
- **NSF CAREER Award,** National Science Foundation, 2019-2024.
- **Selected by the National Academy of Engineering** to participate in the 2020 Japan-American Frontiers of Engineering Symposium, 2021.
- **Best Paper Award**, ASCE Construction Research Congress, Infrastructure Systems and Sustainability Track, for the paper entitled: "Human Well-being and Infrastructure Systems in Disasters: An Empirical Study of Hurricane Harvey", 2020.
- **Selected by the National Academy of Sciences** to participate in the 7th Arab-American Frontiers of Science, Engineering, and Medicine Symposium, 2019.
- **Engineering Genesis Award** (*for lead-PI role of significant multidisciplinary research*)**,** College of Engineering, Texas Engineering Experiment Station, Texas A&M University, 2018.
- **Research Impact Award** (*for excellence in research*), Zachry Department of Civil Engineering, Texas A&M University, 2018.
- **Machine Learning Award**, Amazon Web Services (AWS), 2017.
- **Early-Career Research Fellowship,** National Academies of Sciences, Engineering, and Medicine, Gulf Research Program, 2017.
- **Rising Stars in Civil Engineering,** Civil + Structural Engineer Magazine, 2018.
- **Editor's Choice Article,** ASCE Natural Hazards Review for the article entitled: "Adaptive Capacity under Chronic Stressors: Assessment of Water Infrastructure Resilience in 2015 Nepalese Earthquake Using a System Approach," 2018.
- **Editor's Choice Article,** ASCE Journal of Construction Engineering and Management for the article entitled: "Metrics That Matter: Core Predictive and Diagnostic Metrics for Improved Project Controls and Analytics," 2018.
- **ASCE ExCEEd Fellowship,** American Society of Civil Engineers, 2017.
- **Engineering News Record (ENR) Top 20 under 40**, Southeast Region, 2015.
- **Distinguished Professor Award,** Construction Industry Institute, 2015**.**

- **Best Conference Paper Award,** Computing in Civil Engineering Conference 2015, American Society of Civil Engineers, for paper titled: "Integrated Performance Assessment of Construction Projects using Dynamic Network Analysis."
- **Citation in 2014 Marquis Who's Who in the World.**
- **NSF-ASCE Sponsored Construction Engineering Conference Travel Stipend Recipient**.
- **Highly Commended Journal Paper Award**, Journal of Built Environment Project and Asset Management, Emerald Literati Network Awards for Excellence 2013, for paper titled: "System-of-systems Approach for Assessment of Financial Innovations in Infrastructure."

Peer-reviewed Journal Papers

Journal Impact Factor Summary

The following table summarizes the impact factors of journals in which Mostafavi has published/submitted his work.

Journal Name	Impact Factor (2021) (JCR)	Journal Name	Impact Factor (2021) (JCR)
International Journal of Information Management	18.958	*Nature Scientific Reports*	4.997
Environmental Science and Technology	11.4	*Environmental Modeling and Software*	5.69
Sustainable Cities and Society	10.696	*IEEE Systems Journal*	4.802
Computer-Aided Civil and Infrastructure Engineering	10.066	International Journal of Digital Earth	4.606
International Journal of Project Management	9.037	Natural Hazards and Earth System Science	4.58
Journal of Environmental Management	8.91	*Earthquake Spectra*	4.33
Nature Communications Earth & Environment	7.29	Risk Analysis	4.302
Reliability Engineering and System Safety	7.09	*Journal of Royal Society Interface*	4.293
Transportation Research—Part D transport and environment	7.041	*Natural Hazards Review*	4.2
IEEE Transactions on Automation Science and Engineering	6.636	*Sustainability*	3.889
Journal of Transportation Research Part A: Policy and Practice	6.615	*Engineering Construction and Architectural Management*	3.85
Cities	6.4	PLoS One	3.752
Computers Environment and Urban Systems	6.454	*Water*	3.53
Journal of Management in Engineering-ASCE	6.415	*IEEE Access*	3.476

Journal of Computing in Civil Engineering	5.802	Journal of Infrastructure Systems	3.462
Journal of Construction Engineering and Management-ASCE	5.292	Nature Humanities and Social Sciences Communications	2.731
International Journal of Disaster Risk Reduction	4.842		

Total citations of 4990 – h-Index: 37 – Listed in the Stanford/Elsevier Top 2% Scientists since 2020 based on annual and career impact (sub-fields: Building and Construction; Artificial Intelligence).

Journal Papers Published (Total: 148)

*denotes Ph.D. student/post-doc advisee of Dr. Mostafavi

**denotes MS student advisee of Dr. Mostafavi

***denotes undergraduate research student advisee of Dr. Mostafavi

1. Coleman*, N., Liu*, C., Zhao**, Y., and Mostafavi, A. (2023). "Lifestyle Pattern Analysis Unveils Recovery Trajectories of Communities Impacted by Disasters," Nature Humanities and Social Science Communications, DOI: 10.1057/s41599-023-02312-7.
2. Liu*, C., and Mostafavi, A. (2023). "Network Diffusion Model Reveals Recovery Multipliers and Heterogeneous Spatial Effects in Post-Disaster Community Recovery," Nature Scientific Reports, DOI: 10.1038/s41598-023-46096-x.
3. Hsu*, C. W., Liu*, C., Nguyen**, K. M., Chien**, Y. H., & Mostafavi, A. (2023). "Do Human Mobility Network Analyses Produced from Different Location-based Data Sources Yield Similar Results across Scales?" Computers, Environment, and Urban Systems, 10.1016/j.compenvurbsys.2023.102052.
4. Yuan*, F., Farahmand*, H., Blessing, R., Brody, S., and Mostafavi, A. (2023). "Unveiling Vulnerability and Inequality in Disrupted Access to Dialysis Centers During Urban Flooding," Transportation Research: Part D, DOI: https://doi.org/10.1016/j.trd.2023.103920.
5. Liu*, Z., Liu*, C., and Mostafavi, A. (2023). "Beyond Residence: A Mobility-based Approach for Improved Evaluation of Human Exposure to Environmental Hazards," Submitted to Environmental Science and Technology, DOI: 10.1021/acs.est.3c04691.
6. Ma*, J., Li*, B., and Mostafavi (2023). "Characterizing Urban Lifestyle Signatures Using Motif Properties in Network of Places," Environment and Planning B: Urban Analytics and City Science, DOI: 10.1177/23998083231206171.
7. Hsu*, C., Ho**, M., and Mostafavi, A. (2023). "Human Mobility Networks Manifest Dissimilar Resilience Characteristics at Macroscopic, Substructure, and Microscopic Scales," Scientific Reports, DOI: 10.1038/s41598-023-44444-5.
8. Liu*, CF., and Mostafavi, A. (2023). "Equitable Optimization of Patient Re-allocation and Temporary Facility Placement to Maximize Critical Care System Resilience in Disasters," Healthcare Analytics, DOI: 10.1016/j.health.2023.100268.
9. Rajput*, A., and Mostafavi, A. (2023). "Latent sub-structural resilience mechanisms in temporal human mobility networks during urban flooding" Nature Scientific Reports, DOI: 0.1038/s41598-023-37965-6.
10. Esparza**, M., Farahmand*, H., Brody, S., and Mostafavi, A. (2023). "Examining Data Imbalance in Crowdsourced Reports for Improving Flash Flood Situational Awareness," International Journal of Disaster Risk Reduction, DOI: 10.1016/j.ijdrr.2023.103825.
11. Rajput*, A., Nayak**, S., Dong*, S., Mostafavi, A. (2023). "Anatomy of Perturbed Traffic Networks during Urban Flooding," Sustainable Cities and Society, DOI: 10.1016/j.scs.2023.104693.

12. Jiang*, Y., Yuan*, F., Farahmand*, H., Acharya**, K., and Zhang**, J., and Mostafavi, A. (2023). "Data-driven Tracking of the Bounce-back Path after Disasters: Critical Milestones of Population Activity Recovery and Their Spatial Inequality," International Journal of Disaster Risk Reduction, DOI: 10.1016/j.ijdrr.2023.103693.
13. Patrascu, F., Mostafavi, A., Vedlitz, A. (2023). "Relationship of Access to Critical Facilities During Normal Times with Disparities in Disrupted Access During Extreme Weather Events," Heliyon, DOI: 10.1016/j.heliyon.2023.e18841.
14. Farahmand*, H., Xu**, Y., and Mostafavi, A. (2023). "A Spatial-temporal Graph Deep Learning Model for Urban Flood Nowcasting Leveraging Heterogeneous Community Features," Nature Scientific Reports, DOI: 10.1038/s41598-023-32548-x.
15. Patrascu*, F., and Mostafavi, A. (2023). "Spatial Model for Predictive Recovery Monitoring Based on Hazard, Built Environment, and Population Features and Their Spillover Effects," Environment and Planning B: Urban Analytics and City Science, DOI: 10.1177/23998083231167433.
16. Liu*, C., and Mostafavi, A. (2023). "Hazard Exposure Heterophily: A Latent Characteristic in Socio-spatial Networks Influencing Community Resilience," Nature Scientific Reports, DOI: 10.1038/s41598-023-31702-9.
17. Afroogh, S., Mostafavi, A., Akbari, A., Pouresmaeil, Y., Goudarzi, S., Hajhosseini, F., and Rasoulkhani, K. (20XX). "Embedded Ethics for Responsible Artificial Intelligence Systems (EE-RAIS): A Conceptual Model," Ethics and Information technology, DOI: 10.1007/s43681-023-00309-1.
18. Coleman*, C., Esmalian*, A., Lee*, C., Gonzalez***, E, Koirala**, P., and Mostafavi, A. (2023). "Energy Inequality in Climate Hazards: Empirical Evidence of Social and Spatial Disparities in Managed and Hazard-Induced Power Outages," Sustainable Cities and Society, DOI: 10.1016/j.scs.2023.104491.
19. Kaur, N., Lee*, N., Mostafavi, A.. Mahdavi-Amiri, A. (2023). "DAHiTrA: Damage Assessment Using a Novel Hierarchical Transformer Architecture," Computer-Aided Civil and Infrastructure Engineering, DOI: 10.1111/mice.12981.
20. Yuan*, F., Lee*, C., Mobley, W., Farahmand*, H., Xu, Y., Blessing, R., Dong*, S., Mostafavi, A., and Brody, S. (2023). "Predicting Road Flooding Risk with Machine Learning Approaches Using Crowdsourced Reports and Fine-grained Traffic Data," Computational Urban Science, DOI: 10.1007/s43762-023-00082-1.
21. Dong*, S., Gao*, X., Mostafavi, A., Gao, J., and Gangwal, U. (2023). "Characterizing Resilience of Flood-disrupted Dynamic Transportation Network through the Lens of Link Reliability and Stability," Reliability Engineering and System Safety, DOI: 10.1111/mice.12972.
22. Fan*, C., Xu*, J., Natarajan*, Y., and Mostafavi, A. (2023). "Interpretable Machine Learning Automatically Learns Complex Interactions of Urban Features to Understand Socio-economic Inequality," Submitted to Computer-Aided Civil and Infrastructure Engineering, DOI: 10.1111/mice.12972.
23. Lee*, C., Rajput*, A., Hsu*, C., Fan*, C., Yuan*, F. Dong, S., Esmalian*, A., Farahmand*, H., Patrascu*, F., Liu*, C., Li*, B., Ma*, J., and Mostafavi*, A. (2022). "Quantitative Measures for Integrating Resilience Assessment into Transportation Planning Practice: Study of the State of Texas," Transportation Research Part D, DOI: 10.1016/j.trd.2022.103496.
24. Esmalian*, A., Yuan*, F., Coleman*, N., Xiao**, X., and Mostafavi, A. (2022). "Characterizing Equitable Access to Grocery Stores During Disasters Using Location-based Data," Nature Scientific Reports, DOI: 10.1038/s41598-022-23532-y.
25. Lee*, C., Maron, M., and Mostafavi, A. (2022). "Community-scale Big Data Reveals Disparate Impacts of the Texas Winter Storm of 2021 and Its Managed Power Outage," Nature Humanities and Social Science Communications, DOI: 10.1057/s41599-022-01353-8.
26. Li*, B., and Mostafavi, A. (2022). "Location Intelligence Reveals the Extent, Timing, and Spatial Variation of Hurricane Preparedness," Nature Scientific Reports, DOI: 10.1038/s41598-022-20571-3.

27. Lee*, C., Chou**, C., and Mostafavi, A. (2022)."Specifying Evacuation Return and Home-Switch Stability During Short-Term Disaster Recovery Using Location-Based Data," Nature Scientific Reports, DOI: 10.1038/s41598-022-20384-4.
28. Fan*, C., Jiang**, X., Lee*, R., & Mostafavi, A. (2022). Data-driven Contact Network Models of COVID-19 Reveal Trade-offs between Costs and Infections for Optimal Local Containment Policies. Cities, DOI: 10.1016/j.cities.2022.103805.
29. Dargin*, J., and Mostafavi, A. (2022). "Dissecting Heterogeneous Pathways to Disparate Household-level Impacts due to Infrastructure Service Disruptions," International Journal of Disaster Risk Reduction, DOI: 10.1016/j.ijdrr.2022.103351.
30. Coleman*, N., Gao*, X., DeLeon***, J., and Mostafavi, A. (2022). "Human Activity and Mobility Data Reveal Disparities in Exposure Risk Reduction Indicators among Socially Vulnerable Populations during COVID-19," Scientific Reports, DOI: 10.1038/s41598-022-18857-7.
31. Yuan*, F., Xu**, Y., Li*, Q., and Mostafavi, A. (2022). "Spatio-Temporal Graph Convolutional Networks for Road Network Inundation Status Prediction during Urban Flooding," Computers, Environment and Urban Systems in April 2021, DOI: 10.1016/j.compenvurbsys.2022.101870 .
32. Dvir, R., Vedlitz, A., and Mostafavi, A. (2022). "Far from home: Infrastructure, access to essential services, and risk perceptions during hazard events," International Journal of Disaster Risk Reduction in January 2022, DOI: 10.1016/j.ijdrr.2022.103185.
33. Yuan*, F., Fan*, C., Farahmand*, H., Coleman*, N., Esmalian*, A., Lee*, C., Patrascu*, F., Zhang*, C., Dong*, S., Mostafavi, A. (2022). "Smart Flood Resilience: Harnessing Community-Scale Big Data for Predictive Flood Risk Monitoring, Rapid Impact Assessment, and Situational Awareness," Environmental Research: Infrastructure and Sustainability, DOI: 10.1088/2634-4505/ac7251.
34. Yuan*, F., Esmalian*, A., Oztekin***, B., and Mostafavi, A. (2022). "Unveiling Spatial Patterns of Disaster Impacts and Recovery Using Credit Card Transaction Fluctuations," Environment and Planning B: Urban Analytics and City Science, DOI: 10.1177/23998083221090246.
35. Lin, B., Zou, L., Duffiel, N., Mostafavi, A., Cai, H., Zhou, B., Tao, J., Yang, M., Mandal, D. and Abedin, J. (2022). "Revealing the Global Linguistic and Geographical Disparities of Public Awareness to Covid-19 Outbreak through Social Media," International Journal of Digital Earth, DOI: 10.1080/17538947.2022.2070677.
36. Fan*, C., Jiang**, X., and Mostafavi, A. (2022). "Equality of Access Improves Resilience in Urban Population-facility Networks," EPJ Urban Sustainability, DOI: 10.1038/s42949-022-00051-3.
37. Zhou, B., Zou, L., Mostafavi, A., Lin, B., Yang, M., Gharaibeh, N., Cai, H., Abedin, J., and Mandal, D., (2022). "Harvesting Rescue Requests in Disaster Response from Social Media with BERT," Computers, Environment and Urban Systems, DOI: 10.1016/j.compenvurbsys.2022.101824.
38. Dong*, S., Gao*, X., Mostafavi, A., Gao, J. (2022). "Moderate Flooding Triggers Catastrophic Collapses in Road Networks due to Compound Failures," Nature Communications Earth & Environment, DOI: 10.1038/s43247-022-00366-0.
39. Li*, Q., Zhang*, C., and Mostafavi, A. (2022). "Content Analysis of Inter-organizational Communication Networks on Social Media during Disasters," International Journal of Emergency Management, DOI: 10.1504/IJEM.2022.125156.
40. Esmalian*, A., Wang**, W., and Mostafavi, A. (2022). "Multi-agent Modeling of Hazard-Human-Infrastructure Nexus for Equitable Resilience Assessment of Communities Facing Hurricane-Induced Power Outages," Computer-Aided Civil and Infrastructure Engineering, DOI: 10.1111/mice.12818.
41. Zhang*, C., Pradkar**, A., Yuan*, F., and Mostafavi, A. (2022). "Examining the consistency between geo-coordinates and content in geo-tagged tweets for enhanced disaster situational awareness," Submitted to the International Journal of Disaster Risk Reduction, DOI: 10.1016/j.ijdrr.2022.102878.
42. Farahmand*, H., Liu, X., Dong*, S., Mostafavi, A., and Gao, J. (2022). "Network Observability Framework for Optimal Sensor Placement in Flood Control Networks to Improve Risk Management," Reliability Engineering and System Safety, DOI: 10.1016/j.ress.2022.108366.

43. Rachunok, B., Fan*, C., Lee**, R., Nateghi, R., and Mostafavi, A. (2022). "Is the data suitable? The comparison of keyword versus location filters in crisis informatics using Twitter data," International Journal of Information Management: Data Insights, DOI: 10.1016/j.jjimei.2022.100063.
44. Redha*, T., Ross, A., and Mostafavi, A. (2022). "Public Risk Perception of Infrastructure Systems in Coastal Urban Areas and Factors influencing it," International Journal of Disaster Risk Reduction, DOI: 10.1016/j.ijdrr.2022.102883.
45. Esmalian*, A., Yuan*, F., Rajput*, A., Farahmand*, H., Dong*, S., Li*, Q., Gao*, X., Fan*, C., Lee*, C., Hsu*, C., Patrascu*, F., and Mostafavi*, A. (2022). "Operationalizing Resilience Practices in Transportation Infrastructure Planning and Project Development," Transportation Research-Part D, DOI: 10.1016/j.trd.2022.103214.
46. Afroogh*, S., Esmalian*, A., Mostafavi, A., Akbari, A., Rasoulkhani*, K., Esmaeili, S., and Hajiramezanali, e., (2022) "Tracing app technology: An ethical review in the COVID-19 era and directions for post-COVID-19," Ethics and Information Technology in August 2021, DOI: 0.1007/s10676-022-09659-6.
47. Dong*, S., Yu**, T., Farahmand*, H., and Mostafavi, A. (2022), "Predictive Multi-Watershed Flood Monitoring Using Deep Learning on Integrated Physical and Social Sensors," Environment and Planning B: Urban Analytics and City Science, DOI: 10.1177/23998083211069140.
48. Farahmand*, H., Wang**, W., Maron, M., and Mostafavi, A. (2022). "Anomalous Human Activity Fluctuations from Digital Trace Data Signal Flood Inundation Status," Environment and Planning B: Urban Analytics and City Science, DOI: 10.1177/23998083211069990.
49. Rajput*, A., Li*, Q., Gao*, X., and Mostafavi, A. (2022). "Revealing Critical Characteristics of Mobility Patterns in New York City During the Onset of COVID-19 Pandemic," Frontiers in Built Environment, DOI:10.3389/fbuil.2021.654409.
50. Yuan*, F., Yang**, Y., Li*, Q., and Mostafavi, A. (2021). "Unraveling the Temporal Importance of Community-scale Human Activity Features for Rapid Assessment of Flood Impacts," IEEE Access, 10.1109/ACCESS.2021.3137651.
51. Li*, Q., and Mostafavi, A. (2021). "Local Interactions and Homophily Effects in Actor Collaboration Networks for Urban Resilience Governance," Applied Network Science, DOI: 10.1007/s41109-021-00433-z.
52. Fan*, C., Jiang*, X., and Mostafavi, A. (2021). "Adaptive Reinforcement Learning Model for Simulation of Urban Mobility during Crises," Sustainable Cities and Society, DOI: 10.1016/j.scs.2021.103367.
53. Dargin*, J., Li*, Q., Jawer***, G., Xiao**, X., and Mostafavi, A. (2021). "Compounded Hazards of Colliding Hurricanes and Pandemics: An Examination of How Hurricane Protective Actions Could Increase Transmission Risk of COVID-19," International Journal of Disaster Risk Reduction in November 2020, DOI: 10.1016/j.ijdrr.2021.102560.
54. Fan*, C., Lee***, R., Yang**, Y., and Mostafavi, A. (2021). "Fine-grained data reveal segregated mobility networks and opportunities for local containment of COVID-19," Nature Scientific Reports, DOI: 10.1038/s41598-021-95894-8.
55. Wu**, F., Du, M., Fan*, C., Tang, R., Yang**, Y., Mostafavi, A., Hu, X. (2021). "Understanding Social Biases behind Location Names: Addressing Social Biases Encoded in Contextual Word Embedding Models," IEEE Transactions on Computational Social Systems, Transactions On Computational Social Systems, DOI: 10.1109/TCSS.2021.3106003.
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164. Ma*, J., and Mostafavi, A. (20xx). "Urban Form and Structure Explain Variability in Spatial Inequality of Property Flood Risk among US Counties," Submitted to Nature Communications Earth & Environment in June 2023, under review.

165. Ho*, Y., Lee*, C., Diaz, N., Brody, S., and Mostafavi, A. (20XX). "ELEV-VISION: Automated Lowest Floor Elevation Estimation from Segmenting Street View Images," Submitted to Landscape and Urban Planning in June 2023, under review.

166. Rajput*, A., Jiang*, Y., Nayak**, S., and Mostafavi. A. (20XX). "Mapping Inequalities in Activity-based Carbon Footprints of Urban Dwellers using Fine-grained Human Trajectory Data," Submitted to Cities in April 2023, under review.

167. Hsu*, C., Liu*, Z., Liu*, C., and Mostafavi, A. (20XX). "Unraveling Extreme Weather Impacts on Air Transportation and Passenger Delays using Location-based Data," Submitted to Transportation research: Part D, in March 2023, under review.

168. Fan*, C., Wu**, F., and Mostafavi, A. (20XX). "Discovering the Influence of Facility Distribution on Lifestyle Patterns in Urban Populations," Submitted to Developments in the Built Environment in March 2023, under review.

169. Ridha*, T., Ross, A., and Mostafavi, A. (20XX). "Impact of Public Perceptions and Attitudes on their Responses to Infrastructure Adaptation Processes in Coastal Urban Areas," Submitted to Sustainable Cities and Society in May 2023, under review.

170. Li*, X., Jiang*, Y., and Mostafavi, A. (20XX). "AI-assisted Protective Action: Study of ChatGPT as an Information Source for a Population Facing Climate Hazards," Submitted to the International Journal of Disaster Risk reduction in March 2023, under review.

171. Liu*, Z., Felton***, T., and Mostafavi, A. (20XX). “Interpretable machine learning for predicting urban flash flood hotspots using intertwined land and built-environment features,” Submitted to Computers, Environment, and Urban Systems in February 2023, under review.

172. Afroogh, S., and Mostafavi, A. (20XX). “Intelligent Environmental Empathy (IEE): A new power and platform to fostering green obligation for climate peace and justice,” Submitted to Ethics and Information Technology in April 2023, under review.

173. Huang*, X., Jiang*, Y., and Mostafavi, A. (20XX). “Emergence of Urban Heat Traps from the Intersection of Human Mobility and Heat Hazard Exposure in Cities,” Submitted to npj Urban Sustainability in May 2023, under review.

174. Jiang, Z., Han, X., Zou, N., Fan*, C., Mostafavi, A., Hu, X. (20XX). “Fair Graph Message Passing” Submitted to Transactions on Machine Learning Research in March 2023, under review.

175. Hsu*, C., Fan*, C., and Mostafavi, A. (20XX). “Limitations of gravity models in predicting fine-scale spatial-temporal urban mobility networks,” Submitted to Transportation Data Science in January 2023, under review.

176. Liu*, Z., and Mostafavi, A. (20XX). “Collision of Environmental Injustice and Sea Level Rise: Assessment of Risk Inequality in Flood-induced Pollutant Dispersion from Toxic Sites in Texas,” Submitted to the Journal of Environmental Management in December 2022, under review.

177. Fan*, C., Wu, F., and Mostafavi, A. (20XX). “Dynamics of Collective Information Processing for Risk Encoding in Social Networks during Crises,” Submitted to Information Processing and Management in June 2023, under review.

178. Liu*, C., Fan*, C., and Mostafavi, A. (20XX). “Graph Attention Networks Unveil Determinants of Intra- and Inter-city Health Disparity,” Submitted to Nature Scientific Reports in October 2022, under review.

179. Ma*, J., Li*, B., Li*,Q., Fan*, C., and Mostafavi, A. (20XX). “Attributed Network Embedding Model for Exposing COVID-19 Spread Trajectory Archetypes,” Submitted to Travel Research in September 2022, under review.

180. Lee*, C., Comes, T., Finn, M., and Mostafavi, A. (20XX). “Roadmap Towards Responsible AI in Crisis Resilience Management,” Submitted to ACM Computing and Sustainable Societies in April 2023, under review.

181. Fan*, C., Chien**, YH., and Mostafavi, A. (20XX). “Human Mobility Disproportionately Extends PM2.5 Emission Exposure for Low Income Populations,” Submitted to Nature Communications Earth & Environment in May 2022, under review.

182. Lee*, C., Namburi**, S., Xiao**, X., and Mostafavi, A. (20XX). “Homophilic and Heterophilic Characteristics Shaping Community Formation in Human Mobility Networks during Extreme Weather Response,” Submitted to International Journal of Disaster Risk Reduction in Dec 2022, under review.

183. Esparza**, M., Farahmand*, H., Liu, X., and Mostafavi, A. (20XX). “Enhancing Inundation Monitoring of Road Networks Using Crowdsourced Flood Reports,” Submitted to Computers, Environment and Urban Systems in January 2022, under review.

184. Fan*, C., Yang**, Y., and Mostafavi, A. (20XX). “Neural Embeddings of Urban Big Data Reveal Emergent Structures in Cities,” Submitted to Nature Humanities and Social Sciences Communications in September 2021, under review.

185. Gao*, X., Dong*, S., Mostafavi, A., and Gao, J. (20XX). “Macroscopic and Microscopic Characteristics of Networks with Time-variant Functionality for Evaluating Resilience to External Perturbations,” Submitted to Nature Scientific Reports in June 2020, under review.

Peer-reviewed Conference Papers

*denotes Ph.D. student/post-doc advisee of Dr. Mostafavi

**denotes MS student advisee of Dr. Mostafavi

***denotes undergraduate research student advisee of Dr. Mostafavi

C81. Jiang, Z., Han, X., Fan*, C., Zou, N., Mostafavi, A., Hu, X. (2023). "Chasing Fairness in Graphs: A GNN Architecture Perspective, The 38th Annual AAAI Conference on Artificial Intelligence, Vancouver, Canada.

C80. Jiang, Z., Han, X., Fan*, C., Zou, N., Mostafavi, A., Hu, X. (20XX). "Topology Matters in Fair Graph Learning: a Theoretical Pilot Study," Submitted to NeurIPS 2023, under review.

C79. Jiang, Z., Han, X., Fan*, C., Zou, N., Mostafavi, A., Hu, X. (20XX). "Robust Fairness via Aligned Sharpness-Aware Minimization under Demographic Shift," Submitted to AAAI Conference on Artificial Intelligence, Feb 7-14, 2023, Washington DC, under review.

C78. C77. Jiang, Z., Fan*, C., Mostafavi, A., Hu, X. (2022). "Generalized Demographic Parity for Group Fairness," International Conference on Learning Representations, International Conference on Machine Learning (ICML), July 17-23, 2022, Baltimore, MD.

C76. Esmalian*, A., Yuan*, F., Rajput*, A., Farahmand*, H., Dong*, S., Li*, Q., Gao*, X., Fan*, C., Lee*, C., Hsu*, C., Patrascu*, F., and Mostafavi*, A. (2022). "Operationalizing Resilience Practices in Transportation Infrastructure Planning and Project Development," Submitted to 2022 Transportation Research Board, Washington DC, January 9-13, 2022, under review.

C75. Farahmand*, H., Wang*, W., Mostafavi, A. and Maron, M. (2021). "Human Activity Telemetry Data for Rapid Flood Inundation Assessment: A Hurricane Harvey Study," ASCE Computing in Civil Engineering Workshop 2021 Orlando, FL: American Society of Civil Engineers.

C74. Yao, W., Zhang*, C., Huang, R., and Mostafavi, A. (2020). "Weakly-supervised Fine-grained Event Recognition on Social Media for Disaster Management," AAAI Conference on Artificial Intelligence, Feb 7-12 2020, New York, accepted (*acceptance rate 20.6%*).

C73. Fan, C., Farahmand, H., and Mostafavi, A. (2020). "Rethinking Infrastructure Resilience Assessment with Human Sentiment Reactions on Social Media in Disasters," The Hawaii International Conference on System Sciences (HICSS) 2020, January 7-10, Grand Wailea, Maui, accepted.

C72. Rasoulkhani*, K., Mostafavi, A., Presa Reyes, M., and Batouli, M. (2020). "Simulation-based Assessment of Adaptive Planning in Coastal Water Supply Infrastructure Systems," ASCE Construction Research Congress 2020, March 8-10, 2020, Tempe, Arizona, accepted.

C71. Dargin*, J., and Mostafavi, A. (2020). "Human Well-being and Infrastructure Systems in Disasters: An Empirical Study of Hurricane Harvey" ASCE Construction Research Congress 2020, March 8-10, 2020, Tempe, Arizona, accepted.

C70. Li, Q., Dong, S., and Mostafavi, A. (2020). "Community Detection in Actor Collaboration Networks of Resilience Planning and Management in Interdependent Infrastructure Systems," ASCE Construction Research Congress 2020, March 8-10, 2020, Tempe, Arizona, accepted.

C69. Esmalian*, A., Dong*, S., and Mostafavi A. (2020). "Empirical Assessment of Household Susceptibility to Hazards-induced Prolonged Power Outages," ASCE Construction Research Congress 2020, March 8-10, 2020, Tempe, Arizona, accepted.

C68. Farahmand*, H., Dong*, S., and Mostafavi, A. (2020). "Vulnerability Assessment in Co-located Flood Control and Transportation Networks," ASCE Construction Research Congress 2020, March 8-10, 2020, Tempe, Arizona, accepted.

C67. Fan*, C., Jiang***, Y., and Mostafavi, A. (2020). "Integrated Natural Language Processing and Meta-network Analysis for Social Sensing of Location-Event-Actor Nexus in Disasters," ASCE Construction Research Congress 2020, March 8-10, 2020, Tempe, Arizona.

C66. Cox*, C., and Mostafavi, A. (2020). "Modeling of Networks of Intangible Risks in Portfolio of Projects," ASCE Construction Research Congress 2020, March 8-10, 2020, Tempe, Arizona.

C65 . Rasoulkhani*, K., Alsharef, A., Li*, Q., Chowdhury, S., Banejee, S., Mostafavi, A., Zhu, J., Jaselskis, E., Stoa, R. (2020). "A Process Model for Regulatory Adaptation in the Construction Industry," ASCE Construction Research Congress 2020, March 8-10, 2020, Tempe, Arizona.

C64. Stoa, R., Mostafavi, A., Jaselskis, E., Zhu, J., Li*, Q., Rasoulkhani*, K., Banejee, S., Chowdhury, S., Alsharef, A., and Petty, C. (2019). "Regulatory Adaptation in The Energy Sector: Common Challenges and Emerging Solutions," the Proceedings of the 65th Annual Rocky Mountain Mineral Law Institute, Monterey, CA, July 18-20, 2019.

C63. Ridha*, T., and Mostafavi, A. (2019). "Assessment of the Dynamics of Human System Networks in Water Infrastructure Adaptation to Sea-level Rise Impacts." *The International Conference on Sustainable Infrastructure 2019*, Los Angeles, CA, November 7–9, 2019, accepted.

C62. Alsharef, A., Jaselskis, E., Mostafavi, A., Jin, Z., Stoa, R., Banerjee, S., Rasoulkhani*, K., Li*, Q., and Chowdhury, S. (2019). "Assessing the Impact of Regulatory Changes on Capital Projects in the United States." CIB World Building Congress, International Council for Research and Innovation in Building and Construction, Hong Kong, under review.

C61. Esmalian*, A., Ramaswamy, M., Rasoulkhani*, K., and Mostafavi, A. (2019). "Agent-based Modeling Framework for Simulation of Societal Impacts of Infrastructure Service Disruptions during Disasters." *ASCE International Conference on Computing in Civil Engineering*, June 17–19 2019, Atlanta, GA, accepted.

C60. Li*, Q., Dong*, S., and Mostafavi, A. (2019). "Characterization of Inter-organizational Coordination Dynamics in Resilience Planning: A Multilayer Network Simulation Framework." *ASCE International Conference on Computing in Civil Engineering*, June 17–19 2019, Atlanta, GA, accepted.

C59. Abula*, B., Mostafavi, A., and Birgisson, B. (2019). "Characterization of the Vulnerability of Road Networks to Pluvial Flooding Using Network Percolation Approach." *ASCE International Conference on Computing in Civil Engineering*, June 17–19 2019, Atlanta, GA, accepted.

C58. Fan*, C., Jiang*, Y., and Mostafavi, A. (2019). "Seeding Strategies in Online Social Networks for Improving Information Dissemination of Built Environment Disruptions in Disasters." *ASCE International Conference on Computing in Civil Engineering,* June 17–19 2019, Atlanta, GA, accepted.

C57. Rasoulkhani*, K., Mostafavi, A., and Sharvelle, S. (2019). "A Computational Simulation-Based Comparison of Dual and Singular Water Distribution Infrastructure Systems for the City of Fort Collins, Colorado." *ASCE International Conference on Computing in Civil Engineering*, June 17–19 2019, Atlanta, GA, accepted.

C56. Fan*, C., Yao, W., Mostafavi, A., and Huang, R. (2018). "A Graph-based Approach for Detecting Critical Infrastructure Disruptions on Social Media in Disasters." *The Hawaii International Conference on System Sciences (HICSS) 2019*, Hawaii, accepted.

C55. Fan*, C., Zhang*, C., and Mostafavi, A. (2018). "Meta-network Framework for Analyzing Disaster Management System-of-Systems;" *IEEE System of Systems Engineering Conference (SoSE),* June 13–15, 2018, Paris, France.

C54. Fan*, C., and Mostafavi, A. (2018). "A System Analytics Framework for Detecting Infrastructure-related Topics in Disasters Using Social Sensing." *25th International Workshop on Intelligent Computing in Engineering (EG-ICE),* June 10–13 2018, Lausanne, Switzerland.

C53. Fan*, C., and Mostafavi, A. (2018). "Establishing a Framework for Disaster Management, System-of-Systems." *IEEE SysCon 2018*, April 23–26, Vancouver, BC, Canada, Accepted.

C52. Zhu*, J., and Mostafavi, A. (2018). "Enhancing Resilience in Disaster Response: A Meta-Network Analysis Approach." *2018 ASCE Construction Research Congress*, Baton Rouge, LA, April 2–5, 2018.

C51. Palagi, S., Mostafavi, A., and Javernick-Will (2017). "Establishing a Model of Post-disaster Risk Reduction and Relocation Decision-making." *8th International i-Rec Conference*, Toronto, June 1–2, 2017.

C50. Zhu*, J., and Mostafavi, A. (2017). "Characterization of the Underlying Mechanisms of Vulnerability in Complex Projects Using Dynamic Network Simulation." *Winter Simulation Conference*, Las Vegas, NV, Dec 3–6, 2017.

C49. Rasoulkhani*, K., Presa Reyes**, M., and Mostafavi, A. (2017). "Emergence of Resilience from Infrastructure Dynamics: A Simulation Framework for Theory Building." *ASCE International Workshop on Computing in Civil Engineering*, June 2017, Seattle, WA.

C48. Rasoulkhani*, K., Logasa***, B., Presa Reyes**, M., and Mostafavi, A. (2017). "Agent-based Modeling Framework for Simulation of Complex Adaptive Mechanisms Underlying Household Water Conservation Technology Adoption." *Winter Simulation Conference*, Las Vegas, NV, Dec 3–6, 2017.

C47. Zhu*, J., Mostafavi, A., and Whyte (2017). "Towards Systems Integration Theory in Megaprojects: A System-of-Systems Framework." *Lean and Computing in Construction Congress (LC3)*, Heraklion, Crete, Greece, July 4–12, 2017.

C46. Batouli*, M., Bienvenu, M., and Mostafavi, A. (2017). "Putting Sustainability Theory into Roadway Design Practice: Implementation of LCA and LCCA Analysis for Pavement Type Selection in Real World Decision Making." *Transportation Research Board Annual Meeting 2015*, January 8–12, 2017 Washington DC.

C45. Nazarnia*, H., Mostafavi. A., Pradhananga, N., Ganapati, E., and Khanal*, R. (2016). "Assessment of Infrastructure Resilience in Developing Countries: A Case Study of Water Infrastructure in the 2015 Nepalese Earthquake." *International Conference on Smart Infrastructure and Construction (ICSIC)*, June 27–29, 2016, Cambridge, UK.

C44. Batouli*, M., and Mostafavi, A. (2016). "A Simulation Framework for Sustainability Assessment in Evolving Socio-Technical Infrastructure Systems." *International Conference on Sustainable Design, Engineering, and Construction (ICSDEC),* May 18–20, 2016, Tempe, AZs.

C43. Inyim*, J., Carmenate, T., Pachekar, N., Chauhan, G., Bobadilla, L., and Mostafavi, A. (2016). "Modeling Occupant-Building-Appliance Interaction for Energy Waste Analysis." *International Conference on Sustainable Design, Engineering, and Construction (ICSDEC)*, May 18–20, 2016, Tempe, AZ.

C42. Batouli*, M., and Mostafavi, A. (2016). "Assessment of Sea-Level Rise Adaptation in Coastal Infrastructure Systems: Robust Decision-Making under Uncertainty." *ASCE Construction Research Congress*, May 31–June 2, 2016, San Juan, PR.

C41. Inyim*, J., Carmenate, T., Hidalgo, D., Reyes, M., Leante, D., Bobadilla, L., and Mostafavi, A. (2016). "Smart Application for Integrated Sensing, Simulation, and Feedback of Occupant Behaviors to Enable Personalized Interventions for Energy Saving in Buildings." *ASCE Construction Research Congress*, May 31–June 2, 2016, San Juan, PR.

C40. Zhu*, J., and Mostafavi, A. (2016). "Dynamic Meta-Network Modeling for Integrated Project Performance Assessment under Uncertainty." *ASCE Construction Research Congress*, May 31–June 2, 2016, San Juan, PR.

C39. Pereyra**, J., He, X., and Mostafavi, A. (2016). "Multi-Agent Framework for Complex Adaptive Modeling of Interdependent Critical Infrastructure Systems." *ASCE Construction Research Congress*, May 31–June 2, 2016, San Juan, PR.

C38. Orgut, R., Batouli*, M., Zhu, J., Mostafavi, A., and Jaselskis, E. (2016). "Metrics that Matter: Evaluation of Metrics and Indicators for Project Progress Measurement, Performance Assessment, and Forecasting in Construction Phase." *ASCE Construction Research Congress*, May 31–June 2, 2016, San Juan, PR.

C37. Carmenate, T., Rahman, M., Leante, D., Bobadilla, L., and Mostafavi, A. (2015). "Modeling and Analyzing Occupant Behaviors in Building Energy Analysis Using an Information Space Approach." *2015 IEEE International Conference on Automation Science and Engineering*, August 24–28, 2015, Gothenburg, Sweden.

C36. Jia, J., Ibrahim, M., Orabi, W., Hadi, M., and Mostafavi, A. (2015). "Estimation of the Total Cost of Bridge Construction for use in Accelerated Bridge Construction Selection Decisions." *Transportation Research Board Annual Meeting 2016*, January 10–14, 2016, Washington DC.

C35. Batouli*, M., Swei, O.A, Zhu, J, Gregory, J., Kirchain, R., and Mostafavi, A. (2014). "An Integrated Methodology for Network-Level Cost Analysis in Roadway Infrastructure Management." *ASCE Computing in Civil Engineering Workshop 2015*, June 21–23, 2015, Austin, TX.

C34. Carmenate, T., Leante, D., Zanlongo, S., Bobadilla, L., and Mostafavi, A. (2014). "Decoding and Simulating Occupancy Behaviors in Building Energy Performance." *ASCE Computing in Civil Engineering Workshop 2015*, June 21–23, 2015, Austin, TX.

C33. Zhu, J., and Mostafavi, A. (2014). "Integrated Performance Assessment of Construction Projects using Dynamic Network Analysis." *ASCE Computing in Civil Engineering Workshop 2015*, June 21–23, 2015, Austin, TX.

C32. Rahman, M., Carmenate, T., Bobadilla, L., Zanlongo, S., and Mostafavi, A. (2014). "A Coupled Discrete Event and Motion Planning Methodology for Automated Safety Assessment in Construction Projects." *IEEE International Conference in Robotics and Automation,* May 26–30, 2015, Seattle, WA.

C31. Orgut, R., Zhu*, J., Batouli*, M. Mostafavi, A., and Jaselskis, E. (2014). "A Review of the Current Knowledge and Practice Related to Project Progress and Performance Assessment." *2015 International Construction Specialty Conference,* Canadian Society for Civil Engineering, June 8–10, 2015, Vancouver, BC, Canada.

C30. Zhu*, J. and Mostafavi, A. (2014). "An Integrated Framework for Ex-ante Assessment of Performance Vulnerability in Complex Construction Projects." *2015 International Construction Specialty Conference*, Canadian Society for Civil Engineering, June 8–10, 2015, Vancouver, BC, Canada.

C29. Batouli*, M. and Mostafavi, A. (2014). "Assessment of Network-level Environmental Sustainability in Infrastructure Systems using Service and Performance Adjusted LCA." *2015 International Construction Specialty Conference, Canadian Society for Civil Engineering*, June 8–10, 2015, Vancouver, BC, Canada.

C28. Inman**, A. and Mostafavi, A. (2014). "Exploratory Analysis of the Pathway towards Operationalizing Resilience in Transportation Infrastructure Systems." *Transportation Research Board Annual Meeting 2015*, January 11–15, 2015, Washington DC.

C27. Batouli*, M., and Mostafavi, A. (2014). "A Hybrid Simulation Framework for Integrated Infrastructure Management." *2014 Winter Simulation Conference*, December 7–10, 2014, Savannah, GA.

C26. Zhu*, J. and Mostafavi, A. (2014). "Integrated Simulation Approach for Assessment of Performance in Construction Projects: A System-of-Systems Framework." *2014 Winter Simulation Conference*, December 7–10, 2014, Savannah, GA.

C25. Rahman, M., Carmenate, T., Bobadilla, L., and Mostafavi, A. (2014). "Ex-Ante Assessment of Struck-by Safety Hazards in Construction Projects: A Motion Planning Approach." *2014 IEEE International Conference on Automation Science and Engineering*, August 18–22, 2014, Taipei, Taiwan.

C24. Zhu*, J. and Mostafavi, A. (2014). "An Integrated Framework for Bottom-Up Assessment of Performance in Construction Projects." *Project Management Symposium,* June 9–10, 2014, College Park, MD (paper accepted).

C23, Zhu*, J., Mostafavi, A., and Romero, G. (2014). "Project Organizations as Complex System-of-Systems: Integrated Performance Assessment at the Interface of Emergent Properties, Complexity, and Uncertainty." Engineering Project Organizations Conference (EPOC 2014).

C22. Inman**, A., Mostafavi, A., Ganapati, E., Guo, H., and Comu, S. (2014). "Towards Operationalizing Resilience in Transportation Infrastructure Management." *Project Management Symposium*, June 9–10, 2014, College Park, MD.

C21. Bobadilla, L., Mostafavi, A., Bista, S., and Carmenate, T. (2014). "Predictive Assessment and Proactive Monitoring of Struck-by Safety Hazards in Construction Sites: An Information Space

Approach." *International Society for Computing in Civil and Building Engineering (ISCCBE)*, June 23–25, 2014, Orlando, FL.

C20. Zhu*, J., Mostafavi, A., and Ahmad, I. (2014). "System-of-Systems Modeling of Performance in Complex Construction Projects: A Multi-Method Simulation Paradigm." *International Society for Computing in Civil and Building Engineering (ISCCBE),* June 23–25, 2014, Orlando, FL.

C19. Zhu*, J. and Mostafavi, A. (2014). "Towards a New Paradigm for Management of Complex Engineering Projects: A System-of-Systems Framework." *IEEE Systems Conference 2014*, March 31–April 3, 2014 Ottawa, ON, Canada.

C18. Mostafavi, A. (2013). "Integrated Policy Simulation in Complex System-of-Systems." *Winter Simulation Conference 2013,* December 8–11, Washington DC.

C17. Mostafavi, A., and Abraham, D.M. (2014). "Resilience-Based Planning in Civil Infrastructure using System-of-Systems Analysis." *ASCE Construction Research Congress 2014*, pp. 1249-1258, May 19-21, 2014, Atlanta, GA.

C16. Mostafavi, A. and Abraham, D.M. (2013). "A Framework for Policy Simulation in Complex Infrastructure Systems." *2013 INFORMS Annual Conference*, October 6 – 9, 2013, Minneapolis, MN.

C15. Mostafavi, A., Abraham, D. M., and Lee, J. (2013). "Assessment of the Determinants of Financial Innovations in Transportation Infrastructure." *Transportation Research Board Annual Meeting 2013*, January 13–17, Washington, DC.

C14. Mostafavi, A., Abraham, D. M., and Vives, A. (2013). "Assessment of Social Dimensions of Sustainable Innovative Financing in Transportation Infrastructure Projects." *Transportation Research Board Annual Meeting 2013*, January 13–17, Washington, DC.

C13. Huff, J., Mostafavi, A., Abraham, D. M., and Oakes, W. C. (2012). "Exploration of New Frontiers for Educating Engineers through Local and Global Service-Learning Projects." *Proceedings of ASCE Construction Research Congress 2012*, pp. 2081– 2090, May 21–23, 2012, Purdue University, West Lafayette, IN.

C12. Mostafavi, A., Abraham, D. M., Mannering, F. L., Vives, A., and Valentin, V. (2012). "Assessment of Social Attitudes towards Innovative Financing of Infrastructure Systems." *Proceedings of ASCE Construction Research Congress 2012*, pp. 2260–2269, May 21–23, 2012, Purdue University, West Lafayette, IN.

C11. Mostafavi, A., Abraham, D. M., DeLaurentis, D. A., Sinfield, J., and Queiroz, C. (2012). "Innovation Policy Assessment for Civil Infrastructure System-of-Systems." *Proceedings of ASCE Construction Research Congress 2012,* pp. 2300–2309, May 21–23, 2012, Purdue University, West Lafayette, IN.

C10. Mostafavi, A., Abraham, D. M., and DeLaurentis, D. A. (2012). "Simulation of the Policy Landscape of Transportation Infrastructure Financing Using Agent-Based Modeling." *Proceedings of 2012 ASCE International Workshop on Computing in Civil Engineering*, Raymond Issa and Ian Flood, Eds., pp. 121–128, ASCE, June 17–20, 2012, Clearwater Beach, FL.

C9. Valentin, V., Abraham, D. M., Mannering, F., and Mostafavi, A. (2012). "Assessment of Public Opposition to Infrastructure Developments: The Case of Nuclear Power Projects." *Proceedings of ASCE Construction Research Congress 2012*, pp. 1550–1559, May 21–23, 2012, Purdue University, West Lafayette, IN.

C8. Mostafavi, A. and Abraham, D. M., (2012). "Risk-Based Assessment of the Inspection of Transportation Construction Activities." *Transportation Research Board Annual Meeting 2012*, January 22–26, 2012, Washington, DC.

C7. Mostafavi, A., Valentin, V., Abraham, D. M. (2011). "Research-to-Practice (R2P) Tools for Improving Safety in Nighttime Highway Construction Work Zones." *Electronic Proceedings of Safety and Health in Construction, CIB W099,* Jeffrey Lew, Ed., August 24–26 2011, Washington, DC.

C6. Mostafavi, A., Abraham, D. M., and DeLaurentis, D. A. (2011). "Towards Sustainable Financial Innovation Policies in Infrastructure: A Framework for Ex-Ante Analysis." *Proceedings of 2011 ASCE Workshop of Computing in Civil Engineering,* Yimin Zhu and Raymond Issa, Eds., pp. 41–50, June 19–22, 2011, Miami, FL.

C5. Mostafavi, A., Abraham, D. M., Sullivan, C. A, and Valentin, V. (2011). "Evaluation of Innovative Financing Alternatives as Options for Accelerating Infrastructure Projects." *Electronic Proceedings of 3rd International/9th Construction Specialty Conference (CSCE 2011),* June 14–17, 2011, Ottawa, ON, Canada.

C4. Mostafavi, A., Abraham, D. M., and Sullivan, C. A. (2011). "Drivers of Innovation in Financing Transportation Infrastructure: A Systemic Investigation." *Electronic Proceedings of the Second International Conference on Transportation Construction Management*, February 7–10, 2011, Orlando, FL.

C3. Mostafavi, A. and Abraham, D. M. (2010). "Frameworks for Systemic and Structural Analysis of Financial Innovations in Infrastructure." working paper, Electronic Proceedings of 2010 Engineering Project Organization Conference (EPOC 2010), John E. Taylor and Paul Chinowsky, Eds., Engineering Project Organizations Society, November 4–6, 2010, South Lake Tahoe, CA.

C2. Mostafavi, A., Iseley, T., and Abraham, D. M. (2010). "Evaluating the Appropriateness of Project Delivery Systems for Different Trenchless Methods." Electronic Proceedings, *No Dig 2010 Conference*, North American Society of Trenchless Technology, May 2–7, 2010, Chicago, IL.

C1. Mostafavi, A., Karamouz, M., and Beigzadeh, S. (2008). "Project Procurement System and Project Delivery Systems." Electronic Proceedings of the *Second National Conference on Project Procurement Systems*, Center of Technology Studies at Sharif University of Technology, February 4–5, 2008, Tehran, Iran.

Book Chapters

- Chapter 14: GeoAI for Disaster Response, in Handbook of Geospatial Artificial Intelligence, doi: 10.1201/9781003308423-14, Lei Zou, Ali Mostafavi, Bing Zhou, Binbin Lin, Debayan, Mandal, Mingzheng Yang, Joynal Abedin, and Heng Cai.
- Chapter 3: Resilience Assessment Methods, in Hazard-Resilient Infrastructure: Analysis and Design, Manual of Practice, American Society of Civil Engineers (ASCE). doi:10.1061/9780784415757.ch3 (Mostafavi contributed to Chapter 3 along with Prof. John Van de Lindt (CSU) and Prof. Paolo Gardoni (UIUC).

Invited Workshops and Technical Panels

- Invited by the National Academies to participate on a panel in the Forum on Medical and Public Health Preparedness for Disasters and Emergencies and presented "AI for Augmenting Urban Resilience to Health Emergencies", November 2023.
- Invited by the U.K. Royal Academy of Engineering for an International Workshop to discuss Safer Complex Systems Programme (coordinated by Engineering X and founded by the Royal Academy of Engineering and the Lloyd's Register Foundation), 2020.
- NSF Natural Hazards Engineering Research Institute (NHERI) Idea Workshop, Washington DC, March 18, 2019. (Invited workshop participant)
- NSF Coastlines and People (CoPe) Scoping Workshop, Chicago, IL, October 2018. (Invited workshop participant)
- NSF Interdisciplinary Methods for Disaster Research Workshop, Boulder, CO, February 2018. (Invited workshop participant)
- NSF Interdisciplinary Methods for Disaster Research Workshop, Washington DC, March 2017. (Invited workshop participant)

Invited Technical Talks

- "AI-Empowered Digital Twin for Flood Resilience," Rice SSPEED Conference 2023, Rice University, Oct 2023.
- "Urban AI and Disaster Resilience," Computational Sciences and Engineering Division Seminar, Oak Ridge National Laboratory, June 2023.
- "The Next Big Leap: How AI and Data Science Can Transform Disaster Resilience Research and Practice," Ignite Workshop on AI for Crisis and Climate Security, TU Delft, May 9 2023.
- "Next Frontier of Resilience: Combating Disasters with AI and Data Science," ARISE-US Symposium for Digital Technology and Disaster Risk Reduction, Feb 14, 2023.
- "Probabilistic Economic Analysis for Climate Resilience Investments in Transportation Infrastructure", International Road Federation (IRF) Conference, Barbados, June 2022.
- "The Business Case for Climate Resilience Investments in Transportation infrastructure: The Study of Haiti", Urban Resilience 2022 (UR 22), Dec 2022.
- "Disaster-Proofing with AI and Data: The Next Frontier of Resilience," Liles Distinguished Seminar, Clemson University, April 2022.
- "Smart Resilience: Harnessing Big Data and AI to Augment Disaster Resilience," KTH Royal Institute of Technology, May 13, 2022.
- "Augmenting Urban Flood Resilience Using Big Data and Artificial Intelligence" SSPEED Center, Rice University, April 2022.
- "AI-driven Community Resilience" Liles Distinguished Seminar, Department of Civil Engineering, Clemson University April, 2022.
- "Smart Resilience: Harnessing Big Data and AI to Augment Disaster Resilience," IBM Future of Climate Seminar Series, IBM, July 27, 2021.
- "Smart Resilience to Health Crises: Predictive Pandemic Monitoring using Big Data and AI," FEMA R6 Interagency Recovery Coordination, August 3, 2021.
- "Towards Human-Centric Infrastructure Resilience," Structures Seminar, Oregon State University, March 2021.
- "Human Network Dynamics during Built Environment Disruptions using Digital Trace Data" Leading Scholar Seminar Series of the Urban Resilience Initiative, University of Central Florida, December 10, 2020.
- "Interdisciplinary Disaster Research in the Digital Age: Uncovering Human Network Dynamics during Built Environment Disruptions," Department of Civil and Environmental Engineering, Rice University, October 11, 2019.
- "Interdisciplinary Disaster Research in the Digital Age: Uncovering Human Network Dynamics during Built Environment Disruptions," School of Industrial Engineering Research Seminar, Purdue University, September 16, 2019.
- "Convergence Research for Integrating Societal Dimensions into Engineering and Planning of Resilient Infrastructure Systems," NSF Natural Hazards Engineering Research Institute (NHERI) Idea Workshop, Washington DC, March 18, 2019.
- "Anatomy of Coupled Human-Infrastructure Systems Resilience to Urban Flooding: Integrated Assessment of Social, Institutional, and Physical Networks," NSF CRISP Grantees PI Meeting, Washington DC, December 6, 2018.
- "Integrated Assessment of Social, Institutional, and Infrastructure Networks in Flood Hazard Mitigation Planning and Resilience Governance: Study of Houston in Hurricane Harvey," Natural Hazards Workshop Researchers Meeting, Boulder, CO, July 11, 2018.
- "System-of-Systems Modeling of Urban Resilience," Urban Infrastructures: Analysis And Modeling for Their Optimal Management and Operation, NSF Workshop, New York, December 2017.

- “Modeling Resilience in Complex Urban Infrastructure Systems,” International Workshop on Smart Cities, Human Behaviors, and Sustainable Development, NSF-NSFC Workshop, Beijing, China, September 2017.
- “Complex Adaptive Modeling of Infrastructure Resilience,” Department of Construction Management, Tsinghua University, Beijing, China, May 2017.
- “Emergence of Resilience from Network Dynamics in Project Systems,” School of Management Science and Engineering, Central University of Finance and Economics, Beijing, China, May 2017.
- “Assessment of Roadway Infrastructure Resilience and Adaptation to Sea-level Rise Impacts,” Department of Civil and Environmental Engineering, University of Washington, Seattle, April 2017.
- “Metrics that Matter: Improving Project Progress and Performance Assessment,” Northwest Construction Consumer Council, Seattle, April 2017.
- “Resilience of Post-Disaster Logistics and Supply Chain Systems: Case Study of the 2015 Nepalese Earthquake,” Disaster Resilient Supply Chain Operations (DROPS), Cambridge University, UK, November 2016.
- “Infrastructure System-of-Systems: A Holistic Paradigm for Sustainable and Resilient Civil Systems,” Department of Civil Engineering, Imperial College, London, June 2016.
- “Towards a new paradigm for management of complex engineering projects: A system-of-systems framework,” SoS Engineering Collaborators Information Exchange, The Deputy Assistant Secretary of Defense for Systems Engineering (DASD(SE)), November 2015.
- “Toward Theory of Infrastructure Ecology: Complex Adaptive Systems Analysis of Civil Infrastructure at the Interface of Engineering, Science, and Policy,” Sharif University of Technology, Tehran, 2014.
- “Toward Theory of Infrastructure Ecology: Complex Adaptive Systems Analysis of Civil Infrastructure at the Interface of Engineering, Science, and Policy,” University of Tehran, Tehran, 2014.
- “Ex-Ante Analysis of Sustainable Policies in Infrastructure System-of-Systems,” Durham Ph.D. Symposium, University of Nebraska–Lincoln, 2013, Lincoln, NE.
- “Ex-Ante Analysis of Financing Policies in Transportation Infrastructure Systems,” Revenue and Finance Committee (ABE 10), Transportation Research Board, 92nd Annual Meeting, January 14, 2013, Washington, DC.
- “Policy Simulation for Sustainable Infrastructure Planning,” Pecha Kucha Session: Transforming Urban Mobility Takes Innovation of All Kinds, Transportation Research Board, 92nd Annual Meeting, January 16, 2013, Washington, DC.
- “Ex-ante Simulation of Infrastructure Financing Policies,” Let’s Rebuild America Leadership Council Working Group, U.S. Chamber of Commerce, June 26, 2012, Washington DC.
- “Simulation and Visualization of Financing Policies in Transportation Infrastructure Systems,” Research and Innovative Technology Administration, U.S. Department of Transportation, January 26, 2012, Washington, DC.
- “Model for Ex-ante Policy Analysis in Infrastructure Systems,” Marketing Transportation Programs Session (Session 764), *Transportation Research Board, 91st Annual Meeting*, January 25, 2012, Washington, DC.
- “Model for Visualization and Simulation of Financing Policies in Infrastructure Systems,” Performance Measurement Committee (ABC30), *Transportation Research Board, 91st Annual Meeting*, January 24, 2012, Washington, DC.
- “Visualization of Financing Policies in Transportation Systems,” Visualization in Transportation Committee (ABJ95), *Transportation Research Board, 91st Annual Meeting*, January 24, 2012, Washington, DC.

Research Reports

Mostafavi et al. Establish TxDOT Transportation Resilience Planning Scorecard and Best Practices (No. FHWA/TX-20/0-7079-R1.

Mostafavi et al. Hurricane Harvey Infrastructure Resilience Investigation Report. http://dx.doi.org/10.17603/ds2-gcrf-h607

Kruse, C. J., Mostafavi, A., Fan, C., Moya, J., & Risko, A. (2019). Enhancing the Sustainability of Gulf Intracoastal Waterway Dredge Material Placement Areas (No. FHWA/TX-19/0-6962-R1).*

Mostafavi, A., Batouli, M., Bienvenu, M. (2016). "Development of Life-Cycle Assessment (LCA) and Life-Cycle Cost Analysis (LCCA) for Pavement-Type Selection for SR-836 Extension," Miami-Dade Expressway, August 2016.*

Orgut, R., Zhu, J., Batouli*, M., Mostafavi, A., and Jaselskis, E. (2016). "Metrics That Matter: Improving Project Progress and Performance Assessment," Construction Industry Institute, August 2016.*

Mostafavi, A., Abraham, D.M., and Sullivan, C. (2013). "Assessment of Policies for Innovative Financing in Infrastructure Systems," Global Policy Research Institute, Purdue University, August 2013.

Mostafavi, A. and Abraham, D. M. (2012). "Indiana Department of Transportation Construction Inspection Priorities," Final Report, Joint Transportation Research Program of Purdue University and the Indiana Department of Transportation, Grant No. SPR-3400, PI: Professor Dulcy M. Abraham, May 2012.

Valentin, V., Mostafavi, A., Faust, K., and Abraham, D. M. (2011). "Safety of Nighttime Construction Operations," Final Report, National Institute of Occupational Safety and Health (NIOSH), Grant No.1 R01 0H07553, PI: Professor Dulcy M. Abraham, March 2011.

Peer-reviewed/Invited Poster Presentations

*denotes graduate student advisee

P13. Zhu, J., and Mostafavi, A. (2015) "Meta-Network Modeling Framework for Integrated Assessment of Risk, Vulnerability, and Resilience in Complex Construction Projects," CII Annual Conference, August 3-5, 2015, Boston, MA.

P12. Batouli*, M. and Mostafavi, A. (2014). "Ex-Ante Simulation and Visualization of Sustainability Policies in Infrastructure Systems: A Hybrid Methodology for Modeling Agency-User-Asset Interactions," ASCE Construction Research Congress 2014, May 19-21, 2014, Atlanta, GA.

P11. Zhu, J. and Mostafavi, A. (2014). "Ex-Ante Assessment of Performance in Construction Projects: A System-of-Systems Approach," ASCE Construction Research Congress 2014, May 19-21, 2014, Atlanta, GA (poster was presented by Jin Zhu).

P10. Mostafavi, A. and Abraham, D. M. (2012). "Policy Analysis in Complex Infrastructure Systems under Deep Uncertainty," Construction Industry Institute Annual Conference, July 23–25, 2012, Baltimore, MD (poster was presented by Ali Mostafavi).

P9. Mostafavi, A. and Abraham, D. M. (2012). "Dealing with Uncertainties and Complexities in Infrastructure System-of-Systems," NSF CMMI Engineering Research and Innovation Conference, July 9-12, 2012, Boston, MA (poster was presented by Ali Mostafavi).

P8. Mostafavi, A. and Abraham, D. M. (2012). "Simulation and Visualization of Financing Policies in Infrastructure Systems," Construction Research Congress 2012, ASCE, May 21-23, 2012, Purdue University, West Lafayette, IN (poster was presented by Ali Mostafavi and was the recipient of third place poster award).

P7. Mostafavi, A. and Abraham, D. M. (2012). "Prioritization of Inspection of Construction Activities," 98th Annual Purdue Road School, March 6-7, 2012, Purdue University, West Lafayette, IN (poster was presented by Ali Mostafavi).

P6. Mostafavi, A. and Abraham, D. M. (2012). "Landscape of Financing Policies in Transportation Infrastructure," 98th Annual Purdue Road School, March 6-7, 2012, Purdue University, West Lafayette, IN (poster was presented by Ali Mostafavi).

P5. Mostafavi, A. and Abraham, D. M. (2011). "Assessment of the Dynamics of Financial Innovations in Infrastructure Systems," Construction Industry Institute Annual Conference, July 25-27, 2011, Chicago, IL (poster was presented by Ali Mostafavi).

P4. Mostafavi, A., Valentin, V., and Abraham, D. M. (2011). "Assessment of Safety in Nighttime Highway Work Zones," 2011 NORA Symposium, July 12-13, 2011, Cincinnati, OH (poster was presented by Ali Mostafavi).

P3. Mostafavi, A. and Abraham, D. M. (2011). "Risk-Based Assessment of Construction Inspection Priorities," 97th Annual Purdue Road School, March 8-10, 2011, Purdue University, West Lafayette, IN (poster was presented by Ali Mostafavi).

P2. Mostafavi, A. and Abraham, D. M. (2011). "Assessment of Sustainable Innovation for Financing Transportation Infrastructure," 97th Annual Purdue Road School, March 8-10, 2011, Purdue University, West Lafayette, IN (poster was presented by Ali Mostafavi).

P1. Mostafavi, A. and Abraham, D. M. (2010). "Frameworks for Systemic and Structural Analysis of Financial Innovations in Infrastructure," 2010 Engineering Project Organization Conference (EPOC 2010), November 4-6, 2010, South Lake Tahoe, CA (poster was presented by Ali Mostafavi).

External and Internal Research Grants and Funding

The summary of external and Internal grant amounts and Mostafavi's share is shown in the table below:

	All Grants	
	Total Amount	*Mostafavi Amount Share*
Total	$8,245,557	$5,033,984
TAMU (8/16–8/24)	$7,495,123	$4,741,222
FIU (8/13–8/16)	$750,434	$292,762

**Total number of external grant projects: 18 (Lead PI on 14 external grants with total amount of $5.95M)*

The following table presents the list of external grants and summaries:

Role	Agency	Grant Type	Duration	Title	Collaborators/ Co-PI (credit share)	Total Amount	Mostafavi Share Amount
PI	National Science Foundation	Federal	9/1/23-5/31/24	Understanding Drivers of Inequality in Environmental Hazard Exposures in Overburdened Communities using Interpretable Machine Learning	-	$75,000	$75,000
PI	Texas A&M Office of the Vice President for Research	Internal	9/1/23-8/31/25	AI-Empowered Digital Twin for Climate Resilience Analytics	-	$100,000	$100,000
PI	CREATE University Transportation Center (UTC)	Federal	9/1/23-8/31/24	Transportation Assets Risk and Resilience Analysis to Reduce Societal Risks to Vulnerable Populations	-	$112,500	$112,500
PI	TDEM	Intra-System	4/1/23-5/1/24	Applied Emergency Management Uses Cased of AI for Situational Awareness	-	$35,000	$35,000
Co-PI	TXDOT	State	9/1/23-8/31/25	Develop Systematic and Quantitative Approach to Assess the Probability of Extreme Weather and Resilience Risks for TxDOT Highways and Bridges	Andrew Burt (TTI); Jorge Prozzi (UT Austin)	$750,000	$100,000
PI	NSF	Federal	4/1/20 – 3/31/22	Urban Resilience to Health Emergencies: Revealing Latent Epidemic Spread Risks from Population Activity Fluctuations and Collective Sense-making	-	$200,000	$200,000
PI	TXDOT	State	9/1/20-8/31/22	Establish TxDOT Transportation Resilience Planning Scorecard and Best Practices	-	$500,000	$500,000

Role	Agency	Grant Type	Duration	Title	Collaborators/ Co-PI (credit share)	Total Amount	Mostafavi Share Amount
PI	Texas A&M Office of the Vice President for Research	Internal	9/1/2020 - 8/31/2023	X-Grant: Disaster City Digital Twin: Integrating Machine and Human Intelligence to Augment Flood Resilience	Sam Brody (25%); Xia Hu (10%);	1,000,000	$625,000
PI	Microsoft AI for Health	Industry	5/1/2020 – 12/31/2021	Predictive Pandemic Monitoring in Urban Systems	-	$105,000 (in Azure cloud computing credits)	$105,000
PI	NSF	Federal	2/115/19 – 2/14/24	CAREER: Household Network Modeling and Empathic Learning for Integrating Social Equality into Infrastructure Resilience Assessment	-	$570,000	$570,000
PI	NSF	Federal	1/1/19–12/31/23	CRISP 2.0 Type 2: Anatomy of Coupled Human-Infrastructure Systems Resilience to Urban Flooding: Integrated Assessment of Social, Institutional, and Physical Networks	Philip Berke (20%), Arnold Vedlitz (15%), Sierra Woodruff (2.5%), Bjorn Birgisson (5%)	$2,000,000	$1,180,422
Co-PI	National Academies Gulf Research Program	Federal	1/1/20-12/31/22	Measuring and Improving Blended Project-Safety Culture in Operations of Offshore Oil and Gas Facilities	Ivan Damnjanovic (PI); John Walewski (Co-PI)	$733,631	$150,000
PI	Amazon AWS Award	Industry	Unrestricted Gift	AWS Machine Learning Award	–	$75,000 ($25,000 funds + $50,000 AWS credit)	$75,000
PI	NSF	Federal	10/1/17–9/31/19	Houston in Hurricane Harvey (H3): Establishing Disaster System-of-Systems Requirements for Network-Centric and Data-Enriched Preparedness and Response	Xia Hu (5%), Ruihong Huang (10%), Bjorn Birgisson (2.5%)	$49,915	$40,000
PI	NSF	Federal	10/15/17 – 10/14/19	Assessment of Risks and Vulnerability in Coupled Human-physical Networks of Houston's Flood Protection, Emergency Response, and Transportation Infrastructure in Harvey	Arnold Vedlitz (10%), Philip Berke (20%), Xia Hu (2.5%), Bjorn Birgisson (5%)	$188,873	$156,000
PI	National Academies	Federal	9/1/17–10/31/20	Early-Career Research Fellowship	–	$119,543	$119,543
PI	NOAA Sea Grant Program	Federal	2/1/18–1/31/20	Resilient Adaptation of Interdependent Built, Ecological, and Governance Systems to Sea-level Rise Impacts in Texas Coastal Communities	–	$147,203 (+$76,704 in cost sharing*)	$147,203 (+$76,704 in cost sharing)
Co-PI	Texas DOT	State	9/1/17–9/31/18	Determine Placement Area Sustainability	Jim Kruse (PI) (75%)	$297,635	$75,000
PI	Construction Industry Institute	Industry	5/1/17–8/31/19	Identifying and Evaluating the Impacts of Regulations throughout the Project Lifecycle	Ed Jaselskis (NC State) (30%) Ryan Stoa (Concordia School of Law) (25%), Jin Zhu (U Conn) (15%)	$469,297	$151,266

Role	Agency	Grant Type	Duration	Title	Collaborators/ Co-PI (credit share)	Total Amount	Mostafavi Share Amount
Co-PI	NSF	Federal	3/1/17–8/31/20	Urban Water Innovation Network (U-WIN): Transitioning Toward Sustainable Urban Water Systems	Network of faculty from FIU, ASU, UC Berkeley, CSU, University of Miami, OSU. University of Oregon	Total Network Award: $12M; FIU Share $900,000**	$140,000 ($71,526 transferred from FIU to TAMU)
					Total TAMU	$6,491,097	$4,060,960
Research Grants at FIU							
PI	NSF	Federal	8/2015–8/2016	RAPID: Assessment of Cascading Failures and Collective Recovery of Interdependent Critical Infrastructure in Catastrophic Disasters in Nepal	E. Ganapati and N. Pradhananga (FIU)	$49,962	$43,962
PI	Construction Industry Institute	Industry	8/2014–8/2016	Improving Project Progress and Performance Assessment	Other PI: E. Jaselskis (NC State)	$239,781	$83,570
Co-PI	NSF	Federal	9/2015–9/2017	Strategies for Leaning: Augmented Reality and Collaborative Problem-Solving	S. Vassigh (PI-FIU), E. Newman (FIU), D. Davis (FIU) A. Behzadan (Missouri State)	$219,637	$32,230
PI	Miami-Dade Expressway (MDX)	Industry	2/2015–5/2016	Development of LCA and LCCA for Pavement-type selection for MDX SR 836 Extension	Other PI: M. Bienvenu (FIU)	$109,765	$93,000
Co-PI	ABC UTC	State	7/2014–7/2016	Estimating total cost of bridge construction using ABC and conventional methods of construction	M. Hadi (PI), and W. Orabi (all FIU)	$131,289	$40,000
					Total FIU	$750,434	$292,762
					Total (TAMU+FIU)	$6,241,531	$3,728,722

**Cost share has not been counted in calculation of total grants*
***In calculation of total awarded funds, only Mostafavi's share was calculated (not FIU share nor total project)*

External Media Coverage and Highlights

- Big data-derived tool facilitates closer monitoring of recovery from natural disasters, NSF Research News: https://www.nsf.gov/discoveries/disc_summ.jsp?cntn_id=303264&org=NSF&from=news
- Tools derived from big data facilitate more in-depth monitoring of recovery from natural disasters, Florida News Times, July 2021, https://floridanewstimes.com/tools-derived-from-big-data-facilitate-more-in-depth-monitoring-of-recovery-from-natural-disasters/310502/
- Big data-derived tool facilitates closer monitoring of recovery from natural disasters. ScienceDaily. ScienceDaily, 22 July 2021. www.sciencedaily.com/releases/2021/07/210722171220.htm
- Covid-19 and the bushfire season, Saturday Paper (Australian Media), November 2020: https://www.thesaturdaypaper.com.au/news/health/2020/11/21/covid-19-and-the-bushfire-season/160587720010735
- Proposed 'contagion' model predicts roadway flooding in urban areas, ASCE Civil Engineering Magazine, November 2020: https://source.asce.org/proposed-contagion-model-predicts-roadway-flooding-in-urban-areas/
- Deep Learning Model Predicts COVID-19 Surges 7 Days into the Future, Health IT Analytics, October 2020: https://healthitanalytics.com/news/deep-learning-model-predicts-covid-19-surges-7-days-into-the-future
- Using AI and big data to predict the future spread of COVID-19 cases, October 2020, Medical News: https://www.news-medical.net/news/20200929/Using-AI-and-big-data-to-predict-the-future-spread-of-COVID-19-cases.aspx
- Texas A&M predicting COVID-19 spread with deep-learning model, EdScoop, October 2020: https://edscoop.com/texas-am-covid19-deep-learning-ai/
- Researchers develop flood prediction tool, National Science Foundation News (***featured on NSF front page***) , March 10, 2020: https://www.nsf.gov/discoveries/disc_summ.jsp?cntn_id=300168
- Hurricanes and Wildfires Are Colliding with the COVID-19 Pandemic – and Compounding the Risks – August 2020:
  - Government Executive: https://www.govexec.com/management/2020/08/hurricanes-and-wildfires-are-colliding-covid-19-pandemic-and-compounding-risks/168027/
  - Scientific America: https://www.scientificamerican.com/article/hurricanes-and-wildfires-are-compounding-covid-19-risks/
- Real-Time Data Can Save Lives in a Disaster, FreeThink, April 2020: https://www.freethink.com/articles/emergency-response
- Almost Real-time Flood Prediction Tool May Boost Emergency Response During Hurricanes, The Insider (Newsletter of Association of State Floodplain Managers (ASFPM), April 2020.
- Complaining about climate change on Twitter might actually help scientists, Quartz, Feb 2020: https://qz.com/1797415/scientists-are-studying-your-climate-change-complaints-on-twitter/
- In Houston, Thousands Continue to Wait for Harvey Relief Money, Texas Observer, August 2019: https://www.texasobserver.org/in-houston-thousands-continue-to-wait-for-harvey-relief-money/
- Create a solution in response to wildfires while keeping sensitive data safe, IBM Blog, May 3, 2019: https://developer.ibm.com/callforcode/blogs/create-a-solution-in-response-to-wildfires/
- Texas A&M's Disaster IQ App Helps Improve Disaster Response, EDM Digest, September, 25, 2018: https://edmdigest.com/original/disaster-iq-app/
- Better coordination networks to strengthen interdependent infrastructure resilience, National Science Foundation, September 21, 2018: https://www.nsf.gov/discoveries/disc_summ.jsp?cntn_id=296559&WT.mc_id=USNSF_1#.W6p2wpqh_vw.twitter
- If you shelter in place during a disaster, be ready for challenges after the storm, August 24, 2018.
  - Los Angeles Times: http://www.latimes.com/sns-if-you-shelter-in-place-during-a-disaster-be-ready-for-challenges-after-the-storm-101496-20180824-story.html

- Chicago Tribune: http://www.chicagotribune.com/sns-if-you-shelter-in-place-during-a-disaster-be-ready-for-challenges-after-the-storm-101496-20180824-story.html
- Houston Chronicle: https://www.houstonchronicle.com/news/article/If-you-shelter-in-place-during-a-disaster-be-13179459.php
- Public Radio International (PRI): https://www.pri.org/stories/2018-09-11/if-you-shelter-place-during-disaster-be-ready-challenges-after-storm
- Seattle pi: https://www.seattlepi.com/news/article/If-you-shelter-in-place-during-a-disaster-be-13179459.php

- Texas Standard: http://www.texasstandard.org/stories/fema-has-funded-less-than-one-percent-of-harvey-infrastructure-projects/
- Texas A&M University's 12th Man Spirit Defeats Natural Disasters, US News, August 2018, https://usnewsbrandfuse.com/TexasAM/12th-Man-Spirit-Defeats-Natural-Disasters/
- Why Another Hurricane Can Devastate Puerto Rico and Texas—Again, Engineering News Record (ENR), June 6 2018, https://www.enr.com/articles/44633-why-another-hurricane-can-devastate-puerto-rico-and-texasagain
- Texas A&M professor advises Congress on windstorm issues, The Battalion, November 12, 2017, http://www.thebatt.com/science-technology/texas-a-m-professor-advises-congress-on-windstorm-issues/article_968b53de-c827-11e7-bc27-cb8df9e1075c.html
- After Harvey: Texas A&M System researchers awarded $1.2M, tasked with collecting data to analyze impact of storm, The Eagle, October 22, 2017, https://www.theeagle.com/news/local/after-harvey-texas-a-m-system-researchers-awarded-m-tasked/article_cb386406-6b55-5f27-8c39-ac69aedf1c02.html
- Texas A&M awarded $2M grant for flood, human response research. https://www.theeagle.com/news/local/texas-a-m-awarded-m-grant-for-flood-human-response/article_3f53eaf1-580d-5304-a5d0-fb581c652ad6.html

Internal Media Coverage and Highlights

- Leveraging big data and AI for disaster resilience and recovery, August 2023, (Mostafavi featured).
- Fighting COVID-19 in the Cloud with Data-Driven Research, September 2021, (Mostafavi featured).
- Big data-derived tool facilitates closer monitoring of recovery from natural disasters, July 2021 (Mostafavi featured).
- Texas A&M civil engineering researchers are using a deep learning model to forecast the growth of COVID-19 cases, Texas A&M Today, October 2020 (Mostafavi featured).
- Texas A&M Researchers Create Model To Predict Flooding In Urban Areas, Texas A&M Today, August 2020 (Mostafavi featured).
- Researchers create a contagion model to predict flooding in urban areas, August 2020 (Mostafavi featured).
- Improving the use of social media for disaster management, August 2020 (Mostafavi featured).
- Four interdisciplinary engineering projects receive funding from X-Grants program, July 2020 (Mostafavi featured).
- Texas A&M's Mostafavi to research urban resilience to pandemics, April 2020 (Mostafavi interviewed)
- Almost real-time flood prediction tool may boost emergency response during hurricanes, Engineering News Digest, March 2020 (Mostafavi interviewed)
- Texas A&M Researchers Develop Flooding Prediction Tool, Texas A&M Today, March 2020 (Mostafavi interviewed)
- Undergraduates dedicate summer to studying effects of natural disasters on communities, August 2019 (Mostafavi and his student advisees featured)
- 10 Challenges of Water Utilities, TxH_2O Magazine, July 2019 (Mostafavi interviewed)

https://twri.tamu.edu/publications/txh2o/2019/summer-2019/10-challenges-of-water-utilities/

- Experience explored: Engineering freshman improves disaster response through AggiE_Challenge (Mostafavi and his student advisee featured)
- Civil Eng./TEES News: "Mostafavi receives National Science Foundation CAREER Award" (Mostafavi interviewed)
- TEES News: "Mostafavi from Texas A&M Engineering receives $2M NSF award on infrastructure resilience to urban flooding:" (Mostafavi interviewed)
- TEES News: "AggiE-Challenge students develop solutions for responding to, recovering from, natural disasters" (Mostafavi featured)
- Civil Engineering News: "Civil engineering faculty awarded NSF RAPID grants for Hurricane Harvey Investigation" (Mostafavi featured)
- Civil Eng. News: "Mostafavi receives National Academies' GRP Early-Career Research Fellowship" (Mostafavi featured)

Advising and Mentoring Activities

Post-Doctoral Fellows and Visiting Scholars (Principal Advisor) (Total: 9 – Current: 3)

1. *Dr. Zhewei Liu, Ph.D. in Geo AI. (Honk Kong University), Post-doc training period: 12/2022–Present, Texas A&M University.*
2. *Dr. Yuqin Jiang, Ph.D. in Geo AI. (U of South Carolina), Post-doc training period: 07/2022–Present, Texas A&M University.*
3. *Dr. Chao Fan, Ph.D. in Civil Eng. (TAMU), Post-doc training period: 12/2020–08/2022, Texas A&M University. (Current Position: Assistant Professor of Civil Engineering, Clemson University)*
4. *Dr. Cheng-Chun (Barry) Lee, Ph.D. in Civil Eng. (TAMU), Post-doc training period: 06/2021–Present, Texas A&M University.*
5. *Dr. Faxi Yuan, Ph.D. in Civil Eng. (University of Florida), Post-doc training period: 8/2020–03/2022, Texas A&M University.*
6. *Dr. Shongjia Dong, Ph.D. in Civil Eng. (Oregon State), Post-doc training period: 9/2018–7/2020, Texas A&M University (Current Position: Assistant Professor of Civil Engineering, University of Delaware)*
7. *Dr. Cheng Zhang, Ph.D. in Civil Eng. (ASU), Post-doc training period: 1/2018-8/2020, Texas A&M University (Current Position: Assistant Professor of Civil Engineering, Purdue University Northwest)*
8. *Dr. Jin Zhu, Ph.D. in Civil Engineering, Post-doc training period: September 2016–July 2017, Texas A&M University (Current Position: Assistant Professor of Civil Engineering, University of Connecticut)*
9. *Dr. Peeraya Inyim, Ph.D. in Civil Engineering, Post-doc training period: May 2015–March 2016, Florida International University*

Ph.D. Students (Principal Advisor) – *Total 20 (Current: 11)*

1. *Yu-Hsuan H, PhD. in Civil Engineering (TAMU), Expected Graduation: May 2026.*
2. *Kai Yin, PhD. in Civil Engineering (TAMU), Expected Graduation: May 2026.*
3. *Chia-Fu Liu, PhD. in Civil Engineering (TAMU), Expected Graduation: May 2025.*
4. *Bo Li, PhD. in Civil Engineering (TAMU), Expected Graduation: May 2025.*
5. *Junwei Ma, PhD. in Civil Engineering (TAMU), Expected Graduation: May 2025.*
6. *Natalie Coleman, PhD. in Civil Engineering (TAMU), Expected Graduation: May 2024.*
7. *Chenyue Liu, PhD. in Civil Engineering (TAMU), Expected Graduation: May 2025.*
8. *Flavia Patrascu, PhD. in Civil Engineering (TAMU), Expected Graduation: May 2024.*
9. *Chia-Wei Hsu, PhD. in Civil Engineering (TAMU), Expected Graduation: May 2024.*

10. *Akhil Rajput, PhD. in Civil Engineering (TAMU), Expected Graduation: May 2024.*
11. *Tamarah Ridha, PhD. in Civil Engineering (TAMU), Expected Graduation: August 2023.*
12. *Hamed Farahmand, PhD. in Civil Engineering (TAMU), Graduation: Dec 2022. (Current Position: Data Scientist, One Concern)*
13. *Amir Esmalian, PhD. in Civil Engineering (TAMU), Graduation: May 2022. (Current Position: Associate at McKinsey and Company)*
14. *Jennifer Dargin, PhD. in Civil Engineering (TAMU), Graduation: May 2022.*
15. *Qingchun Li, PhD. in Civil Engineering (TAMU), Graduation: May 2021. (Assistant Professor at Purdue University starting Fall 2023).*
16. *Chao Fan, PhD. in Civil Engineering (TAMU), Graduation: Dec 2020. (Current Position: Assistant Professor at Clemson University).*
17. *Chris Cox, Ph.D. in Civil Engineering (TAMU), Graduation, Dec 2020 (Current Position: faculty at Western Carolina University).*
18. *Kambiz Rasoulkhani, Ph.D. Student in Civil Engineering (TAMU), Dec 2019 (Current position: Senior Consultant, AMCL).*
19. *Jin Zhu, Ph.D. in Civil Engineering (FIU), Graduation: August 2016 (Current position: Assistant professor, Department of Civil and Environmental Engineering, University of Connecticut)*
20. *Mostafa Batouli, Ph.D. in Civil Engineering (FIU), Graduation: May 2017 (Current position: Assistant professor, Department of Civil an Environmental Engineering, The Citadel)*

Master Students (Major Advisor/research Advisor):

Wanqui Wang, M.S. in Computer Engineering, Advisor in research, Graduation: May 2021
Tianbo Yu, M.S. in Computer Engineering, Advisor in research, Graduation: December 2020
Xiangqi Jiang, M.S. in Computer Engineering, Advisor in research, Graduation: May 2021
Yang Yang, M.S. in Computer Science (TAMU), Advisor in research, Graduation: May 2021
Fangsheng Wang, M.S. in Computer Science (TAMU), Advisor in research, Graduation: May 2021
Rana Abu-Hamdia, M.S. in Civil Engineering (TAMU), Graduation: Dec 2018
Jose Pereyra, M.S. in Construction Management (FIU), Graduation: May 2016
Maria Reyes, M.S. in Computer Science (FIU), Graduation: August 2016
Alex Inman, M.S. in Construction Management (FIU), Graduation: August 2014

Membership in Ph.D. Committees:

Zhimeng Jiang, Ph.D. student in Computer Science, TAMU (Major Advisor: Dr. Hu)
Hongrak Pak, Ph.D. Student in Civil Engineering, TAMU (Major Advisor: Dr. Paal)
Rohan Singh Wilkho, Ph.D. Student in Civil Engineering, TAMU (Major Advisor: Dr. Nasir Gharaibeh)
Cheng-Chun Lee, , Ph.D. Student in Civil Engineering, TAMU (Major Advisor: Dr. Nasir Gharaibeh)
Walter Olarte, , Ph.D. Student in Civil Engineering, TAMU (Major Advisor: Dr. Damnjanovic)
Isaac Otey, Ph.D. Student in Civil Engineering, TAMU (Major Advisor: Dr. Nasir Gharaibeh)
Vincent Teguh, Ph.D. Student in Civil Engineering, TAMU (Major Advisor: Dr. David Ford)
Mahmudur Rahman, Ph.D. Student in Computer Science (Major Advisor: Dr. Leonardo Bobadilla)
Ramin Taghinezhad, Ph.D. Student in Civil Engineering (Major Advisor: Dr. Atorod Azizinamini)
Huy Pham, Ph.D. Student in Civil Engineering (Major Advisor: Dr. Atorod Azizinamini)
Amir Naeiji, Student in Civil Engineering (Major Advisor: Dr. Iaonnis Zisis)
Jeisson Rodriguez, Ph.D. Student in Public Administration (Major Advisor: Dr. Allan Rosenbaum)
Nida Azhar, Ph.D. Student in Civil Engineering (Major Advisor: Dr. Irtishad Ahmad), Graduated in August 2014

External Ph.D. Dissertation Committee/Examination:

Pranavesh Panakkal (Major Advisor: Dr. Jamie Padgett), Department of Civil and Environmental Engineering, Rice University.

Shaye Palagi, Ph.D. Student in Civil Engineering, University of Colorado Boulder (Major Advisor: Dr. Amy Javernick-Will)

Resulali Orgut, Ph.D. Student in Civil Engineering, NC State University (Major Advisor: Dr. Edward Jaselskis)

Robert Ogie (Major Advisor: Dr. Pascal Perez), Faculty of Engineering & Information Sciences, University of Wollongong (Australia)

MS Student (Research Supervisor/Advisor)

Yang Yang (Computer Science- GRA with Dr. Mostafavi)	*2019- 2021*
Fangsheng Wu (Computer Science- GRA with Dr. Mostafavi)	*2019-2021*
Xiangqi Jiang (Computer Science- GRA with Dr. Mostafavi)	*2020-2021*
Wanqui Want (Computer Eng – GRA with Dr. Mostafavi)	*2019-2021*
Xin Xiao(Computer Science- researcher with Dr. Mostafavi)	*2020-2021*
Sanghyeon Lee (Computer Science- researcher with Dr. Mostafavi)	*2020-2021*

M.E. Students (Major Advisor)

Caroline Salem	*Graduated (8/2017)*
Purvit Soni	*Graduated (8/2018)*
Bharath Reddy Rondla	*Graduated (8/2018)*
Manoj Taddi	*Graduated (8/2018)*
Enrique Jimenez Orozco	*Graduated (8/2018)*
Ross Navarro	*Graduated (12/2018)*
Dhurgham Malallah	*Graduated (8/2019)*
Prathyusha Banglore Ramesh	*Graduated (8/2019)*
Rameez Qureshi	*Graduated (8/2019)*

Undergraduate Advising (involved in research):

Texas A&M University

Funded UG Research Assistants

Allison Clarke	*2021-2022*
Cristian Podesta	*2020-2021*
Sara Garcia	*2020-2021*
Jared DeLeon	*2020 - 2021*
Miguel Esparaza, B.S. in Civil Engineering	*2017– 2020*
Natalie Coleman, B.S. in Civil Engineering	*2018–2020*
Bora Oztekin	*2019–2021*
Yang Yang, B.S. in Computer Science	*2017–2019*
Maitreyi Ramaswamy, B.S. in Computer Science	*2017–2018*
Yucheng Jiang, B.S. in Computer Science	*2017–2019*
Jose Quiros, B.S. in Civil Engineering	*2017–2018*
Jenny Truong, B.S. in Civil Engineering	*2016–2017*

Summer Undergraduate Researchers (Visiting)

Isabel McKnight (University of Alabama), Summer 2018

Taeho Kim (University of Michigan), Summer 2017

Parul Srivastava (IIT Kanpur), Summer 2017

Brian Logasa (UC San Diego), Summer 2016

AggiE Challenge Program

AggiE Challenge Program is a Vertically Integrated Project (VIP) in the College of Engineering Texas A&M University. I have been advising teams of interdisciplinary students in projects focusing of disaster informatics and smart cities.

Academic Year 2018-2019
Sournav Bhattacharya (CPSC), Nathan Dunkley (CPSC), Hamza Iqbal (INEN), Yucheng Jiang (CPSC), Justin Nguyen (CVEN), Madeleine Parkison (CVEN), Hertantya Putera (INEN), Melanie Beattie (ENGE), Jainita Chauhan (ENGE), Romil Deshpande (ENGE), Matthew Kanarr (CPSC), Nicholas Matthews (CECN), Justin Nguyen (CVEN), Saif Mehmood (INEN), Grace Tjeong (CVEN)

Academic Year 2017-2018
Ehab Rebhy Abo Deeb (CVEN), Nicolas Carvajal (CVEN), Nandan Reddy Gade (CPSC), Sriram Natarajan (CEEN), Justin Do Khanh Nguyen (CVEN), Micheal Anthony Peterson (CPSC), Phuong Uyen Dinh Pham (INEN), Hertantya Adhika Putera (INEN), Yang Yang (CPSC)

FIU

Brianne Logasa, B.S. in Urban Planning (visiting from UC San Diego)	*Summer 2016*
Beatriz Azevedo, B.S. in Environmental Eng.	*Summer 2016*
Patrick Foucauld, B.S. in Construction Management	*2015–2016*
Allen Llodra, B.S. in Construction Management	*2015–2016*
Diana Leante, B.S. in Computer Science	*2014–2015*
Fagner Soares, B.S. in Computer Science	*Summer 2015*
Mateus Marcos, B.S. in Civil Engineering	*Summer 2015*
Gianny Romero, B.S. in Construction Management	*2013-2015*
Luciana De Souza, B.S. in Civil Engineering	*Summer 2014*
Geeticka Chauhan, B.S. in Computer Science	*Summer 2014*
Tim Libre, B.S. in Civil Engineering,	*2014*
Triana Carmenate, B.S. in Computer Science,	*2013–2014*

Student Advisee Honors and Awards

Natalie Coleman, NSF Graduate Research Fellowship, 2020-2024.

Natalie Coleman, Undergraduate Research Scholars (URS) Outstanding Thesis Award, LAUNCH Undergraduate Research Program, Texas A&M University, 2019.

Kambiz Rasoulkhani, ACE in Higher Education Research Award, TAMU Student Research Week Symposium, 2019.

Natalie Coleman, Sigma Xi-Interdisciplinary Award for Undergraduate Research, TAMU Student Research Week Symposium, 2019.

Kambiz Rasoulkhani, 3rd Place Best Poster Award, Construction Research Congress, 2018.

Kambiz Rasoulkhani, Sea Grant Best Poster Award, TAMU Student Research Week Symposium, 2018.

Jin Zhu, 2nd Place Best Poster Award, Construction Research Congress, 2016.

Mostafa Batouli, 3rd Place Best Poster Award, Construction Research Congress, 2016.

Jin Zhu, Top 10 Poster Finalist, Academic Poster Session, Construction Industry Institute, 2016.

Jin Zhu, Best Conference Paper Award, ASCE Computing in Civil Engineering Conference, 2015.

Jin Zhu, Top 10 Poster Finalist, Academic Poster Session, Construction Industry Institute, 2015.

Jin Zhu, Dissertation Year Fellowship, FIU University Graduate School, 2015.

Peeraya Inyim, Inaugural Technical Paper Award, Florida ASCE Conference, 2015.

Peeraya Inyim, 1st Place Best Poster Award, FIU Graduate Scholarly Forum, 2015.

Jin Zhu, 2nd Place Best Poster Award, FIU Graduate Scholarly Forum, 2015.

Triana Carmenate, Fiatech Conference Scholarship, Top 6 Research Posters for presentation at Fiatech Annual Conference 2015.

Mostafa Batouli, Student Government Association Graduate Scholarship, Florida International University, 2014

Mostafa Batouli, University-wide Scholarship, Graduate School, Florida International University, 2014

Jin Zhu, 3rd Place Poster Award in Engineering Category at Florida International University's Graduate Scholarly Seminar

Teaching

Courses Taught and Student Evaluations

The students were asked to evaluate the course and the instructor with respect to different criteria (e.g., course materials and learning, communication and availability, and respect and concern for students' learning). The following table summarizes the average scores across all the criteria.
Scale for rating*: 1= Has serious deficiencies in this area which are detrimental to students; 2= Does not perform well in this area; 3= Good; 4= Very Good; 5=Deserves an award in this area; excellent.
**TAMU and FIU have similar scale for student course/teaching evaluation.*

Course	Cr.	University	Role	Level	Semester	Number of Students	Average Evaluation Score
CVEN-641: Construction Engineering Systems	4	TAMU	Instructor	Graduate	Spring 2023	18	4.95
CVEN-668: Advanced EPC Project Development	3	TAMU	Instructor	Graduate	Fall 2022	32	4.41
CVEN-641: Construction Engineering Systems	4	TAMU	Instructor	Graduate	Spring 2022	12	4.83
CVEN-668: Advanced EPC Project Development	3	TAMU	Instructor	Graduate	Fall 2021	42	4.68
CVEN-641: Construction Engineering Systems	4	TAMU	Instructor	Graduate	Spring 2021	24	4.60
CVEN-668: Advanced EPC Project Development	3	TAMU	Instructor	Graduate	Fall 2020	30	4.54
CVEN-641: Construction Engineering Systems	4	TAMU	Instructor	Graduate	Spring 2020	27	4.51
CVEN-668: Advanced EPC Project Development	3	TAMU	Instructor	Graduate	Fall 2019	32	4.50
CVEN-641: Construction Engineering Systems	4	TAMU	Instructor	Graduate	Spring 2019	16	4.63
CVEN-668: Advanced EPC Project Development	3	TAMU	Instructor	Graduate	Fall 2018	27	4.33
CVEN-349: Project Management for Civil Engineers	3	TAMU	Instructor	Undergraduate	Spring 2018	32	4.3
CVEN-668: Advanced EPC Project Development	3	TAMU	Instructor	Graduate	Fall 2017	32	4.7

Course	Cr.	University	Role	Level	Semester	Number of Students	Average Evaluation Score
CVEN-641: Construction Engineering Systems	4	TAMU	Instructor	Graduate	Spring 2017	8	4.7
CVEN-668: Advanced EPC Project Development	3	TAMU	Instructor	Graduate	Fall 2016	24	4.8
BCN-5585: Sustainable Construction	3	FIU	Instructor	Graduate	Spring 2015	15	4.7
BCN-3753: Financial Management of Construction Organizations	3	FIU	Instructor	Undergraduate	Spring 2015	16	4.7
BCN-3753: Financial Management of Construction Organizations	3	FIU	Instructor	Undergraduate	Fall 2014	27	4.7
BCN-5585: Sustainable Construction	3	FIU	Instructor	Graduate	Spring 2014	28	4.4
BCN-3761: Construction Documentation and Communication	3	FIU	Instructor	Undergraduate	Spring 2014	36	4.2
BCN-3727: Construction Sitework and Equipment	3	FIU	Instructor	Undergraduate	Fall 2013	36	4.7
EPICS- Service Learning Project	3	Purdue	Co-advisor	Undergraduate	Spring 2012	12	4.9

Service to Department, College, and University

Texas A&M University

Committee for Creating New Ph.D. Track — Fall 2021-Summer 2022
Faculty Search Committee — Fall 2021-Spring 2022
Committee for Defining Metrics for Research Active Faculty — Spring 2019-Present
Committee on Practice, Management and Professionalism in BS-CVEN Curriculum — Spring 2018

Florida International University

Member of Leadership Committee, Sea-Level Rise Solutions Center — 2015–2016

Leadership, Professional Service, and Community Engagement

Panel/Proposal Reviewer

- Panel Fellow, NSF CMMI Game Changer Academies — 2021 - Present
- National Science Foundation (2014, 2015, 2017-2020) — Dates withheld for confidentiality
- Department of Energy (2020) — Dates withheld for confidentiality
- NWO - the Dutch Research Council (2020)
- National Research and Development Agency (ANID) of the Ministry of Science, Technology, Knowledge and Innovation of Chile
- South Plains Transportation Center — Dates withheld for confidentiality

Editorship of Journal and Other Publications

Member of Editorial Team,	
ASCE Journal of Management in Engineering	*2014– Present*
ASCE Journal of Infrastructure Systems	*2019– Present*
ASCE Natural Hazards review	*2022-Present*
Nature Scientific report	*2021-Present*

Journal Reviewer

Computer-Aided Civil and Infrastructure Engineering	*2018–Present*
ASCE Natural Hazard Review	*2015–Present*
Elsevier Transportation Research Part A	*2015–Present*
ASCE Journal of Computing in Civil Engineering	*2015–Present*
ASCE Journal of Construction Engineering and Management	*2010–Present*
ASCE Journal of Infrastructure Systems	*2013–Present*
IEEE Systems Journal	*2012–Present*
Journal of Automation in Construction	*2014–Present*
ASCE Journal of Management in Engineering	*2012–Present*
ASCE Journal of Computing in Civil Eng.	*2015–Present*

Professional and Research Societies

Member, Infrastructure Resilience Division of American Society of Civil Engineers (ASCE)
Academic Advisor, CII MLS Sector (2018-2020)
Member, American Society of Civil Engineers (ASCE)
Member, ASCE Infrastructure Resilience Division (IRD)
Member, CII Power, Utility, and Infrastructure Committee (2017-2020)
Vice-Chair, CII Annual Conference Poster Session Subcommittee (2014-2016)
Member, ASCE Construction Research Council (CRC)
Member, Academic Committee, Construction Industry Institute (CII) (2013-2016)
Member, Virtual Design and Construction/Civil Integrated Management Sub-Committee of TRB
Member, ASCE Visualization, Information Modeling, and Simulation (VIMS) Committee
Member, ASCE Data Sensing and Analytics (DSA) Committee
Member, ASCE Digital Project Delivery Committee

Conference Organizing

Member, Technical Committee, ASCE the San Fernando Earthquake Conference – 50 years of Lifeline Engineering	*February 7-11, 2022*
Member, Technical Program Committee, ASCE Computing in Civil Engineering,	*June 25–27, 2017*
Member, Technical Program Committee, ASCE CRC 2016	*May 31–June 2, 2016*
Member, Technical Program Committee, CONVR 2015	*October 5–7, 2015*
Member, Review Program Committee, ASCE IWCCE 2015	*June 21–23, 2015*
Member, Technical Program Committee, IEEE SysCon 2015	*April 13–16, 2015*
Member, Ph.D. Track Organizing Sub-Committee, FIATECH 2015	*April 13–16, 2015*
Session Chair, Construction Research Congress 2014	*May 19–21, 2014*
Program Committee, Construction Research Congress 2014	*May 19–21, 2014*

Organizing Committee, FIU-MIT Transp. Infrastructure Sustainability Summit	*October 29, 2013*
Session Chair, Simulation Session, INFORMS 2013	*October 6–9, 2013*
Assistant Track Coordinator, Construction Research Congress 2012	*May 21–23, 2012*
Assistant Track Coordinator, Construction Engineering and Management Global Leadership Forum May 21–23, 2012	*May 21–23, 2012*
Assistant Track Coordinator, Construction Engineering and Management Global Leadership Forum	*March 20–22, 2012*

Conference Reviewer

Construction research Congress 2020	*March 8-10, 2020*
Construction research Congress 2016	*May 1–June 2, 2016*
ASCE Computing in Civil Engineering Workshop	*June–23, 2015*
IEEE SysCon 2015	*April 13–16, 2015*
Winter Simulation Conference 2014	*December 7–10, 2014*
Transportation Research Board Annual Meeting 2014	*January 12–16, 2014*
Construction Research Congress 2014	*May 19–21, 2014*
Transportation Research Board Annual Meeting 2013	*January 13–16, 2013*
Construction Research Congress 2012	*May 21–23, 2012*
CSCE 3rd International/9th Construction Conference	*June 14–17, 2011*
CIB W099 2011 Conference	*August 24–26, 2011*
Engineering Project Organization Conference (EPOC 2010)	*November 4–6, 2010*

TEACHING STATEMENT

Teaching Philosophy

I am committed to educating students to become engineers who will be strong in technical and analytical thinking, effective in communication, cooperative in teamwork, and reliable in community service. My teaching style is flexible and driven by the diverse learning styles of my students, the needs of the profession, and the priorities of the global community. My teaching philosophy can be summarized as follows: teaching and mentoring should release the untapped potential of my students and open doors to them for lifelong opportunities and inspiration.

Approach to Effective Teaching

I consider critical thinking, real-world problem-solving, social commitment, effective communication, global team building, leadership, and empathic skills to be significant capabilities that students should develop in addition to technical competence in their field of study. Unfortunately, the traditional lecture-based pedagogy of engineering education has failed to efficiently promote these skills for training a "new kind of engineer", as advocated by the National Academy of Engineering.

I employ three strategies to develop these skills in my students: (i) adopt learner-oriented and project-based learning methods; (ii) integrate my teaching with my research; and (iii) adopt innovative pedagogical models. I believe that learner-oriented teaching promotes learning that is both purposeful and lasting. As an instructor, it is my responsibility to know who my learners are, what learning styles they have, and what they want to achieve so that I can tailor a curriculum that fits their learning style/needs.

I embrace collaborative, case-based learning, along with other interactive learning activities, because these best stimulate critical thinking and cooperative problem-solving, and lay the groundwork for life-long collaborative practices. To attain this objective, I design problems as a part of each lecture and assign case study assignments and course projects in which my students work in groups and help each other to solve the problems. In addition, I continually collaborate with industry professionals to connect the classroom concepts with real world applications. Inviting industry speakers for guest lectures and using case studies are examples of different methods that I have utilized to sustain student motivation and interest in learning the subject matter. For example, in CVEN-668 (Fall 2016-2021), I invited guest industry speakers to talk about the real-world aspects of project planning theories and methods, which students had previously discussed in class. In addition, I used the Construction Industry Institute (CII) materials in my course to expose the students to best practices in the industry. I have used two case studies (similar to real-world projects) as assignments for the students to apply the concepts and methods covered in the course. My dedication to integrating real-world knowledge and examples into my teaching activities has resulted in my receiving the Outstanding Professor Award from CII.

Integrating teaching with research provides students with the opportunity to develop their skills in problem solving and critical thinking. In particular, my graduate course Construction Engineering Systems (CVEN 641) is tailored to integrate teaching with my research interests. Since I started teaching CVEN-641 at Texas A&M, I have made major changes in the course content by shifting the focus to system thinking and model-based learning pedagogies. I added three new modules to the course, focusing on: (1) complex systems approach to infrastructure project analysis; (2) modeling and design of construction operations; and (3) network modeling and analysis of project organizations. In these modules, students learn about employing the principles of systems thinking in analyzing complex processes and interdependencies in infrastructure projects and systems. In addition, students learn different modeling and simulation methods, such as discrete-event simulation and dynamic network modeling. My approach to teaching effectiveness has led me to consistently receive excellent teaching evaluations from my students for all my classes.

For undergraduate students, I use a Vertically Integrated Project (VIP) approach to incorporate research into undergraduate learning. Since August 2017, I have been advising an interdisciplinary AggiE_Challenge team composed of students from Civil Engineering, Computer Science, and Industrial and Systems Engineering in a project related to development of a system for community resilience to disasters. In 2019, My AggiE_Challenge team was selected to represent TAMU in the 2019 NAE's Global Grand Challenges Summit Competition. This collaborative team-based context provides an environment in which the members learn professional skills and the application of engineering knowledge and theories, as well as experience working in interdisciplinary teams in addressing societal challenges. In addition, the VIP approach also facilitates recruitment and retention in graduate studies. Many of the undergraduate students involved in our VIP project have continued on to graduate studies.

<u>Engineering Education and Pedagogical Research</u>

I continually refine and enhance my teaching skills and learn new pedagogical approaches by attending workshops related to teaching excellence. I am also interested in improving the use of innovative pedagogies in civil engineering education. I recently concluded a NSF-funded project (my role: Co-PI) to examine the use of immersive technologies in team-based learning environments. I have also co-authored multiple journal and conference publications regrading innovative pedagogies (such as service learning) in civil engineering education. My current interest in engineering education focuses on integrating empathy and compassion with human-centric engineering design. The notion of sustainability and resilience has been changing the focus for engineering and has promoted the search for solutions tailored to address the needs of communities across generations. I know of no other pedagogical framework that can emphasize human-centered engineering more than empathic learning. I am currently investigating a pedagogical model for empathic learning as part of my NSF CAREER Award and plan to extend my work in this area through pursuing educational grants.

<u>Teaching Interests</u>

My academic and industry experiences enable me to teach a variety of courses related to civil engineering and infrastructure systems at both the undergraduate and graduate levels. In addition to standard undergraduate and graduate courses in infrastructure engineering, civil systems, and project management, I would be interested in developing new courses that parallels my research interests. One course would be entitled *Complex Modeling of Urban Systems* and would concentrate on problems, theories, and research tools for complex urban infrastructure modeling. Students will learn the fundamentals of complex systems theories, infrastructure interdependencies, resilience engineering, infrastructure adaptation, dynamic and probabilistic network modeling, game theory, and agent-based modeling. Another course would be *Disaster Informatics & Urban Data Science* and would focus on analytical tools for multi-modal data sensing and analytics for urban mapping and situational awareness during disasters. Students will learn about different data modalities (such as social media and digital trace data), as well as urban informatics and analytics techniques (such as machine learning, topic modeling, network embedding, and complex network modeling) for important disaster management and risk reduction tasks.

<u>Mentoring and Supervising Experience</u>

My research mentoring approach is guided by mutual respect, effective communication, constructive feedback, and professionalism. I greatly value undergraduate research experience and have been actively recruiting undergraduate students. I currently advise three post-doctoral researchers, twelve Ph.D. students, eight master-level (MS/ME) students, and six funded undergraduate researchers. In addition, I have graduated six Ph.D. students so far. My former Ph.D. students and post-docs have been hired in tenure-track faculty positions in the U.S. My graduate students have been awarded best paper and poster awards at ASCE and other major conferences. Engagement of undergraduate students in funded research positions has enabled me to ignite their interest in pursuing graduate degrees. More than 50% of my undergraduate research students have continued to pursue graduate degrees. I greatly value undergraduate research experience and have been actively recruiting undergraduate students into my research projects. My research experience exposes my students to current scientific research and gives them the opportunity to effectively develop critical thinking, communication, and leadership skills. Diversity is a core value in my research group. I have been actively recruiting students from underrepresented populations in engineering and science into my research group.

RESEARCH STATEMENT

Overview of Research Focus

My long-term research goal is to improve resilience, sustainability, and equity in infrastructure systems through data-driven and equitable approaches. My research program is a response to a growing concern in the U.S., as well as global level in facing compounding climate hazards and other urban stressors and their societal and economic impacts. In my research program, I employ interdisciplinary methods and theoretical frameworks at the intersection of the fields of civil infrastructure, complex systems, and data science/AI to investigate complex phenomena in the human-disasters-built environment nexus. Specifically, I utilize heterogeneous community-scale big datasets related to physical infrastructure (e.g., flood sensors data, road network topology, traffic data) and human activities and interactions with infrastructure (e.g., location-based, social media, and digital trace data) in creating advanced computational algorithms and machine learning/deep learning models to assess, characterize, understand, and predict various complex phenomena such as resilience and recovery of interdependent infrastructure networks, social equality in risk impacts and access to critical facilities, human mobility, segregation and social connectedness in urban structures, and human collective sense-making and protective actions in response to hazards. Fundamental research and advanced computational models related to these complex phenomena are essential to move us closer to integrated urban/community design for improving resilience and sustainability in a smarter and more equitable fashion. In the following section, I further explain the main discovery areas in my interdisciplinary research program, as well as my community engagement activities for research-to-practice transition.

Current Interdisciplinary Research Program

Since I joined the Zachry Department of Civil and Environmental Engineering at TAMU in 2016, I have established a strong externally-funded interdisciplinary research program focusing on urban resilience and AI and have built synergistic collaborations across various disciplines. I was promoted to Associate Professor with Tenure in 2020. Since then, I revamped my research lab, the *UrbanResilience.AI Lab*, to coalesce innovative data-driven methods and computational models for understanding and improving infrastructure resilience. My research program is strongly funded by diverse sponsors such as NSF, National Academies' Gulf Research Program, TxDOT, CII, and AWS. Since my promotion to an Associate Professor in 2020, my research program has grown (with annual total research expenditures of $711K, $911K, $907K in 2020, 2021, and 2022, respectively). My research lab has produced more than 180 journal papers (145 published and 33 under review). For the past two years, I have been listed in the Stanford/Elsevier list of top 2% scholars. This level of research productivity has enabled my research program to advance *convergence research* in four new interdisciplinary and interrelated discovery areas.

In the **first discovery area (*Resilience of Interdependent Infrastructure Networks*)**, my research efforts have established new theoretical and computational modeling frameworks for understanding the structure and dynamics of human and physical networks that influence resilience in communities. In this discovery area, my research students and I harness various heterogeneous datasets to construct computational models of spatio-temporal networks (such as physical infrastructure networks, mobility networks, network of facilities) embedded in communities. My research in this area is supported through multiple NSF grants including my NSF CRISP 2.0 project. In this project, I lead an interdisciplinary research team from three different colleges (Engineering, Urban Planning, and Public Policy). My investigations of network resilience and recovery has led to fundamental insights and new methods for understanding, analyzing, and predicting vulnerability, failure cascades and collective recovery in interdependent infrastructure systems and processes. For instance, through examining topological properties, sub-graph motifs, and dynamical attributes in physical infrastructure, our work has revealed important network diffusion and percolation processes that contribute to vulnerability, spread of failures, and multi-stage recovery in urban networks during disasters.

In the **second discovery area** (***Equitable and Human-Centric Resilience)***, my interdisciplinary research efforts aim at advancing the understanding of the societal dimensions of infrastructure resilience. My work in this area has resulted in new theoretical frameworks and human-centric computational models that advance the standard model of infrastructure resilience, thus enabling a paradigm shift in research and practice by changing the focus from "systems" to "people." Also, new complex system models are created to capture and simulate the dynamic interactions in populations-infrastructure-hazards nexus in resilience assessments. Accordingly, my work in this area has investigated multiple phenomena such as urban segregation, inequality of access to facilities, and digital divide in communities in the context of crises to reveal the underlying mechanisms affecting disparities in risk exposures and protective actions. These fundamental investigations provide new models and insights for promoting equitable resilience in communities. My research in this interdisciplinary area has been supported by a NSF CAREER Award, NSF Analytics for Equity, and a NOAA Sea Grant projects.

In the **third discovery area (*Urban Artificial Intelligence for Integrated Urban Design*)**, my work focuses on harnessing big data and artificial intelligence to better understand, model, and analyze complex interactions among populations and built environment in cities/communities. In this discovery area, my research students and I utilize various heterogeneous big datasets to construct computational models to characterize and predict various emergent and complex urban phenomena such as human mobility, facility distribution, spatial spillover effects, and public health risks. Such data-driven and network-centric approach is essential for integrated urban design in order to plan for city growth while proactively considering effects to the environment and social inequality, as well as resilience to crises. These research activities are sponsored by different grants such as an Early-Career Research Fellowship from the Gulf Research Program of the National Academies of Engineering, Sciences, and Medicine, an AI for Health Grant from Microsoft Azure, and multiple NSF grants. I have also established partnerships with various technology organizations such as Waze Connected Citizen Program, INRIX, Meta Data for Good, and Spectus to gather fine-grained data related to urban fluctuations and digital traces of population dynamics in creation of computational models to inform integrated urban design for sustainable and resilient development.

In the **fourth discovery area** (***Disaster Data Science for Smart Resilience***), my research activities are geared towards advancing the technologies for intelligent disaster management and emergency response to help residents, civilian volunteers, and emergency responders better cope with disasters. The fields of urban resilience and data science/artificial intelligence are on a collision course giving rise to the interdisciplinary field of smart resilience. My work in the area of smart resilience is focusing on augmenting situational awareness using big data and artificial intelligence solutions. My lab's investigations have created novel computational models and algorithms such as spatio-temporal graph deep learning, network embedding, and natural language processing models to analyze community-scale big data for predictive flood risk monitoring and now-casting, rapid impact assessment, infrastructure network failure predictions, and proactive response and recovery monitoring. While addressing technical challenges in creating AI-based models to promote smart resilience, my work has a particular focus on responsible AI practices to address issues of data bias, model fairness, and explainability of results. These research activities are sponsored by different projects such as a $1 million X-Grant project, two NSF projects, and an AWS Machine Learning Award, and a grant from Microsoft AI for Good.

The outcomes of my research in these four interrelated discovery areas promise significant societal benefits by providing interdisciplinary, science-based building blocks which communities could methodically adapt to in becoming more resilient to disasters. So far, the outcomes of my research has led to multiple internal and external merit-based awards and recognitions, as well as publications in highly-regarded civil engineering and interdisciplinary systems and disaster journals. Due to the interdisciplinary and boundary-spanning nature of my research, I have established collaborative relationships with well-known researchers in civil engineering, computer science, and social sciences across the U.S. and internationally. My research has attracted a lot of attention from industrial collaborators and stakeholders. For example, my research on smart resilience and urban intelligence is strongly supported by leading companies such as Waze, Meta, INRIX, Cuebiq, Microsoft, and AWS in terms of funding, datasets, as well as computational resources. I have been invited for presentation and panel participation in multiple urban resilience forums and workshops in the U.S., U.K., Netherlands, and China. In addition, the findings of my research efforts have received broad coverage from media, such as Los Angeles Times, Houston Chronicle, Public Radio International, the Texas Standard, US News.

I also have made efforts to operationalize my research results for the civil engineering community. I recently established a startup (called Resilitix) to commercialize the research outcomes in my lab. The main technology currently being commercialized is an AI-empowered Digital Twin for Disaster Resilience Analytics. Also, based on my research, I have made recommendations to various state and local agencies that has led to actionable results. Texas Department of Transportation (TxDOT) is promoting the use of the network-level vulnerability assessment framework and decision support tool that my group created to systematically incorporate resilience in transportation infrastructure planning and project development. In fact, the methods and measures created in my work are the foundation of the ongoing State-wide transportation resilience plan in TxDOT. Also, I worked with the World Bank's Disaster Risk Reduction Group to employ my research outcomes for estimation of road network vulnerability in Haiti and Columbia. The probabilistic network resilience analysis method created by my work was the key component in evaluation of a $50M climate resilience investment by the World Bank in Haiti's road infrastructure.

My interdisciplinary research program fits well with the vision and priorities of the Lyles School of Civil Engineering (focusing on Engineering for Humanity). I also expect excellent opportunities for campus-wide collaborations at the intersection of AI, Climate Resilience, and Equitable Infrastructure. So far, I have established a nationally-recognized interdisciplinary research program with strong external support. In collaboration with various interdisciplinary researchers at Purdue, my goal for the next several years will be to establish a globally-recognized hub in the area of urban resilience and artificial intelligence.

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Multi-agent modeling of hazard–household–infrastructure nexus for equitable resilience assessment

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Abstract

Infrastructure service disruptions impact households in an affected community disproportionally. To enable integrating social equity considerations in infrastructure resilience assessments, this study created a new computational multi-agent simulation model, which enables integrated assessment of hazard, infrastructure system, and household elements and their interactions. With a focus on hurricane-induced power outages, the model consists of three elements: (1) the hazard component simulates exposure of the community to a hurricane with varying intensity levels; (2) the physical infrastructure component simulates the power network and its probabilistic failures and restoration under different hazard scenarios; and (3) the households component captures the dynamic processes related to preparation, information-seeking, and response actions of households facing hurricane-induced power outages. We used empirical data from household surveys from three hurricanes (Harvey, Florence, and Michael) in conjunction with theoretical decision-making models to abstract and simulate the underlying mechanisms affecting the experienced hardship of households when facing power outages. The multi-agent simulation model was then tested in the context of Harris County, Texas, and verified and validated using empirical results from Hurricane Harvey in 2017. Then, the model was used to examine the effects of different factors—such as forewarning durations, social network types, and restoration and resource allocation strategies—on reducing the societal impacts of service disruptions in an equitable manner. The results show that improving the restoration prioritization strategy to focus on vulnerable populations is an effective approach, especially during high-intensity events, to enhance equitable resilience. The results show the capability of the proposed computational model for capturing the dynamic and complex interactions in the nexus of households, hazards, and infrastructure systems to better integrate human-centric aspects in resilience planning and assessment of infrastructure systems in disasters. Hence, the proposed model and its results could provide a new tool for infrastructure managers and operators, as well as for disaster managers, in devising hazard mitigation and response strategies to reduce the societal impacts of power outages in an equitable manner.

1 | INTRODUCTION

The objective of this study is to create a computational multi-agent simulation framework for capturing dynamic processes and interactions in the nexus of hazards, households, and infrastructure systems in order to better integrate social impacts and equity considerations in infrastructure resilience assessments. The societal impacts of prolonged disruptions in infrastructure systems are the emergent properties arising from dynamic interactions in complex socio-physical systems (Dai et al., 2020; Guidotti et al., 2019; Rasoulkhani et al., 2020; Williams et al., 2020). Therefore, there is a need for novel computational models to capture and model the dynamic processes and interactions between the complex systems of humans, hazards, and infrastructure systems. With a focus on prolonged power outages during hurricanes, this study proposes a novel computational simulation modeling framework for integrated analysis of hazard, household, and infrastructure systems to examine the societal impacts on infrastructure service disruptions. Examining the impacts of power outages on the households and assessing the effect of different mitigation strategies on the social groups is a fundamental step toward equitable resilience assessment in infrastructure systems.

Existing infrastructure resilience assessment models focus primarily on physical infrastructure but fall short of fully considering interactions between households and hazards and infrastructure (Mostafavi, 2018; Mostafavi & Ganapati, 2019). Computational frameworks properly model the failure and restoration of infrastructure systems in the face of disturbances to the systems (Guikema et al., 2014; Ouyang & Dueñas-Osorio, 2014; Ouyang & Fang, 2017; Tomar & Burton, 2021; Winkler et al., 2010). Several studies have devised ways to assess the resilience of various infrastructure systems (Batouli & Mostafavi, 2018; Gori et al., 2020; Guidotti et al., 2019; Hassan & Mahmoud, 2021; Ma et al., 2019). Particularly related to power infrastructure systems, there are studies that have developed computational models for determining the system's reliability when exposed to potential hazards with respect to topological and inherent vulnerabilities (Figuero-candia et al., 2018; Holmgren, 2006; Mensah & Dueñas-Osorio, 2016; Outages et al., 2018; Ouyang & Zhao, 2014; Reed et al., 2010). Furthermore, there are frameworks that enable modeling and optimizing the restoration of damaged infrastructure systems (Sharma et al., 2020; Sun & Davison, 2019; Xu et al., 2019). While these studies inform about the resilience and reliability of physical infrastructure systems (such as power networks and transportation systems), shed light on the interactions between hazards and infrastructure, and include modeling the restoration process of utilities, the current body of literature lacks integrated computational models and frameworks that consider households' interactions with infrastructure systems vis-à-vis the probabilistic impacts of hazards.

Recent studies highlight the need for accounting for human interaction with infrastructure systems (Simpson et al., 2020). Households do not experience the adverse impacts of natural hazards and damage to infrastructure systems equally (Jones & Tanner, 2017). Integrating household-level attributes with infrastructure systems is essential in achieving resilience goals (Ghanem et al., 2016). Household-level attributes (e.g., previous hazard experience and socio-demographic attributes) and protective actions (e.g., preparedness and information-seeking) and their integration with hazard scenarios, as well as consideration of probabilistic physical infrastructure failures, service disruption duration, and restoration possibilities, are essential components for examining societal impacts of infrastructure service disruptions. Recent studies have shown a significant disparity in the societal impacts of infrastructure service disruptions (Chakalian et al., 2019; Coleman et al., 2019; Esmalian et al., 2020b; Mitsova et al., 2018, 2021). These studies unveil risk disparities and suggest that households are heterogeneous entities as evidenced by varying levels of tolerance for service disruptions. Particularly, shelter-in-place households experience great hardship from infrastructure service disruptions. Thus, there is a need for equitable resilience assessment for infrastructure systems. This equitable resilience assessment includes: (1) examining the disproportionate impact that disruptions in infrastructure systems have on the households and (2) assessing to what extent the mitigation strategies for reducing the societal risks would benefit different social subgroups. Computational frameworks are needed to capture households' interactions with infrastructure systems. A household's decisions related to protective actions are not only influenced by its attributes, such as socio-demographic characteristics, but they are also highly influenced by perceived risk from the hazard (Lindell & Hwang, 2008), information-seeking process (Morss et al., 2016), and their social network's influence (Haer et al., 2016; Kashani et al., 2019). Capturing these dynamic processes and decisions is essential for modeling and understanding the societal impacts of infrastructure service disruptions. In addition, a households' hardship experiences are influenced largely by the duration of service disruptions, which is the result of physical infrastructure failures and the utilities' decisions regarding service restorations. Hence, the societal impacts of infrastructure service disruptions emerge from the complex interactions among various processes in the hazard, households, and infrastructure systems nexus. The current literature, however, lacks computational models that are capable of capturing and modeling the complex interactions in this nexus. Consideration of societal impacts and disparities in infrastructure resilience assessments requires novel integrated complex modeling approaches (Mostafavi, 2018). Integrated complex modeling enables capturing various processes and mechanisms related to physical infrastructure and human decision-making behaviors and their interactions using computational simulation to identify nonlinear and emergent behaviors (Reilly et al., 2017). Integrated complex modeling enables evaluating the combined effects of hazard characteristics, human decision-making behaviors and protective actions, and physical infrastructure network properties and restoration strategies. Such combined evaluation of various processes across different systems is necessary to capture emergent phenomena in civil infrastructure and urban systems, such as societal impacts and disparities due to infrastructure service disruptions.

To address this gap, this study proposes and tests a novel computational multi-agent simulation framework including three components: (1) the hazard component that simulates a hurricane with different intensities; (2) the physical infrastructure component that simulates the dynamic process of failures and restoration; and (3) the households component that captures the dynamic mechanisms related to households behavior facing power outages. The proposed modeling framework was tested and implemented for the examination of strategies to reduce the societal impacts of disruptions of power systems. The model bridges the gap in the abstraction of behaviors of system components and provides a computational implementation of households' interaction with infrastructure systems and probabilistic simulation of hazards and failure scenarios to enable examining equitable ways for reducing the societal risks.

Using the proposed multi-agent computational simulation framework, we examined strategies to reduce the societal impacts of power outages and investigated important questions such as (1) What are the proper strategies for mitigating the societal risks due to prolonged power outages? (2) To what extent are the hazard mitigation and response strategies equitable? The model enables exploratory analysis of the pathways that determine different levels of societal impacts. The model also enables assessing the extent to which different strategies for reducing the societal impacts are equitable (Williams et al., 2020). Computational frameworks and decision-making tools are needed for resilient and sustainable infrastructure systems (Rafiei & Adeli, 2016; Wang & Adeli, 2013; Zavadskas et al., 2018). The computational modeling framework would help disaster managers, infrastructure managers, and utility operators in making informed decisions that consider the specific needs and societal risks in their resilience assessments.

The remainder of the paper unfolds as follows. Section 2 outlines the multi-agent simulation framework, including the detailed description of model development and the description of agents. Section 3 presents the model implementation and model testing; furthermore, the description of model outputs and experimentation are presented in this section. Section 4 presents the results for equitable resilience assessment of power networks and discusses the effectiveness of different strategies for mitigating societal risks. Last, Section 5 discusses the contribution and major findings of the research.

2 | MULTI-AGENT SIMULATION FRAMEWORK

Multi-agent simulation modeling is a proven approach for complex modeling and analysis of coupled human–infrastructure systems (Eid & El-adaway, 2018; Nejat & Damnjanovic, 2012; Rasoulkhani et al., 2020; Reilly et al., 2017; Terzi et al., 2019). The multi-agent simulation model enables the consideration of dynamic processes and complex interactions among different entities (Gutierrez Soto & Adeli, 2017; Haer et al., 2017; Watts et al., 2019; Widener et al., 2013). Furthermore, multi-agent simulation approach has the advantage of enabling the consideration of interrelation within agents and their heterogeneity (Morss et al., 2017; Navarrete Gutiérrez et al., 2017). Therefore, multi-agent simulation provides a powerful approach for modeling the nexus of hazard–human–infrastructure. This approach also enables better incorporating equity in both impact assessment and resource allocations (Bills & Walker, 2017). For example, Gurram et al. (2019) developed an agent-based model to examine the exposure inequality related to traffic air pollution. Chen et al. (2019) created a computational framework for examining the equity in access to bike-sharing systems. Williams et al. (2020) developed an agent-based model to assess the equity in the resilience enhancement plans for smallholder farming systems. In the current study, we create a multi-agent simulation model to examine the equity in the impact and recovery of infrastructure systems, in particular power outages, in the context of natural hazards. In the context of this study, the hazard component would cause damage to the infrastructure systems and also influence the preparation time for households. The infrastructure system would be damaged due to the impacts of the natural hazard. The system's physical vulnerability and restoration decisions affect the duration of service outages. The experienced hardship due to service disruptions by individual households is a function of their susceptibility and protective actions. The susceptibility and protective actions of households are influenced by various factors (e.g., income and race) and processes and shape the level of tolerance of households to durations of service outages. Households perceive threats from the hazard, inform their social network, and make decisions about their protective actions (such as preparedness). Households in the community have unique attributes and interact with each other to inform their decision to take protective actions depending on their capabilities, perception of risks, and their immediate social network's actions. Thus, the dynamic process of information-seeking behavior and decision-making about the protective actions are integral aspects of determining the level of tolerance to power outages. In this study, we used the household service gap model (Esmalian et al., 2021) to characterize societal risks at the household level. The model examines service disruptions as threats, households' tolerance as susceptibility, and experienced hardship as an indicator for the realized impacts of risk. When the duration of service outages exceeds the tolerance level of households, they would experience hardship (which is the indicator of societal impact in this study).

2.1 | Model overview

Figure 1 depicts the underlying mechanisms and processes in the hazard–households–infrastructure nexus captured in the proposed framework. In this framework, each of the underlying mechanisms leading to the societal impacts (experienced hardship) could be captured as dynamic processes. The integration of these processes enables simulating the extent of infrastructure failures, tolerance level of households, and service restoration duration, and hence determines the proportion of households in the community that experience hardship under different scenarios of hazard intensity and response/restoration strategies. The detailed descriptions of these interactions are discussed in the following sections.

The hazard component simulates the intensity of hazard and exposure of components of infrastructure systems. The infrastructure component captures the physical vulnerability and network topology of power infrastructure systems. The extent of damage to the infrastructure system depends on the components' fragility and the network topology. The more fragile the systems' components, the greater the probability of severe damage. Furthermore, network topology influences the system's physical vulnerability due to the cascading failure and connectivity loss in the network. The extent of damage and the restoration process of the utility determines the duration of a service outage. The duration of power service outages affects the hardship experienced by households (Miles & Chang, 2011).

The household component captures the dynamic processes and interactions influencing the level of tolerance of households to service outages. In particular, this research focused on the shelter-in-place-households, as these households are vulnerable to the impacts of power outages. The rapidity of the unfolding of a hazard event affects how far in advance households are informed about the upcoming hazard event (i.e., hurricane), allowing them to take adequate protective actions. Households interact with each other to share information about the hurricane and form perceptions about the potential duration of the outages based on the information they receive and characteristics specific to the household, such as prior hazard experience. Households make decisions about their protective action to reduce the impacts of service losses. Their decisions are not solely influenced by their risk perception and socio-demographic attributes; they are also influenced by other households' decisions. A household is more likely to prepare for an upcoming hurricane if other households in their social network take protective actions. Hence, the model captures the dynamic process related to the households' information search behavior, risk perception, and decisions related to preparedness actions that determine their tolerance. The experienced hardship of households would be determined by comparing their tolerance with their experienced duration of disruptions. The model could then simulate the hardship profile of the affected communities to examine societal impacts of varying hurricane intensities based on the physical condition of the power network, restoration activities, and households' protective actions to better tolerate the disruptions.

2.2 | Hazard component

The hazard component of the proposed model considers the failure of the power network due to damage by severe windstorms to components not designed to withstand strong winds. It is important to mention that the damages to components of the power network are not limited to those induced by intense winds; other risks such as debris flows and potential flooding could also cause damages to power networks. However, wind-induced damages are the most prevalent causes of damage during hurricanes as

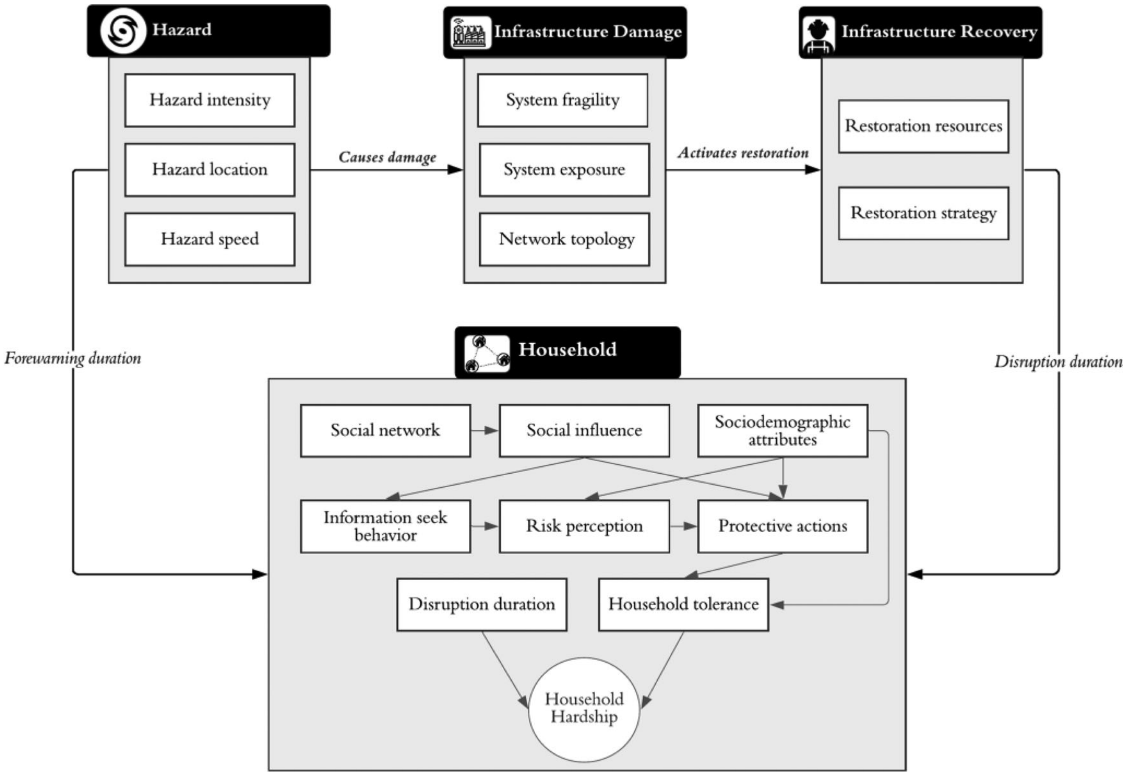

FIGURE 1 Human–hazard–infrastructure nexus framework for equitable resilience assessment of power systems

suggested by a review of the literature (Dunn et al., 2018; Panteli et al., 2017).

The hazard component simulates different hurricane categories and also includes the historical wind speed of Hurricane Ike and Hurricane Harvey in Harris County. The wind speed model is obtained from the HAZUS-MH wind model (Vickery et al., 2006). The wind model probabilistically generates the full profile of wind speed during the duration of a hurricane event with various return periods. The generated hurricane scenarios are grouped based on the maximum gust wind speed in the county. This model generates wind speed values for each census tract across the study area. Then, the generated hurricane scenarios are used to simulate the hurricane hazard in the multi-agent model. The wind gust speeds for different coordinates are implemented for the fragility analysis of the power network.

2.3 | Power network agent

2.3.1 | Network structure

The hurricane wind model poses stress on the power network and could cause multiple damages to the power network. The power network is a connected grid consisting of elements such as generators, substations, transmission lines, poles, conductors, and circuits. The data for modeling actual power networks within an area are either unavailable or difficult to access due to security issues. Therefore, the power network in this study is modeled by using a synthetic power network introduced by Birchfield et al. (2017) and Gegner et al. (2016). The implemented synthetic power network is a near-real representation of the power network in the study area, which matches the topological characteristics of the actual network in Harris County. The synthetic power network determines the geographic coordinates of the synthetized generations and loading substations based on the required loads and the publicly available power plant data in the study area. Then, the substations and generators are connected by transmission lines through a network that has structural and topological properties of an actual network and a converged power Alternating Current (AC) flow.

The distribution network consists of distribution poles and conductors. The number of distribution poles is estimated based on the population of each tract, assuming each pole serves 40 customers (Ouyang & Dueñas-Osorio, 2014). In the presence of actual data, the assumed values could be updated to provide context to the model outputs. The poles are directly linked via a distribution line to the distribution pole. Similarly, each distribution pole is con-

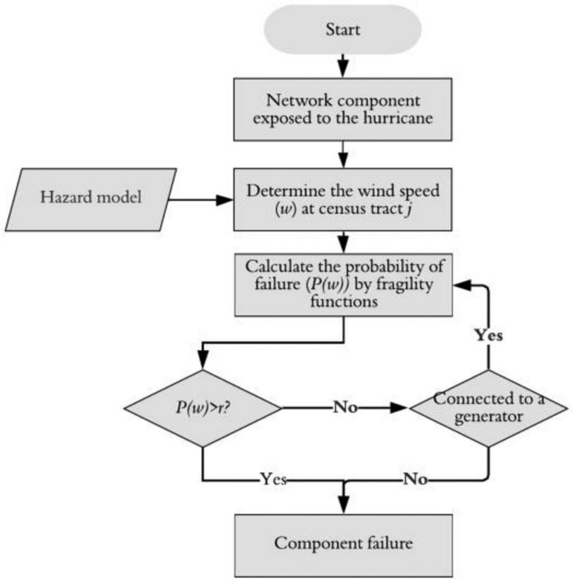

FIGURE 2 Schematic overview of the process for modeling the power system failure

nected to households through conductors. This methodology enables investigating damage to the power network in the absence of real data to model the actual system. Components of the power network, including power generators, substations, transmission lines, the distribution network, and their linkages are captured in the modeled synthetic power network.

Failures in the power network occur not only due to the direct damage to the power network components due to wind forces, but connectivity loss and cascading failures also cause disruptions to the network. Figure 2 shows the overview of the failure-modeling process in a power infrastructure network. The model includes two elements capturing the failure of the network from its exposures to a hurricane: (1) *component damage*: Failure in the power network components, which is modeled by incorporating fragility functions. The fragility functions help determine the probability of damage to the network components based on hazard intensity; (2) *connectivity disruptions*: The failure of a network component may lead to a series of consecutive connectivity losses. We used connectivity analysis of the network to model such cascading failures in the power network. The following describes the detailed modeling approach.

2.3.2 | Component damage

Fragility curves are used to model the failure in the components of the power network. Fragility curves are commonly used for modeling damages to infrastructure systems in response to natural hazards (Winkler et al., 2010). Fragility curves, in this model, determine the failure probability ($P(w)$) based on the imposed wind speed. To this end, the failure probability would be compared to a random variable $r \in [0, 1]$ from a uniform distribution in each iteration (Figure 2). A component, such as a power pole, would fail if the failure probability becomes greater than the generated random number (r). In this model, we consider the failure in the critical components of the power network: substations, transmission lines, distribution poles, and conductors. Damage to power plants by hurricanes, being highly unlikely, was not being considered as structural damage (Ouyang & Dueñas-Osorio, 2014).

Substations

The damage to substation loads is modeled by implementing the aggregated fragility functions developed in HAZUS-MH 4 (FEMA, 2008). The fragility functions provide failure probability based on the local terrain, wind speed at the area, and the structural characteristics of the substation. Equation (1) shows the general form of the fragility function. In this equation, the probability of failure (P_f) is related to the exposed wind speed (x). The two parameters, mean (μ) and variance (σ^2) are used to define the lognormal fragility curve. The fragility curves used for modeling damage to the substations are plotted in Figure B4 in Appendix B:

$$P_f\ (damage|w = x) = \int_{x}^{-\infty} \frac{1}{\sqrt{2\pi}\sigma} \exp\left(\frac{-(\ln(x) - \mu)^2}{2\sigma^2}\right) d_x \quad (1)$$

Transmission elements

Transmission elements include the transmission lines and the transmission towers, which support the lines. The length of the transmission lines is determined based on the specific latitude and longitude of the generators and substations loads in the synthetic network. The number of necessary transmission towers is estimated by assuming 0.23 km between two consecutive towers. Similar to the fragility function in Equation (1), we implemented a lognormal fragility function for determining the (P_f) of the transmission towers. The implemented fragility curves for modeling damage to the transmission tower are shown in Figure B2 in the Appendix. Damage to transmission towers is modeled so that towers fail independently of one another (Panteli et al., 2017); therefore, the total failure probability for the transmission element due to damage to the support structure between two substations that have n towers would be calculated using the following approach. In Equation (2), $P_{T(w)}$ is the probability of failure in the transmission element, $P_{k,w}$ represents the probability of failure of an individual tower between substations, and N

is the number of required towers for supporting the lines:

$$PT(w) = 1 - \prod_{k=1}^{N} \left(1 - P_{k,w}\right) \tag{2}$$

Extreme weather conditions could cause great damage to transmission lines; thus, separate fragility curves are used to model such damage. Following the approach proposed by Panteli et al. (2017), a linear fragility function (interpolated linearly), as shown in Equation (3) and Figure B2 (Appendix B), is implemented for calculating the probability of failure for the transmission lines.

$$PL\ (w) = \begin{cases} 0.01, & \text{if } w < w_{\text{critical}} \\ PL, & \text{if } w_{\text{critical}} < w \leq w_{\text{collapse}} \\ 1, & \text{if } w \geq w_{\text{collapse}} \end{cases} \tag{3}$$

This equation considers three conditions. First, if the wind speed is below a certain level of "good weather condition," the probability of failure is small (0.01). Here, w_{critical} is the wind speed at which the transmission lines can sustain damage, and w_{collapse} represents a situation when the survival probability of the component is very small. Then, the component's probability of failure (PL) is calculated by considering a linear relation in the intermediate phase between w_{critical} and w_{collapse}. These wind speed thresholds are assumed to be between 30 and 60 m/s following empirical studies (Murray & Bell, 2014; Panteli et al., 2017). In the presence of data from utilities, the equations and thresholds could be adjusted to reflect the real behavior of the components; pseudo algorithms are presented in Table A1 in Appendix A.

Distribution elements

The synthetic distribution network considers the failure of the conductors that connect the households to the power network and the poles that support the conductors. The empirical damage models, developed by Quanta Technology and implemented by Quanta (2009) and Mensah and Dueñas-Osorio (2016) are used in the absence of field data. The fragility equation for modeling the failure to the conductors is shown in Equation (4). This equation (also see Figure B3) draws the relationship between the wind speed (w) and the probability of failure to the conductors ($PC(w)$) in the distribution network.

$$PC\ (w) = 8 \times 10^{-12} \times w^{5.1731} \tag{4}$$

Last, the fragility function for modeling failure in the distribution poles is implemented in the model. Several studies have developed fragility equations for the distribution poles depending on their material, age, and maintenance (Salman & Li, 2016; Salman et al., 2015; Shafieezadeh et al., 2014). The fragility equation developed by Shafieezadeh et al. (2014) is used in this study to model the failure in the distribution poles. An example of the fragility curves is shown in Figure B3 in Appendix B.

2.3.3 | Connectivity disruption

The failure of a component in the power network may propagate through the network and lead to connectivity loss (also called cascading failures; Winkler et al., 2010). The model also considers the cascading failures due to the interdependencies among the components of the power network. For example, when a substation experiences damage, if the distribution network elements connected to the damaged substations are no longer connected to a power generator through other network components, these subsequent distribution networks would also be removed from the power network (Mensah & Dueñas-Osorio, 2016). Therefore, at each iteration of the model, the connectivity of the subsequent network component to a generator will be assessed. The pseudo-codes of the developed algorithm are shown in Table A2 in Appendix A.

2.3.4 | Restoration process

Restoration activity takes place after the hurricane passes through the affected area. After the failures in the power network are detected, the utility repairs damaged components of the power network. The downtime of different system elements depends on three main factors: (1) the extent of damage to the power network, (2) the available resources to the utility for restoring service, and (3) the utility's strategy for restoring the power (Duffey, 2019; H. Liu et al., 2007). Severe hurricanes pose more danger to the infrastructure elements and make it difficult for the utilities to restore services. The number of crews and the spare equipment in place also affect the restoration time (Xu et al., 2019). Finally, the priority of restoration activities influences the duration of outages. For example, restoration in more populated areas may sometimes be prioritized to meet the needs of a higher number of affected households (H. Liu et al., 2007). The pseudo algorithms are shown in Table A4 in Appendix A.

To determine restoration duration, the model determines the duration of the power outages by considering the dynamic repair process (Figure 3). The process involves multiple steps (Sharma et al., 2020). First, the priorities are given to the power restoration in different areas to implement repair and restoration strategies. Then, for each damaged element, the required resources and time to repair

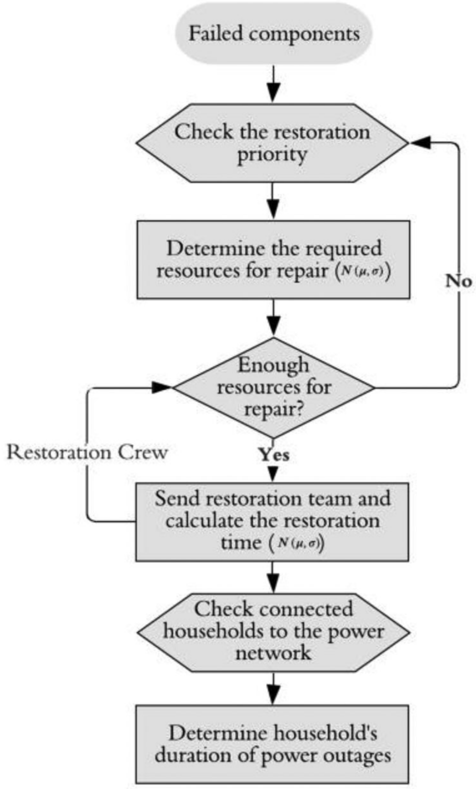

FIGURE 3 Schematic overview of the process for modeling the restoration activity

will be calculated based on Table B1 (Appendix B). The time to restore each element is calculated by considering a normal distribution and checking for non-negativity, $N(\mu, \sigma)$, with specific mean and standard deviation (Mensah, 2015). The resources in this model are crews, materials, and machines. The number of teams needed for the repair task is given in Table B1. The utility could have a finite number of resources in place, but then these resources could be augmented daily by assistance from other utilities through Regional Mutual Assistance Groups and collaborations (Edison Electric Institute, 2016). A linear relationship is assumed for the increase in repair resources (Figure B1) based on the results of previous studies (Ouyang & Dueñas-Osorio, 2014). The model inputs resources and initially implements 800 teams increasing by 15 teams per hour for a week as the base case scenario.

2.3.5 | Restoration strategies

Based on a review of the literature, there is no standard way of restoring power when a severe weather event damages a power network (Applied Technology Council, 2016). Some utilities would prioritize the restoration of the service areas with greater populations; however, this restoration strategy might favor residents living in a larger metropolitan area and might adversely affect people in rural areas (H. Liu et al., 2007). Other strategies mainly focus on physical characteristics, such as prioritizing the components with a high criticality, such as failed substations and transmissions (C. Liu et al., 2021; Ouyang & Dueñas-Osorio, 2014). The model uses priorities assigned to the components in the network to generate the different repair strategies.

In this study, we tested the influence of three main strategies for restoring the power for residents, *component-based restoration*, *population-based restoration*, and *social vulnerability-based restoration*. In component-based restoration, the model prioritizes the restoration of critical components, such as failed substations and transmissions. The critical components are those that require more resources and serve a large number of users. After the repair of these components, the model initiates the repair of the damaged distribution network comprising conductors and poles in a random sequence. Restoration based on population and the social vulnerability index (SVI) focuses on the prioritization of the repair of the components, which serve areas with larger populations or higher social vulnerability scores informed by census data and an SVI (Flanagan et al., 2011). Depending on the selected strategies, the ranges of service restoration duration would vary in different areas. Therefore, in this model, households would experience varying levels of power outage durations due to the differences in the restoration duration, which is a function of the extent of damage and the utility's restoration strategy.

2.4 | Household agent

Households have varying levels of tolerance for withstanding power outages. Empirical data from household surveys collected in the aftermath of three major hurricane events (Harvey, Florence, and Michael) together with theoretical decision-making models were implemented to simulate the underlying mechanisms that influence households' tolerance. The tolerance depends on households' decisions about protective actions and their inherent needs for the service (Baker, 2011; Coleman et al., 2020; Esmalian et al., 2020b). The model includes the process through which households know about the event and form perceptions about the risks. Then, empirical models developed based on the survey data used in conjunction with decision-making processes are used to determine the probability of a household taking protective actions. This probabilistic characteristic of the households' behaviors enables consideration of the uncertainties regarding the individual's behavior in the model. Finally, the household's hardship status would be determined based on tolerance and the

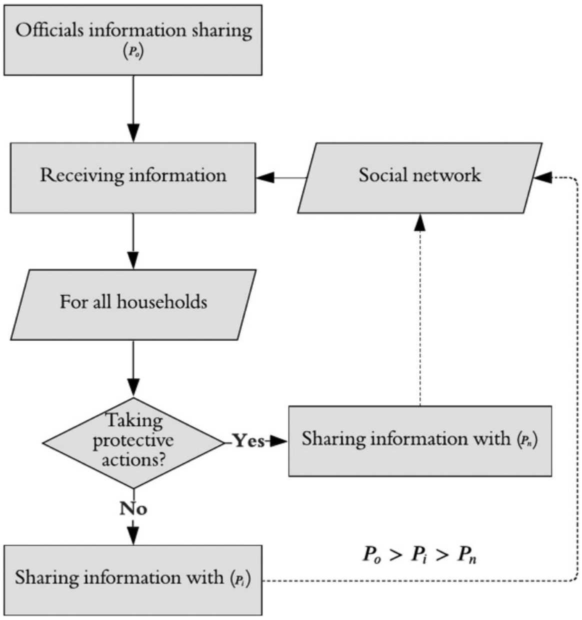

FIGURE 4 Schematic overview of the information seek/share behavior

duration of outages. The pseudo algorithms are shown in Table A3 in Appendix A.

2.4.1 | Information propagation process

Two information propagation processes are considered in this model (Figure 4). First, we modeled information-sharing through official sources (such as mass media). In the days before hurricane landfall, officials disseminated information about the upcoming hurricane, which is modeled by implementing a probability of receiving the information by the households through officials (P_o). In addition, those who receive the message might also share the information with their immediate social network, depending on how important they perceive the risks of the hazard, and then take protective action themselves. Hence, two probability values of (P_i) and (P_n) are considered for implementing the information-sharing process by households. Those who perceive great risk from the hazard and take protective actions (P_i) are more likely to share information with their social network than those who do not take protective actions (P_n). These probabilities are determined using the empirical data and considering a higher value for the probability of receiving information from the officials.

2.4.2 | Household agent's social network

Agents interact with each other and influence the decisions of others through their social networks. The social network of the agent would not only influence the information propagation process; it would also affect other agents' decisions regarding protective actions (Anderson et al., 2014; Tran, 2012). Multiple network structures—random network, small-world (SW) network, scale-free (SF) network, and distance-based network—characterize how households are connected with each other. These network structures are present in real-life social settings. For example, the literature suggests that information-sharing through online social media, which follows an SF network structure, could expedite information propagation (Nocaj et al., 2015; Schnettler, 2009). Therefore, we considered multiple network structures to account for various modes through which households could interact and share information, and we tested the impact of such structures on the overall impact of the hazard on the communities. The social network would affect both the information propagation process and the household decision-making on the protective actions through peer effect.

2.4.3 | Household agent's risk perceptions

Household agents form a perception about the potential duration of the power outages. We analyzed data collected from the household surveys to determine households' expectations of the disruptions; the summary statistics of household survey data could be found in Esmalian et al. (2020b). Households' expectation of the duration of the disruption affects their decisions regarding taking protective actions. Those with higher expectations of the disruptions are more likely to take protective actions (Coleman et al., 2020; Lindell & Hwang, 2008). The expected duration of disruptions was measured by the number of days a household expected the power outages. This variable is positive and a count data; thus, a Poisson regression model was selected for modeling the expected duration of the outage. Equation (5) shows how the mean value of the duration of the expectation (μ) is related to the predictors through a *log* link by implementing a Poisson regression model. In this model, x_f refers to the forewarning duration of the event (measured by the number of days), x_i captures if the households receive the information about the hurricane (binary variable), x_o is home ownership, x_a captures whether the head of the household is elderly, x_m captures if any of the household members have a mobility/disability issue, and x_{fz} refers to if the households live in a flood zone:

$$\mu = exp\left[1.74700 + 0.30471 log\left(x_f + 1\right) + 0.12369 x_i - 0.27720 x_o - 0.21065 x_a - 0.51210 x_m - 0.28153 x_{fz}\right] \quad (5)$$

2.4.4 | Household agent's socio-demographic characteristics

Households' demographic characteristics influence their perceptions of the risk, decisions regarding the protective actions, and consequently their tolerance for the disruptions (Baker, 2011; Coleman et al., 2019; Horney, 2008). In this model, households' demographic characteristics are considered by developing a sample of agents based on publicly available census data. A population is sampled by considering the probability of being from a specific segment of a community by using the actual proportions in the census data. In particular, data about income level, race, age, education, mobility/disability conditions, and type of housing of the households were collected. In addition, to determine whether a household was in a flood zone, their location was plotted against a 500-year flood map.

The demographic characteristics of households not only influence their decisions on protective actions, but they also affect households' level of need for the service. The level of need is modeled through the use of empirical data. In the surveys, this variable is measured with an ordered five-level Likert scale; therefore, a cumulative logit model is developed for determining the level of need (Equation 6). The model relates the effect of predictor x on the log odds of response category j or below by coefficient β (Agresti, 2007). This type of modeling helps in determining the probability of Y (the level of need) falling below a certain level (Equation 7). Then, as the summation of each probability level (π_j) equals 1, the probability of each level could be determined. Appendix B outlines the models for estimating the level of needs:

$$\text{logit}\, P(Y \leq j) = \alpha_j + \beta x \tag{6}$$

$$\text{logit}\ [P(Y \leq j)] = \log\left[\frac{P(Y \leq j)}{1 - P(Y \leq j)}\right]$$
$$= \log\left[\frac{\pi_1 + \cdots + \pi_j}{\pi_{j+1} + \cdots + \pi_J}\right], \qquad j = 1, \ldots, J-1 \tag{7}$$

2.4.5 | Household agent's protective action process

Households take protective actions to reduce the impacts of power outages in two ways. First, the general preparedness behavior of households in terms of obtaining food, water, and emergency kit supplies helps them to better cope with the outages. Second, some households might take further actions by purchasing a generator. We modeled the protective action process of households by implementing the diffusion model developed by Banerjee et al.

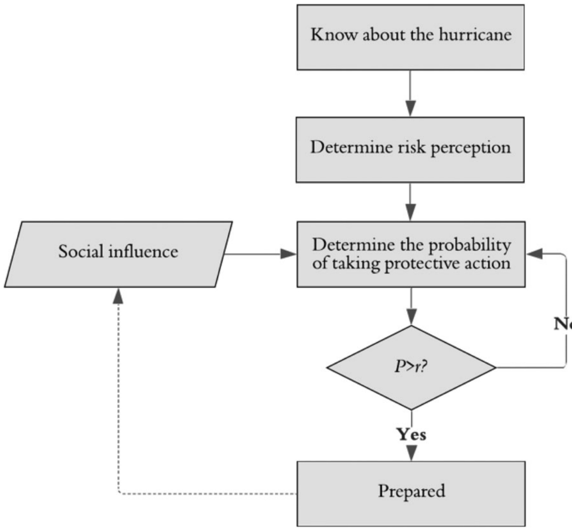

FIGURE 5 Schematic overview of taking protective actions by households

(2013). As shown in Figure 5, households are first informed about the hurricane through the information propagation of officials or their immediate social network. Second, an initial number of households decide to take protective actions depending on their decisions' probability (P_p). Households' probability of taking protective actions (P_p) depends on the households' personal characteristics, such as demographic characteristics, risk perception, and peer influence. Equation (8) shows the implemented logistic function to model this process. Third, those who decide to take protective actions influence their social network by passing the information regarding their protective actions. Fourth, the newly informed households now decide if they want to take protective action. This process initiates as soon as the officials detect the hurricane and ends after (f) days of forewarning:

$$\log\left(\frac{P_p}{1-(P_p)}\right) = X_i \times \beta + \lambda \times F_i \tag{8}$$

In this model, β is the vector of the coefficients that relates the personal characteristics (X_i) to the log-odds ratio of the protective action decisions. F_i is the fraction of the household's social network that had decided to take protective actions divided by the total number of household's social network. The unit-less parameter of λ represents the change in the log-odds ratio of protective actions due to peer influence. A value of zero for λ describes the case in which households make their decision independent of their social network, while larger values of λ refer to a situation when households affect the decision of their social network. The empirical models were implemented to determine the β, and the model has been tested to determine the range of λs. Details related to the factors considered for developing these models are presented in Appendix B.

2.4.6 | Household agent's protective action process

Households have different levels of tolerance for withstanding prolonged power outages (Esmalian et al., 2019). This is why even a similar outage duration would cause varying levels of hardships in different households (Coleman et al., 2019). Households' tolerance for power outages is a function of their protective actions and inherent needs for the service. Household tolerance is determined by implementing accelerated failure time (AFT) models, which are a type of survival analysis approach for the time-to-event data (Dale, 1985). This type of modeling was found to best describe the model and to have the lowest prediction error when compared to generalized linear models (Poisson family and negative binomial regression) and ensemble learning methods (random forests and boosting; Esmalian et al., 2020a). Using AFT models, we can directly relate tolerance to the predictors with a linear relationship as shown in Equation (9):

$$\log \mu_i = x_i^T \beta + \varepsilon_i \tag{9}$$

where μ_i represents the mean tolerance, x_i^T denotes the vector of predictor, β is the vector of parameters, and ε_i is an error term that is assumed to be independently distributed. In this model, three main predictors were used for determining tolerance: households' level of need for the service, their preparedness for the event, and if they obtain a generator to withstand the power outages. The protective actions of the households are determined through a probabilistic approach outlined in the previous sub-section. The level of need is determined based on their socio-demographic characteristics to be considered in calculating the tolerance level.

In the last step, the households' experienced hardship is determined by integrating the results from the restoration process with households' tolerance. Households experience different levels of the duration of disruptions and experience hardship when the duration of the outage exceeds their tolerance. Figure 6 presents the process for determining the households' experienced hardship from service disruptions.

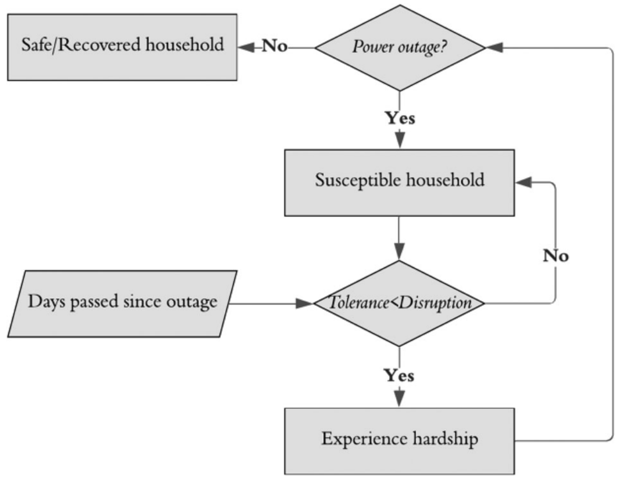

FIGURE 6 Schematic overview of household hardship experience process

3 | MODEL IMPLEMENTATION AND SIMULATION EXPERIMENTS

3.1 | Computational implementation

Computational representation of the proposed multi-agent modeling framework includes developing and implementing algorithms and mathematical models to capture the theoretical logic representing the experienced hardship of households due to disaster-induced disruptions. The computational model is created by using an object-oriented programming platform, AnyLogic 8.3.3. Figure 7 depicts the Unified Modeling Language diagram of the model, which shows the class of the agents, agents' attributes and functions, and their relationships. A sample of 2500 households based on the demographic characteristics of Harris County was generated and placed in the census tracts. The sample is statistically representative of the households in Harris County with a 95% confidence level and a 2% margin of error. The synthetic power network includes a total of 97 substations, 242 transmission elements, and 1433 distribution elements located in Harris County based on latitude and longitude coordinates as described in the power network agent section.

3.2 | Verification and validation

The model is verified and validated through a systematic and iterative process to ensure the quality and credibility of findings. Various internal and external approaches were conducted to verify the data, logic, and computational algorithms in the simulation model (Bankes & Gillogly,

FIGURE 7 Unified Modeling Language class diagram of the multi-agent simulation model

1994; Mostafavi et al., 2016; Rasoulkhani et al., 2020). First, the internal verification of the model was ensured by using the best available theories and standard approaches for implementing the models' logic and rules. Second, we used reliable empirical data collected in the aftermath of three major hurricane events to develop the model. Furthermore, we conducted a component validity assessment for ensuring the model components' completeness, coherence, consistency, and correctness. The extreme conditions were tested to examine the model's ability to generate reasonable outcomes. External verification of the model was ensured by examining the causal relationships among the model components. The behavior of these subcomponents under different values was traced to ensure the external verification of the model. The model logic and functions were examined to discover any unusual patterns to ensure that logic and assumptions in the model are correct.

For validation, the generated patterns in the model outputs were compared against the empirical data to validate model behavior. The mode of each simulated output was used to determine the system's behavior, then the generated patterns from the model were compared with the actual household behaviors from the empirical survey data and similar studies and reports. The developed multi-agent simulation model integrated the processes leading

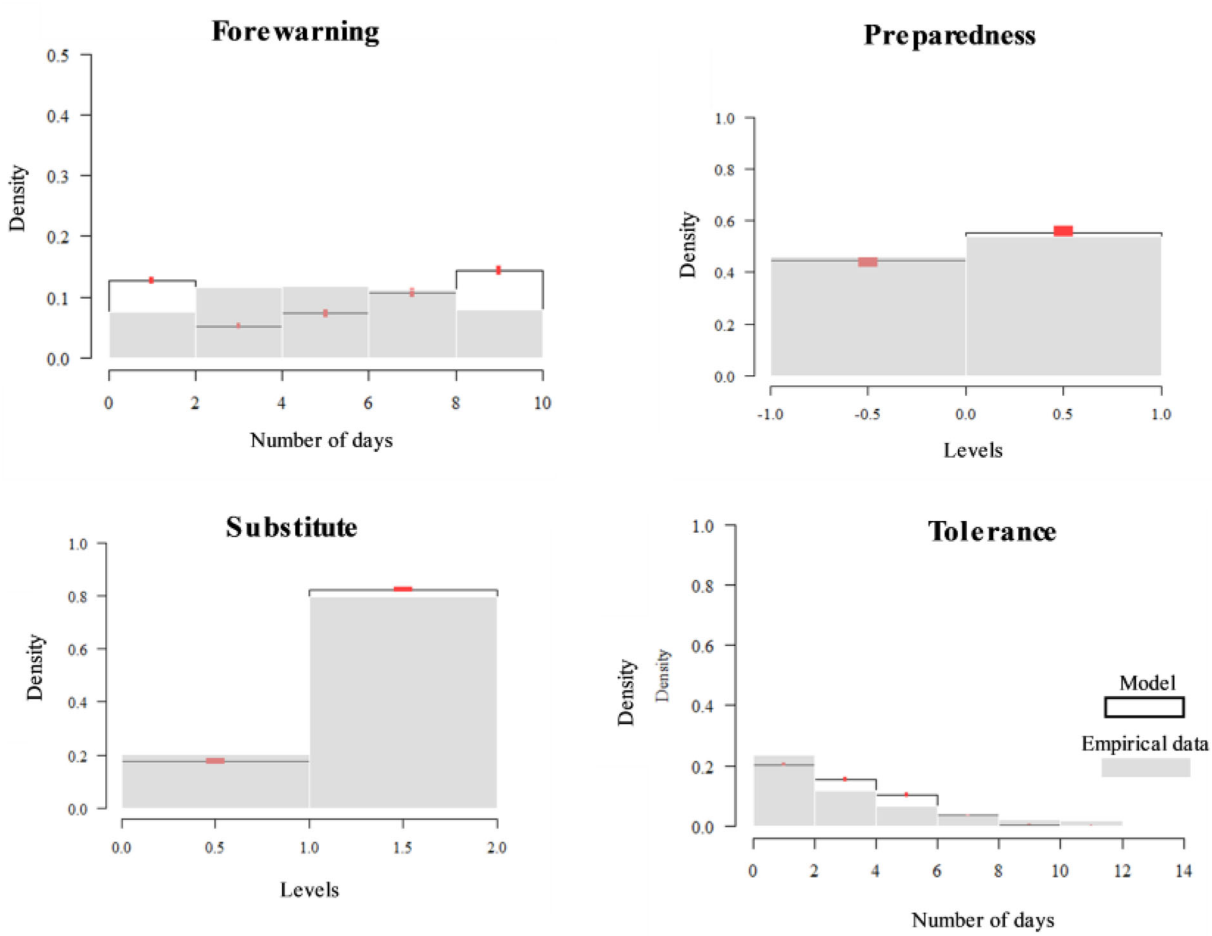

FIGURE 8 Comparing values generated by the model with empirical data. Red whiskers show the model replications' 5% and 95% values

to the generated patterns. These generated patterns were compared against the distribution of parameters of interest to check if the model is able to generate correct behavior. In this study, the intent of the model was to examine the strategies to reduce societal impacts of power outages. In particular, emergent behavior patterns of the outputs were of interest. Furthermore, results from similar studies and reports on the impact of hurricanes on the power networks were used to validate the model's output for the physical system (Mensah & Dueñas-Osorio, 2016; Ouyang & Dueñas-Osorio, 2014). The model is capable of generating patterns and values similar to the empirical data (Figure 8). The model outputs capture the Hurricane Harvey scenario in Harris County, Texas, in 2017 (Figure 8). For example, the generated proportions of households that prepare and obtain substitute energy sources (generators) are similar to those values from empirical data. Some differences arise in the model results for large and small values of the forewarning time; however, the distribution of tolerance is close to the empirical values. It is worth mentioning that the primary objective for the creation and use of multi-agent and agent-based models is not a prediction but rather to generate examples of the probabilities of various possibilities for robust decision-making under uncertainty (Mostafavi et al., 2016).

3.3 | Model output description

The percentage of households experiencing hardship from power outages is recognized as an indicator of the societal impacts on the community. When a households' duration of power disruption exceeds their tolerance, they experience hardship. This indicator includes both the physical impact and the societal susceptibility of the households for the risk posed. This dynamic measure is calculated for all households based on their location and their tolerance during the time without service. Figure 9a shows how the dynamic profile of hardship could be implemented to assess the effectiveness of various strate-

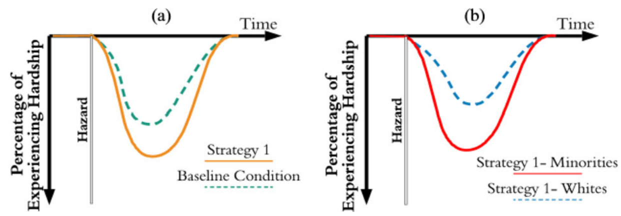

FIGURE 9 Schematic dynamic profile of hardship. (a) Comparison of the effect of strategies, and (b) comparison of the impact of strategies on different social groups

gies in reducing the societal impacts of power disruptions. Different scenarios could be tested to find ways to mitigate the societal risks of disruptions to power networks.

In addition to examining the societal impact on the community, the model enables examining the impact on various sub-populations (Figure 9b). This capability of the model enables an understanding of whether system restoration strategies are equitable. For example, while one strategy might reduce the societal impact on the community as a whole, it is possible that the strategy is in favor of certain demographics in the community. Thus, strategies would be examined to determine how they improve the condition of different social groups in the affected community.

3.4 | Simulation experimentation

The developed simulation model enables testing scenarios through various variables such as household characteristics, household social network structure, forewarning duration, hurricane category, and restoration units and strategy. The user could choose the values related to each of these variables in an interactive user interface (Figure 10a). The model outputs the various values related to different variables, including household protective actions and tolerance, the extent of damages to the different components of the power network, and the households' profile of hardship. In addition, as shown in Figure 10b, the model visualizes the spatial distribution of households' states by color-coding them depending on their states. Households who experience the power outages are shown in orange, those whose tolerance becomes less than their duration of disruption and experience hardship are shown in red, and the color changes to green when the power is restored for these households.

We performed Monte Carlo experimentation in the scenario testing to account for the stochasticity in the model. The primary variable of interest in the model experimentation was the percentage of the households who experienced hardship from the power disruption. Therefore, experiments were replicated as many times as the mean value of proportional of households experiencing hardship reached 95% confidence interval with 5% error (Hahn, 1972). The experiment scenarios were designed by changing the input values of each scenario and replicating iterations for each of the experiments.

3.5 | Scenario analysis

The model is implemented for scenario testing aiming at (1) identifying the combination of the strategies that would lead to the lowest societal impact due to the power outages, and (2) examining the extent to which the strategies are equitable. In this study, we examine three main strategies to reduce the societal impacts of power outages. First, the power utility's restoration strategy would be evaluated to examine its influence on the hardship levels. In this regard, three strategies of restoration based on the importance of the components, population size, and SVI would be evaluated. SVI is a widely adopted measure for examining the susceptibility of populations in disasters. Second, the influence of the forewarning time on the experienced hardship of the households could be examined. Early warning about the upcoming hazard can reduce the societal impacts (Panakkat & Adeli, 2009; Rafiei & Adeli, 2017) by influencing the protective decisions of households (Cremen & Galasso, 2021; Watts et al., 2019). This assessment would determine the effectiveness of identifying an impending hurricane and communicating critical information with the population. Third, the impact of the social network of the households on their experienced hardship would be evaluated. This assessment would show the value of using alternative social networks (such as social media) for disseminating hazard information. Social media platforms, for example, have distinct network characteristics, which enable quicker information-sharing without spatial boundaries (Watts et al., 2019; Zhang et al., 2019). Therefore, the type, density, and weight of the social influences would be examined to explore their effect on reducing the impacts of power outages on the households. The combination of these strategies to lower the hardship experienced by the households was also examined. In addition, the equitable resilience assessment in this study is being implemented by examining the disproportionate impact and effect of strategies on racial groups, while there are other social dimensions in equitable resilience. A similar approach could be implemented for understanding the equity aspect for other social groups; however, this study mainly focused on one group as an example of equitable resilience assessment.

FIGURE 10 Screenshots of the developed simulation model

4 | RESULTS AND DISCUSSION

The hardship experience of households from scenario analysis was used for exploratory analysis of societal risks of prolonged power outages. The analysis included: (1) examining strategies for reducing the societal impacts; (2) examining to what extent these strategies, including restoration strategies, forewarning, and social networks, are equitable; (3) robustness of the strategies for reducing the societal impacts under different scenarios; (4) identifying pathways that lead to low societal impacts. To this end, a base scenario similar to the Hurricane Harvey context was used with a forewarning of 9 days, component-based restoration by utility, and an SF social network between households. Scenarios were then modeled and compared with the base-case scenario through Monte Carlo simulation. In the simulation results, day zero is the time when an impending hurricane is identified by the officials as a threat, and the information is communicated with the residents.

4.1 | Simulating community-scale societal impacts

A baseline scenario of societal impacts of power outage disruption in a community similar to Harris County affected by a category 4 hurricane is shown in Figure 11. Figure 11a shows the mean proportion of households experiencing hardship each day. The results suggest that at maximum, around 50% of the community experienced hardship from the outages, and it took roughly 20 days for the community to fully recover (recovery is determined by having power restored for all households). The impact, however, was not equal among the subgroups in the community. Racial minority groups experienced a higher hardship from disruptions. Figure 11b shows the overall probability of experiencing hardship for each group. Analysis of variance (ANOVA) test showed that the difference between the two groups is statistically significant at 0.05 confidence level ($p = .018$). This result suggests that racial minority groups are more likely to experience hardship from power outages in comparison with others in the base-case scenario. The results overall show the model's capability to capture the societal impact of the disruptions on communities and also reveal the inequities in the impacts of prolonged power outages on vulnerable populations (e.g., minority groups).

4.2 | Examining strategies for reducing societal impacts

4.2.1 | Restoration strategy

Results for comparing different strategies for restoring the power (Figure 12) show that while under the component-based strategy, the maximum proportion of hardship in a day is around 54%. This value would be decreased to around 47% under the population- and SVI-based restoration strategies. The results show that overall, a community similar to Harris County, Texas, would benefit from prioritization of the areas with a higher vulnerable population. In this case, the probability of experiencing hardship for the nonvulnerable population increases and becomes greater than the vulnerable population ($p = .003$); however, the reduction in the probability of experiencing hardship for the socially vulnerable groups leads to an overall reduction in the societal impacts. In addition, giving priority to the areas with a higher population result in the reduction of overall societal impacts on the affected community, while the vulnerable population still faces a greater probability of experiencing hardship ($p = .003$). These findings suggest that overall, the prioritization of areas with a higher social vulnerability level and also with a higher population could lead to the reduction of societal impacts in the affected community.

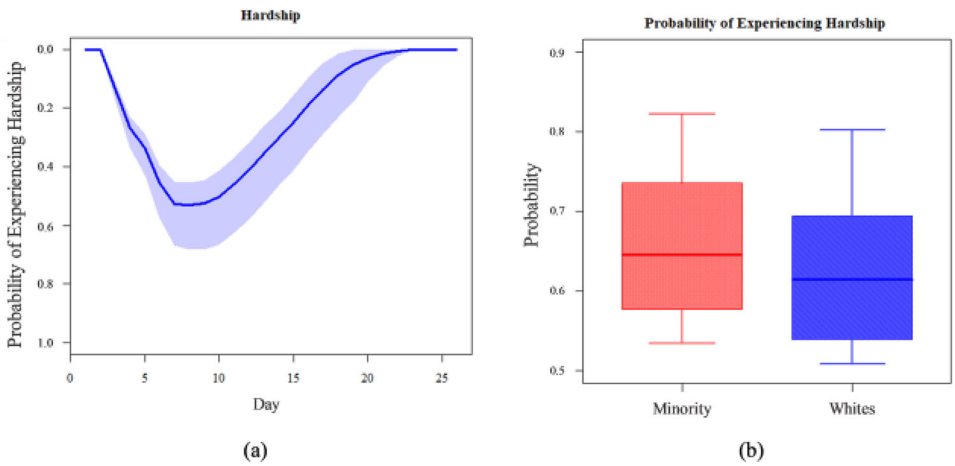

FIGURE 11 Societal impacts of disruptions from power outages in the baseline scenario. (a) Average daily proportion of households experiencing hardship and the 10% confidence intervals, and (b) boxplots and mean lines for the probability of racial minorities and whites experiencing hardship

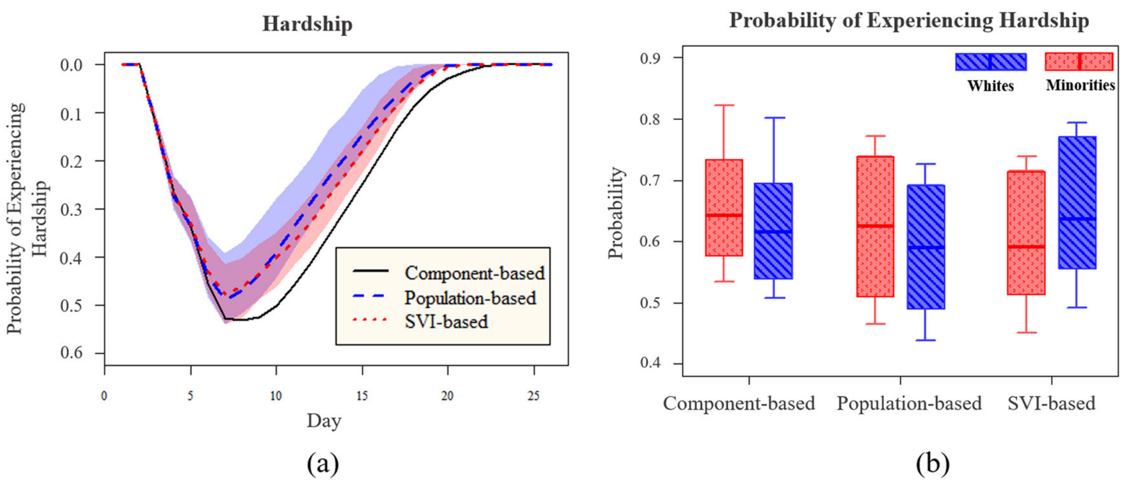

FIGURE 12 Comparing different power restoration strategies. (a) Dynamic patterns of the proportion of households experiencing hardship under each strategy, with shaded areas indicating the 0.25 and 0.75 percentile of the values, and (b) probability of experiencing hardship for different racial groups under each restoration strategy

The results comparing the effect of different prioritization strategies on racial groups are shown in Figure 13. The charts juxtapose the probability of experiencing hardship for two social groups under different restoration strategies. In the SVI-based recovery, the probability of experiencing hardship decreases by 8% for the socially vulnerable groups, while it would increase by 4% for the nonverbal group. The population-based recovery, however, decreases the probability of experiencing hardship by 2% and 4% for the vulnerable and the nonvulnerable groups, respectively. The results suggest that the population-based restorations while improving the overall societal risks, do not favor minority groups. On the other hand, the SVI-based recovery, while increasing the risks for the Whites, reduces the overall societal impact. While the population-based restoration and SVI-based would reduce the overall societal impacts, an SVI-based approach seems to be more equitable.

4.2.2 | The effect of increasing the forewarning period

Providing a longer forewarning to the communities reduces the societal impacts of power outages. As expected, the longer duration of the forewarning helps the households to better prepare for the impacts of the power outages and take protective actions to reduce the impacts

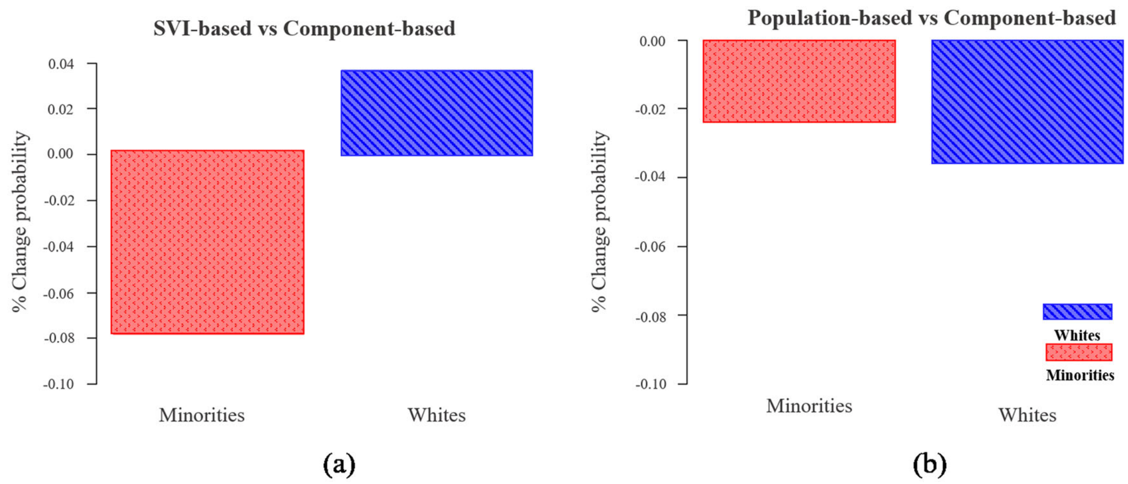

FIGURE 13 Comparing the probability of experiencing hardship for the racial groups under each restoration strategy

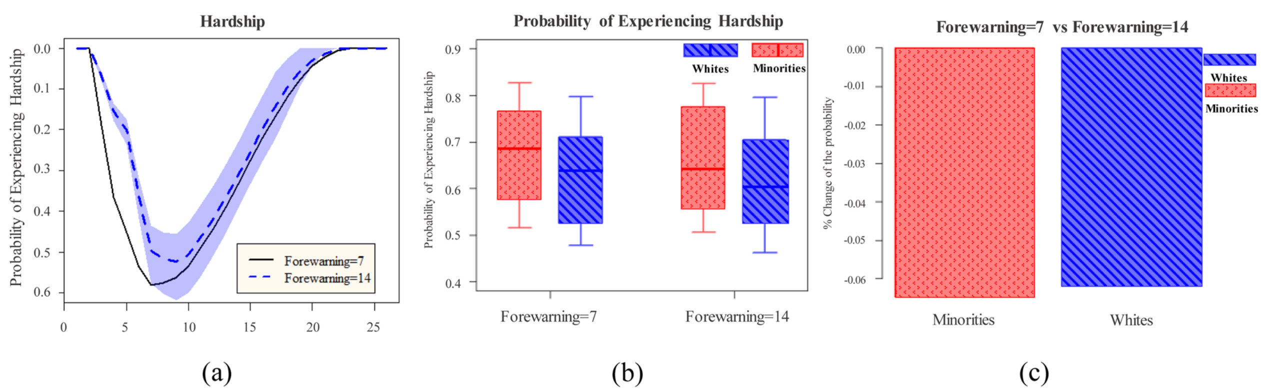

FIGURE 14 Comparing different forewarning levels. (a) Dynamic patterns of the proportion of households experiencing hardship under each forewarning level. The shaded areas show the 0.25 and 0.75 percentile of the values, (b) probability of experiencing hardship for different racial groups under each forewarning level, and (c) change in the probability of experiencing hardship for the racial groups under improvement of the forewarning level

of power outages on their well-being. Comparing an event with a week of forewarning with a scenario in which the household had 2 weeks of forewarning, the results suggest that this early identification of a hazard is very effective for reducing the impacts for the communities (Figure 14). The maximum proportion of households experiencing hardship in a day would decrease around 8% when increasing the forewarning time from 7 to 14 days. With rapidly intensifying hurricanes (such as Hurricane Ida, 2021), the forewarning period is becoming shorter, and hence the results show the effect of shorter forewarning periods on the experienced societal impacts of power outages. Investments in making advancements in predicting and tracking the hurricane pass, and proper communication with households could significantly reduce the societal impacts of power outages. However, the enhancements in providing longer forewarning would not necessarily reduce the societal impact for socially vulnerable populations. In both the base scenario and the enhanced strategy, minorities show a statistically significant higher probability of experiencing hardship (p-values are respectively .002 and .001 for forewarning of 7 and 14), Figure 14b. While the enhanced strategy shows to reduce the impact for the minority groups slightly more than other groups, this strategy seems to treat everyone equally and does not necessarily be in favor of improving the equity in the impact.

4.2.3 | The effect of hazard information dissemination and social network types

The social network type has implications regarding which social network people receive information. The two structures of social networks, namely, SF and SW, are compared as each provides certain characteristics in the propagation of information through the community. For example, as

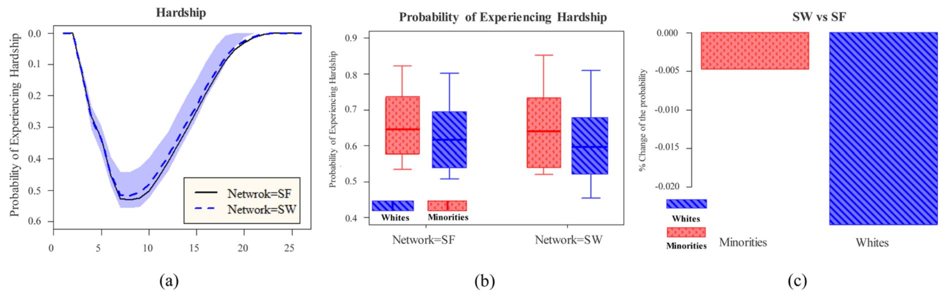

FIGURE 15 Comparing scale-free and small-world social networks. (a) Dynamic patterns of the proportion of households experiencing hardship under each forewarning level. The shaded areas show the 0.25 and 0.75 percentile of the values, (b) probability of experiencing hardship for different racial groups under each network structure, (c) change in the probability of experiencing hardship for the racial groups under a change in the social network structure

discussed earlier, communication among close friends happening offline (in person or on the phone) is through an SW network, and communication on social media is through an SF network (Nocaj et al., 2015; Schnettler, 2009). The results from Figure 15 show that there is a slight difference in the societal impacts of power outages on the community when comparing the two network structures. One reason is due to the delays in acting upon the information received by the social network for taking protective actions. Results suggest that the probability of experiencing hardship is greater in the small-work structure. Both cases show a greater probability of experiencing hardship by the vulnerable population, with *p*-values being .018 and .001, respectively, for SF and SW structures. The change in the network structure from SF to SW seems to have a greater impact on the nonminority group. This means that lack of information communication through social media could have more impacts on minority groups, compared to White households.

4.3 | Combined effect of strategies for reducing the societal impacts

4.3.1 | Robustness of restoration strategy to different hurricane categories

The effectiveness of implementing different strategies for restoring power to reduce the societal impacts varies depending on the intensity of the hurricanes. Figures 16a,b show the probability of experiencing hardship for each strategy and the dynamic impact under the four hurricane categories. While there is no significant advantage for implementing population-based and SVI-based strategies during low-impact events such as hurricane category 1 (*p*-value equal to .297), these strategies seem to over-perform the component-based restoration during hurricane categories 2 and 3 (with *p*-values for ANOVA test being .001 and < .001). The largest difference is related to hurricane category 3, with population-based restoration leading to the mildest societal hardship. However, the difference between the societal impacts of implementing the population-based and SVI-based with component-based, while being statistically different (*p*-value of .01), decreases in hurricane category 4. This result suggests that the effectiveness of the improved restoration strategy may not increase linearly as the intensity increases. When the intensity increases to hurricane category 4, the SVI-based strategy seems to perform slightly better than population-based and component-based restoration. This trend is due to the increased gap between the vulnerable population and others when the intensity increases as the intensity of the hurricane increases. Figures 16c, d compare the probability of experiencing hardship for the racial groups for population-based and SVI-based relative to component-based, respectively. While the population-based recovery seems to improve the condition for both social groups, this strategy seems to be slightly in favor of the nonvulnerable population. However, the SVI-based restoration reduces the societal impacts for the vulnerable population more than others. Therefore, when the intensity increases to hurricane category 4, this strategy reduces the overall hardship even slightly better than the population-based restoration.

4.3.2 | Robustness of forewarning to different hurricane categories

The extent of reduction in the societal impacts of power outages by providing a longer forewarning time varies depending on the hurricane category. The probability of experiencing hardship for different forewarning levels is not equal in different hurricane categories (*p*-values are < .001). The reduction of societal impacts showed significant changes for the forewarning time of more than 6 days

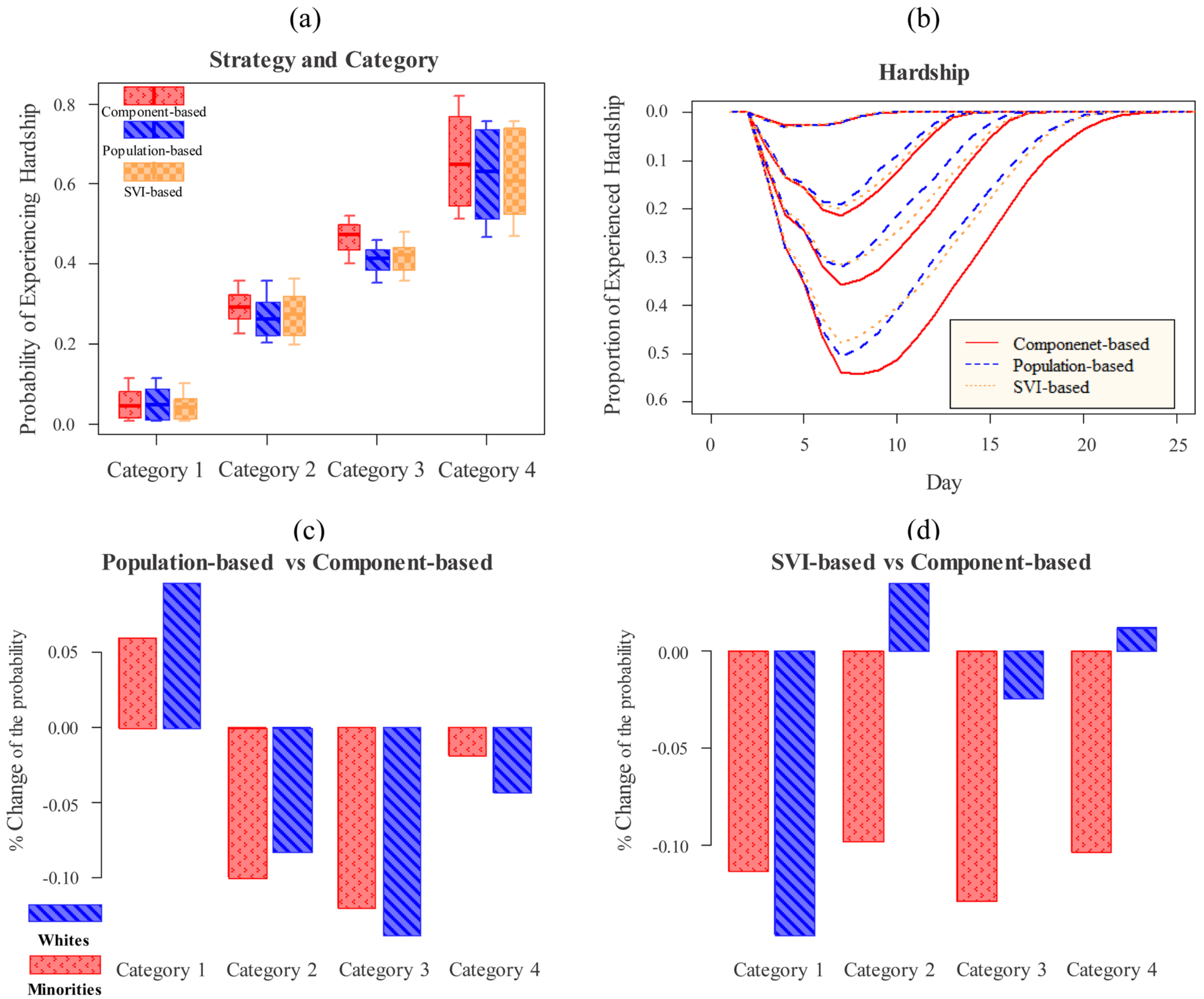

FIGURE 16 Effect of restoration strategy on the societal impacts of power outages under various hurricane intensities. (a) Histograms of the probability of experiencing hardship for each scenario, (b) displays the average daily experienced hardship for each scenario, (c, d) percentage difference of the probability of experiencing hardship for the racial groups under each scenario

(Figure 17a,b). These figures show that both the probability of experiencing hardship and the daily experienced hardship sharply decline when forewarning time increases to more than 6 days. The results explain the major impact of rapid onset hazard events (such as fast-moving hurricanes) on the affected communities. Figure 17c compares the probability of experiencing hardship for scenarios increasing by 3-day increments of forewarning. This result suggests that providing longer forewarning is mainly an effective strategy for low-intensity hurricanes. The effect of providing a longer forewarning in categories 3 and 4 hurricanes seems to diminish. Thus, implementing this strategy may not solely reduce the societal impacts of high-intensity hazard events. Last, Figure 17d shows the percentage of reduction of the probability of experiencing hardship for racial groups if the forewarning increase from 6 to 12 days. The result shows that increasing the forewarning duration does not seem to benefit certain groups. While minorities experience a decrease in the experienced hardship under hurricane categories 1 and 2, the difference does not seem to be significant, especially for the more intense hurricane events.

4.4 | Pathways to different levels of societal impacts

A combination of scenarios was used to create the scenario landscape (Figure 18) and to evaluate the combination of strategies that lead to the least onerous societal impacts of power outages. To this end, classification and regression tree (CART) analysis was implemented to examine the effect of different variables for reducing the societal impacts under various scenarios (Breiman et al., 1984). CART is a tree-based classification technique that explains how a target variable could be determined based on the

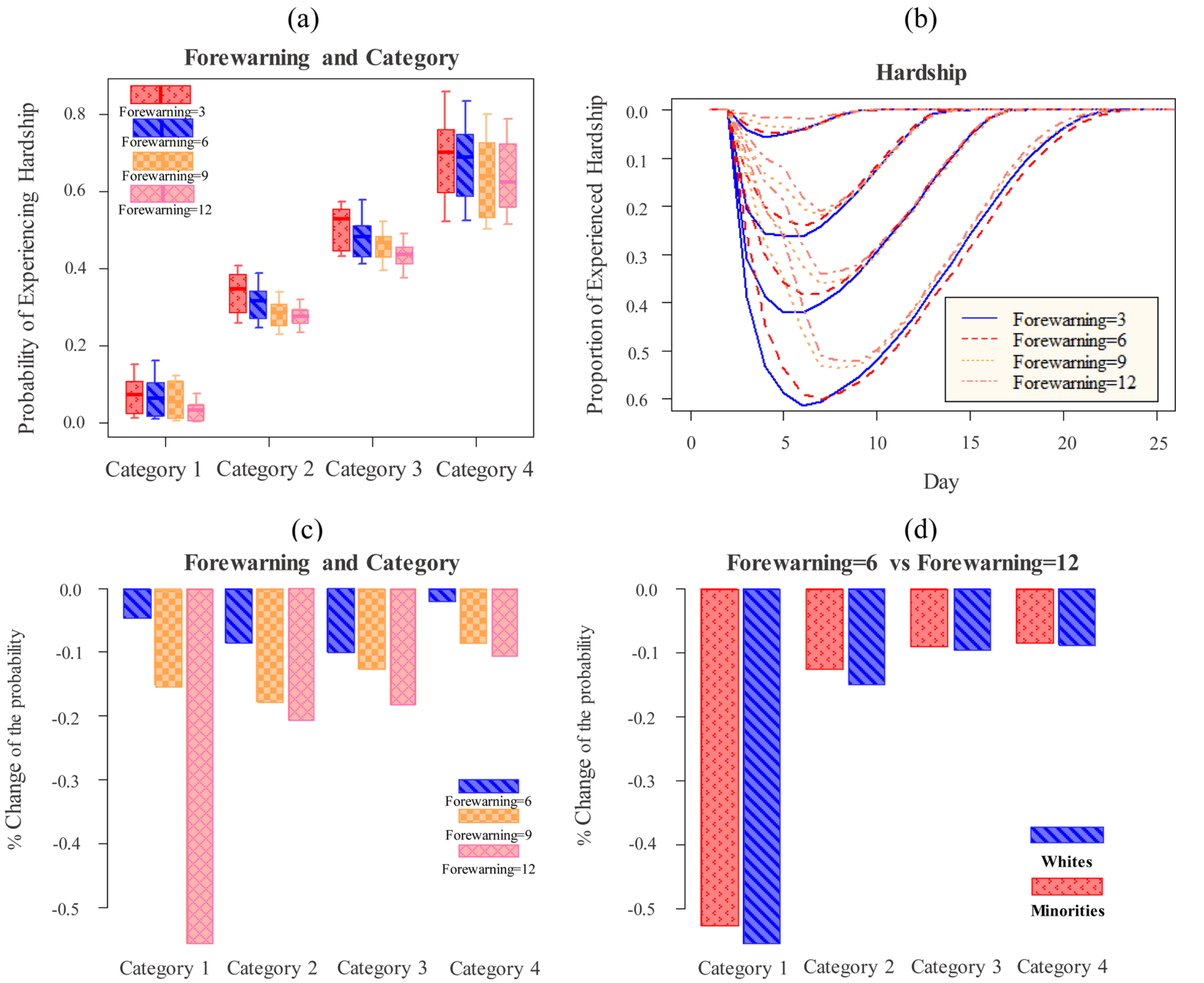

FIGURE 17 Effect of providing longer forewarning on the societal impacts of power outages under various hurricane intensities. (a) Histograms of the probability of experiencing hardship for each scenario. (b) average daily experienced hardship for each scenario, (c) percentage change of the reduction in the probability of experiencing hardship for each scenario compared to the forewarning equal to 3 days, and (d) percentage difference of the probability of experiencing hardship for the racial groups under each scenario

interaction among a large number of predictors. This algorithm recursively partitions into binary splits, which maximizes the homogeneity of the groups in relation to the dependent variable (Prasad et al., 2006). The higher splits show the variables with a stronger influence over changes in the dependent variable, which is the experienced hardship in the scenario landscape. CART analysis is shown to be effective in meta-modeling analysis based on simulation results (Mostafavi, 2018).

In this analysis, in addition to the described strategies for reducing the societal impacts (restoration activity, longer forewarning, and social network structure), also included are the hurricane category, the number of restoration resources, and the information sharing probability of the officials. The hurricane category has the greatest impact on households' experienced hardship. A longer forewarning duration seems to have a great impact on reducing the societal impacts of the power outages. This pattern is consistent for different hurricane categories, which supports the suggestion that providing a longer forewarning could effectively reduce societal impacts. The effect of the restoration strategy and increasing the number of resources varies depending on the hurricane intensity. Improving the restoration strategy to focus on the needs of the population (population-based and SVI-based) seems to more effectively reduce societal impacts than increasing the number of resources in response to high-intensity hurricanes. The effect of increasing the number of resources, however, seems to be an effective approach for lower-severity events. Last, when considering the effect of longer forewarning and information-sharing by the officials, the effect of the social network structure seems to be insignificant in reducing the societal impacts of disaster-induced prolonged power outages. The results show that

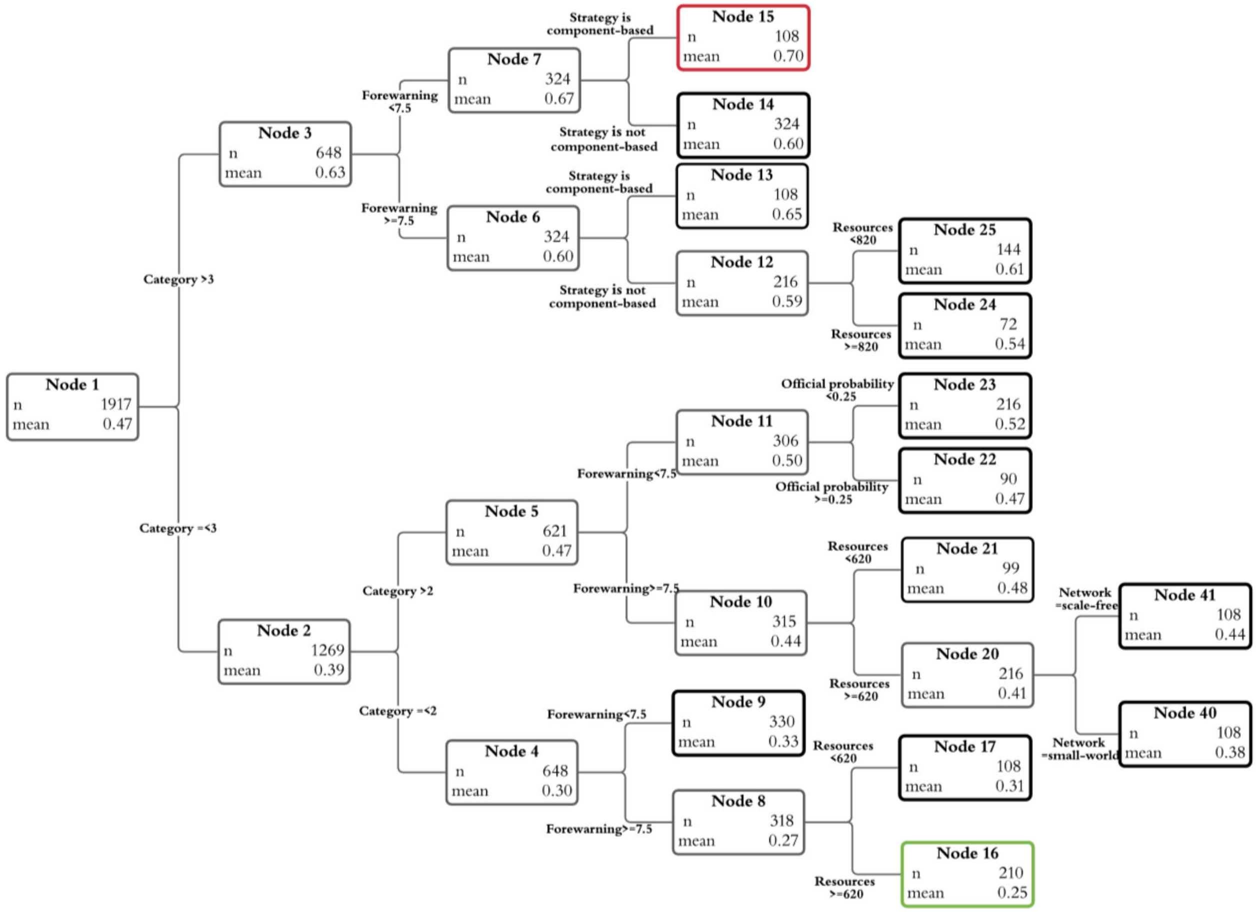

FIGURE 18 Classification and regression tree analysis for analyzing the effect of various strategies in reducing the societal impacts

hardships due to power outages during high-intensity hurricanes would be inevitable for minorities and other vulnerable populations unless power infrastructure systems are strengthened to reduce their likelihood of failure and sufficient resources, focusing on socially vulnerable populations, are earmarked for prioritizing power restoration.

5 | CONCLUDING REMARKS

This study presents a new computational simulation framework for modeling the complex hazard–households–infrastructure nexus to better integrate social equity considerations into resilience assessments. The proposed integrated multi-agent simulation model enables capturing of the complex interactions between hazard, risk and restoration process, and households' decision-making behaviors. This new computational model enables consideration of heterogeneity in the impact of infrastructure service disruption in affected communities.

The model enables a combined evaluation of the effects of hazard characteristics, population attributes and decision-making processes, and physical infrastructure network topology and vulnerability in facilitating more equitable resilience assessments. While the current literature includes various computational models for assessing infrastructure resilience, the majority of existing models focus primarily on physical systems and fail to consider the population's interactions with these systems and their services during disasters. The proposed computational framework captures and models the underlying dynamic mechanisms and complex interactions among hazard, physical networks, and household behavior in determining the societal impacts and disparities. Thus, this paper contributes to the field of computer-aided infrastructure engineering by (1) abstracting the complex mechanisms that lead to the societal impacts of hurricane-induced power outages; (2) simulating societal impacts by using theoretical models and empirical data and capturing and modeling the interactions between hazard, power network, and households' behavior; and (3) devising an approach to meet the need for equitable resilience assessment in infrastructure systems. The multi-agent simulation model enables the inclusion of the social dimension in the resilience assessment of the infrastructure system. The model is capable of assisting in resilience assessment in different contexts given the availability of similar data such as household information.

The output results would inform about the overall societal impact on the community and the distributional impact on the various segments of the community. By enabling decision-makers to conduct scenario analysis of strategies for reducing societal impacts of power outages, such as restoration strategies, forewarning time, and household social network structure, the model provides an approach to reduce overall societal impacts. The proposed model could be used by emergency and infrastructure managers and operators to better prioritize resource allocation to their hazard mitigation investments and restorations to reduce the societal impacts of infrastructure disruptions. Beyond its contribution to equitable infrastructure resilience assessment, the computational simulation model proposed in this study contributes to integrated complex modeling approaches in civil infrastructure and urban systems. Integrated complex modeling is a growingly important approach in analyzing various complex phenomena related to sustainability and resilience of urban resilience and infrastructure systems for robust decision-making, as well as developing interdisciplinary socio-technical system theories of urban infrastructure systems and disaster resilience. The integrated simulation framework that captures the complex interactions among hazard characteristics, population behaviors, and physical infrastructure network properties could provide a tool and simulated data for developing more interdisciplinary disaster resilience theories and examining complex phenomena, which could not be evaluated using empirical and observational data (Mostafavi & Ganapati, 2019).

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APPENDIX A

TABLE A1 Pseudo-algorithms for the damage from hurricanes based on the fragility equations

```
Algorithm 1 fragility curve
input: probability of failure for each element
output: element that fails
function FRAG CURVE(PoF)
    for day d in hurricane duration do
        for element e in agents do
            if e does not fail then
                R(Random) ← windspeed
                if R < PoF then
                    e fails and remove all connection link to e
                end if
            end if
        end for
    end for
end function
```

TABLE A2 Pseudo-algorithms for damage from the cascading effect

```
Algorithm 2 cascade failure
function SUBSTATION FAIL(PoF(Substation), network(ArrayList))
    if Substation s fails then
        for transmission t connected to s do
            t fails
        end for
    end if
end function
function TRANSMISSION FAIL(PoF(transmission), network(ArrayList))
    if transmissions sall connected to Substation s fail then
        s fails
        call substation fail
    end if
end function
```

TABLE A3 Pseudo-households decision-making and protective action

```
Algorithm 3 preparation
function PREPARATION(demographic features, CumulativeLogi formula,prepare lambda)
    for d in information propagation period do
        pre1 − 5 ← CumulativeLogic(demographic)
        PortionPrepare ← NeighborPrepareSum/neighborSize
        r ← Random + PortionPrepare ∗ preparelambda
        if r < pre1 then
            prepare ← 1
        else if R < pre2 then
            prepare ← 2
        else if R < pre3 then
            prepare ← 3
        else if R < pre4 then
            prepare ← 4
        else
            prepare ← 5
        end if
    end for
```

TABLE A4 Pseudo-algorithms for the restoration activity and prioritization

```
Algorithm 4 restoration(use population based scenario)
input: Strategy && resource
function RESTORATION(Strategy scenario,origin resource r,resource increase speed a,number of failedtracts t)
    for h in resource increasing period do
        r ← r + a
    end for
    while r > 0 and fix tracts < t do
        if r > xr then
            fix tract[x]
            r ← r − xr
            fixtracts ← fixtracts + 1
        else
            continue
        end if
    end while
    for Pole p in tract[x] do
        if p.nearest substaion(s) not fixed and r > sr then
            fix s
            r ← r − sr
        end if
    end for
    for transmission t in tract[x] do
        if t not fixed and r > tr then
            fix t
            r ← r − tr
        end if
    end for
    for Pole p in tract[x] do
        if p not fixed and r > pr then
            fix p
            r ← r − pr
        end if
    end for
    for Substation s in tract[x] do
        if s not fixed and r >sr then
            fix s
            r ← r − sr
        end if
    end for
end function
```

APPENDIX B

Model development

Fragility curves and restoration resources

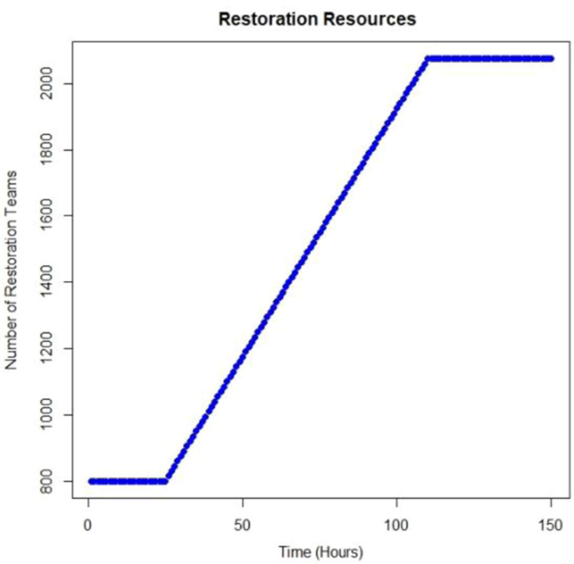

FIGURE B1 Number of added resources for the restoration activity

Household agents

Model description

In these models, the zone of tolerance would be calculated through the process and depending on the three variables. The households' zone of tolerance is a function of the household's need, substitute, and preparedness level. The following equation describes the relationships among the variables:

$$\mu = \exp\left[1.7762 - 0.5130x_s + 0.1827x_n + 0.2664x_p\right]$$

Therefore, in this model, we needed to calculate the three factors of substitute, need, and preparedness.

Need

The needed variable is inherent based on the socio-demographic characteristics of the household. Table B2 shows the influencing factors:

TABLE B1 Required resources for the damage to each component

Damaged component	Restoration time	Needed resources
Load substations	Moderate: *N*[*](72 h, 36 h), severe: *N(168 h, 84 h)* and complete: *N(720 h, 360 h)*	*6* *14* *60*
Transmission towers	*N(72 h, 36 h)*	*6*
Transmission lines	*N(48 h, 24 h)*	*4*
Distribution poles	*N(10 h, 5 h)*	*1*
Distribution lines	*N(8 h, 4 h)*	*1*

[*] $N(a,b)$ refers to the randomly generated number from a normal distribution with mean = a and standard deviation = b (Mensah, 2015).

TABLE B2 Influencing factors of the households' need

Variable	Measure
Race minority	"Yes" = 1, "No" = 2
Mobility issue	"Yes" = 1, "No" = 2
Young children (age 10)	"Yes" = 1, "No" = 2
Medical	"Yes" = 1, "No" = 2

TABLE B3 Model for determining the households' need

Variable	Estimate	*p*-value
(Intercept):1	0.444	.125
(Intercept):2	1.792	<.001
(Intercept):3	3.344	<.001
(Intercept):4	4.992	<.001
Racial minority	0.896	<.001
Mobility issue	−0.519	<.001
Having children (< 10)	0.220	.050
Medical issue	−0.303	<.001

TABLE B4 Influencing factors of the households' protective action (buying a generator)

Variable	Measure
Income	"Less than \$25,000" = 1, "\$25,000–\$49,999" = 2, "\$50,000–\$74,999" = 3, "\$75,000–\$99,999" = 4, "\$100,000–\$124,999" = 5, "\$125,000–\$149,999" = 6, "more than \$150,000" = 7
Expectations	The number calculated in the previous step
Ownership	"Renter" (1), "owner" (0)
Self-efficacy	"Strongly low" = 1, "somewhat low" = 2, "medium" = 3, "somewhat high" = 4, "strongly high" = 5

Logistic regression relates the predictors to the logit based on the following equation:

TABLE B5 Influencing factors of the households' preparation

Variable	Measure
Vehicle vulnerability	"Did not have a car" = 1, "I have it" = 0
Experience	The number calculated in the previous step
Ownership	"Renter" (1), "owner" (0)
Self-efficacy	"Strongly low" = 1, "somewhat low" = 2, "medium" = 3, "somewhat high" = 4, "strongly high" = 5
Elderly	Yes (1), no (0)
Forewarning	Number of days
Distant to supermarket	Miles

Note: Distance was simulated from a normal distribution with mean 5 and variance 30.

TABLE B6 Influencing factors of the households' level of self-efficacy

Variable	Measure
Ownership	Yes (1), no (0)
Social capital	Yes (1), no (0)
Chronic disease	Yes (1), no (0)
Medical	Yes (1), no (0)

TABLE B7 Model for determining the households' level of self-efficacy

Variable	Estimate	*p*-value
(Intercept):1	−3.191	<.001
(Intercept):2	−1.792	<.001
(Intercept):3	−0.551	.009
(Intercept):4	1.458	<.001
Ownership	0.339	<.001
Medical	−0.245	.016
Chronic disease	−0.237	.029
Social capital	0.217	<.04

The variables in the model are socio-demographic characteristics; therefore, we implemented a simulated sample of the population for determining these variables.

The cumulative logit models with proportional odds were used for modeling the parameter; here, there are

TABLE B8 Influencing factors of the households' level of experience

Variable	Measure
Having a child (age 10)	Yes (1), no (0)
Race	Yes (1), no (0)
State duration	Number of years
Elderly	Yes (1), no (0)

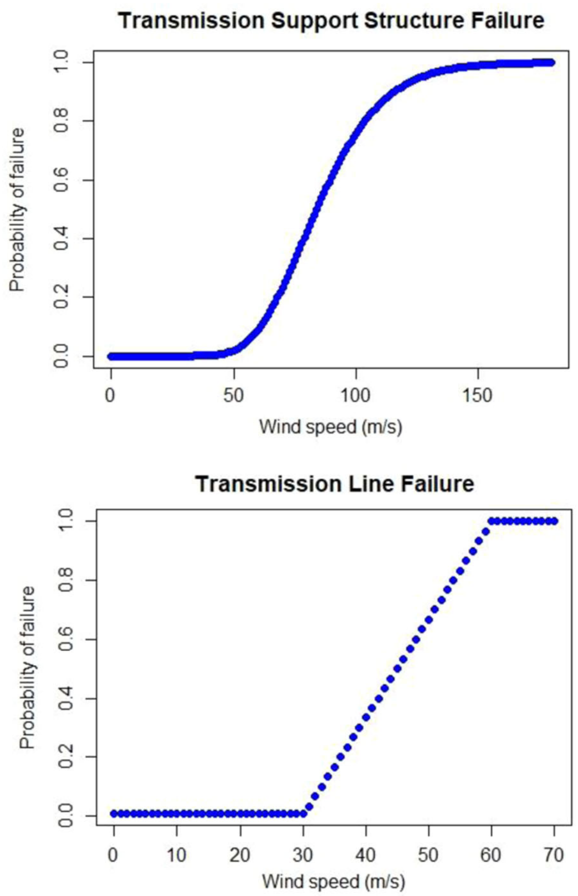

FIGURE B2 Transmission distribution network fragility curve

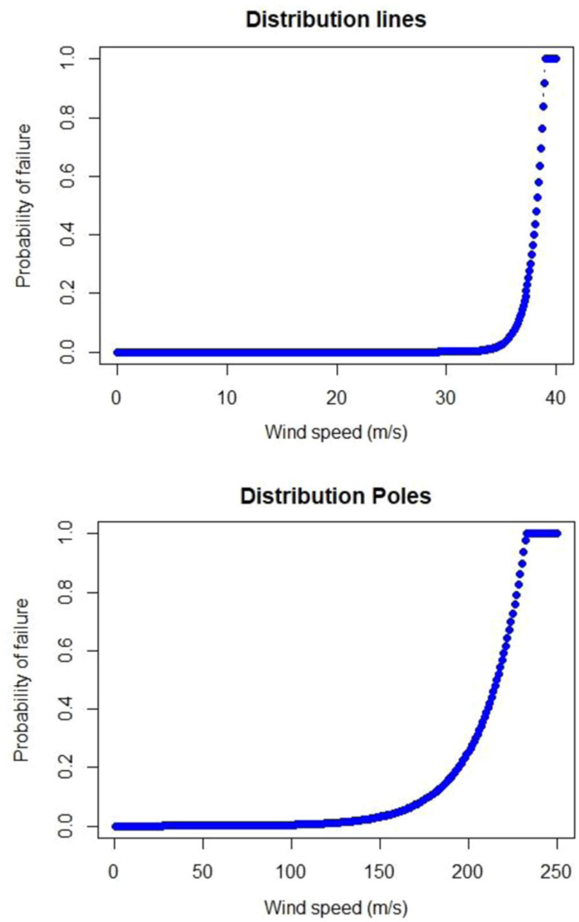

FIGURE B3 Distribution network fragility curve

four intercepts, which means there exist four equations for calculating the probability of the five need levels B3. The general equation for this model is as follows:

$$\operatorname{logit}\left[P\left(Y \leq j\right)\right] = \log\left[\frac{P\left(Y \leq j\right)}{1 - P\left(Y \leq j\right)}\right]$$

$$= \log\left[\frac{\pi_1 + \cdots + \pi_j}{\pi_{j+1} + \cdots + \pi_J}\right], \quad j = 1, \ldots, J-1$$

Here, instead of directly calculating the probability of each level (e.g., the probability of need to be 1 ($p(y = 1)$), we will calculate the $p(Y \leq = 1)$. But $P(y \leq 1) = P(y = 1)$; thus, we can calculate the probability of the first level, $p(y = 1)$, by the following equation:

$$\log\frac{p\left(y=1\right)}{1-p\left(y=1\right)} = 0.44441 + 0.89646x_r - 0.51914x_m$$

$$+0.21971x_a - 0.30319x_m$$

Then, the probability of ($p(y = 1)$ would be determined based on the following equation:

$$p\left(y=1\right) = \frac{e^{[p(y=1)]}}{1+e^{[p(y=1)]}}$$

Then, the next probability would be the probability of $p(Y < = 2)$, which is $P1 + P2$. Therefore, we can calculate the probability of the second one based on the difference between this probability and the one calculated in the previous step:

$$\log\frac{p\left(y1\right)+p\left(y2\right)}{p\left(y3\right)+p\left(y4\right)+p\left(y5\right)} = 1.79242 + 0.89646x_r$$

$$-0.51914x_m + 0.21971x_a - 0.30319x_m$$

Therefore, $p(y \leq 2)$ would be calculated based on the following equation:

$$p\left(y \leq 2\right) = \frac{e^{[p(y\leq 2)]}}{1+e^{[y\leq 2]}}$$

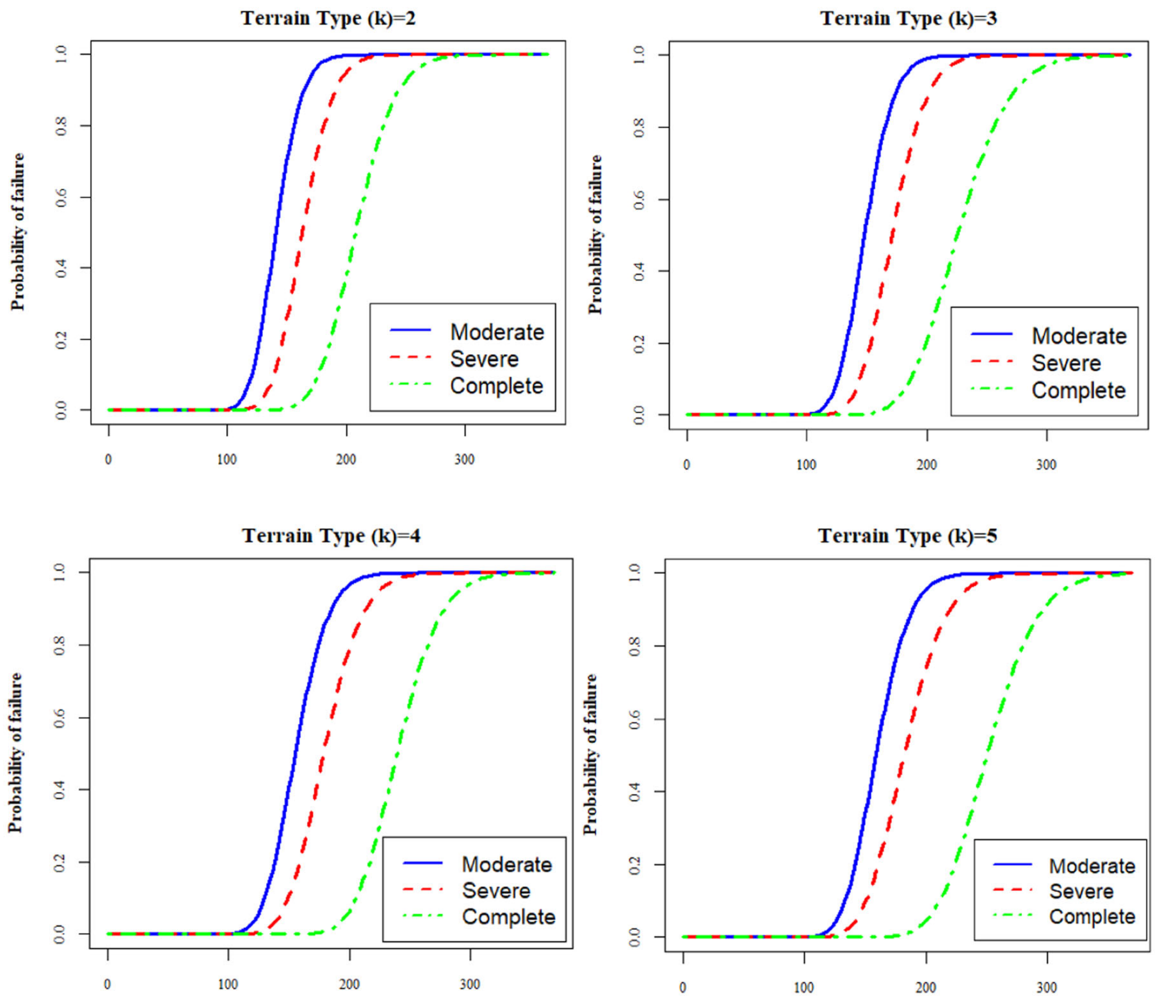

FIGURE B4 Substation fragility curve

Thus, $p(2)$ would be the difference between the two probabilities. This will be continued until we have used the third and fourth intercepts. Last, the probability of the final level $p5$ would be calculated by $1-p(y \leq 4)$. Here, $p(y \leq 4)$ is equal to the last equation using intercept 4.

Substitute
We calculate the probability of getting a generator by using logistic regression. We calculate the probability of getting a generator by using logistic regression. Here, the probability depends on the income, self-efficacy, ownership, and the household's expectations of the disruptions. Table B4 shows the variables.

$$P_s = \log \frac{p(y=1)}{1-p(y=1)} = -2.53950 + 0.07416 x_i$$
$$- 0.93270 x_o + 0.48647 \log(x_e + 1) + 0.26128 x_{se}$$

Here, the log transformation was conducted on the expectation variable. Then, the probability of having a generator or $p(y = 1)$ would be determined based on the following equation:

$$p(y=1) = \frac{e^{[P_s]}}{1 + e^{[P_s]}}$$

Preparation
This variable was modeled in a similar fashion as the substitute. The main variable that makes it a process variable is the forewarning. This variable depends on the following factors: having a vehicle, previous experience, being elderly, ownership, forewarning, distance to the supermarket, and self-efficacy. We calculated the probability of preparedness by using logistic regression. Table B5 below shows the variables.

Logistic regression relates the predictors to the logit based on the following equation:

$$P_p = \log\frac{p(y=1)}{1-p(y=1)} = 1.89292 - 0.58174x_v$$
$$-1.11299x_e + 0.44445x_{el} - 0.60578x_o + 0.08802x_f$$
$$-\ 0.02362x_d +\ 0.50834x_{se}$$

Then, the probability of having a generator or $p(y=1)$ would be determined based on the following equation:

$$p\,(y=1) = \frac{e^{[P_p]}}{1+e^{[P_p]}}$$

Self-efficacy

This variable defines to what extent the households believe in the effectiveness of the preparedness actions. Table B6 shows the influencing variables: ownership, having social capital, having a chronic disease, and a medical condition.

The calculation of the probabilities based on results in Table for each level should be done using the procedure explained in the need section B7.

Experience

This variable is calculated to find those with previous disaster experience. Having previous experience with a disaster depends on the duration of the time they have lived in their state, racial minority, elderly, and having a child (B8).

State duration should be simulated based on a normal distribution and mean 25 and standard deviation 15 (variance of 225). Logistic regression relates the predictors to the logit based on the following equation:

$$\log\frac{p(y=1)}{1-p(y=1)} = 1.371844\ \ + 0.020162x_{sd}$$
$$-0.656271\ x_r - 0.366558x_a + 0.272127x_e$$

Then, the probability of having a generator or $p(y=1)$ would be determined based on the following equation:

$$p\,(y=1) = \frac{e^{[-1.98711+0.12456x_i-0.71779\ x_o+0.37576\log(x_e+1)]}}{1+e^{[-1.98711+0.12456x_i-0.71779\ x_o+0.37576\log(x_e+1)]}}$$

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INDUSTRIAL APPLICATION

COMPUTER-AIDED CIVIL AND INFRASTRUCTURE ENGINEERING WILEY

Interpretable machine learning learns complex interactions of urban features to understand socio-economic inequality

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Abstract

Inequality in cities is a phenomenon arising from the complex interactions among urban systems and population activities. Conventional statistics and mathematical models like multiple regression models require assumptions of feature interactions with specified mathematical forms that may fail to fully capture complex interactions of heterogeneous urban components, creating challenges in systematically assessing socio-economic inequality in cities. To overcome the limitations of these conventional mathematical models, in this work, we propose an interpretable machine learning model to capture the complex interactions of urban variables and the main interaction effects on socio-economic statuses. We extract urban features from high-resolution anonymized mobile phone data with billions of activity records related to people and facilities in 47 US metropolitan areas and predict the attributes of urban areas from six income and race groups. We show that socio-economic inequality in cities can be effectively measured by the predictability of trained machine learning models in controlled experiments. We also examine the tradeoff between spatial resolution, sample size, and model accuracy; test the presence of influential features; and measure the transferability of the trained models to identify the optimal values for controlled factors. The results show that metropolitan areas share similar patterns of inequality, which could be moderated by improved polycentric facility distribution and road density. The generality of associated factors and transferability of machine learning models can help bridge data gaps between cities and inform about inequality alleviation strategies. Despite similarities, 50% to 90% of variations among cities are still present, which shows the need for localized policies for inequality alleviation and mitigation. Our study shows that machine learning models could be an effective approach to examine inequality, which opens avenues for more data-centric and complexity-informed planning, design, policymaking, and engineering toward equitable cities.

1 | INTRODUCTION

Inequality in metropolitan cities has become one of the cornerstone social and economic issues of our age, prompting a debate about the measurement and solutions and fueling public discontent with the built environment and society (Woetzel et al., 2017). Despite great effort (Acemoglu & Robinson, 2009; Balland et al., 2020) having been applied to research and practice for measuring and mitigating inequality, systematic divergence from the optimal equality of facility services and life opportunities in cities still exists (Mirza et al., 2021), a situation that is not well understood. We hypothesize that a contribution to such divergence arises from neglecting to examine equality as an outcome of the complex interactions between the population and the built environment in urban areas (Fan et al., 2021a). Capturing this mechanism by a computational metric can help measure and explain the presence of inequality, pinpoint potential solutions for mitigating inequalities, and inform policy and design promoting equitable cities (Xue et al., 2022).

Understanding and improving socio-economic equality in metropolitan cities is a long-lasting challenge (Acemoglu & Robinson, 2009). A growing and diverse number of studies (Gazzotti et al., 2021) have been investigating this phenomenon over the past two decades. Conventional research (Marger, 1999) mainly focuses on a theoretical understanding of social and economic inequality. The problems of inequality arise with the stratification of socio-economic classes and relations, characterized by income concentration (Thomas & Emmanuel, 2014). The most controversial topics related to income inequality previously focused on the distribution of wealth. As research progressed and cities developed, studies on this front started addressing the inequalities present in people's lives, such as satisfactory public services (Anand & Ravallion, 1993), accessibility to life needs, availability of social capital (Dahl & Malmberg-Heimonen, 2010), and opportunities of higher education (Triventi, 2013). The economic inequality intertwining social needs increases the complexity of the inequality assessment problem. Literature (Cingano, 2014) has been attempting to establish connections between urban features and socio-economic status of people. Theoretical studies, however, are not fully considering socio-economic inequality as a multidimensional phenomenon.

Urban inequality represents the level of disparity in diverse socio-economic contexts across different areas of a city, which has been unveiled in a variety of aspects including infrastructure services and population activities (Casali et al., 2021). The infrastructure statuses and human activities are heterogeneous and dynamic, leading to high variations in socio-economic patterns (Niu et al., 2020). Recall that inequality is defined from such a variation that exists in the relationship between urban components and socio-economic patterns. Quantifying the variation in socio-economic patterns is one of the key steps to evaluating inequality in cities (Li et al., 2019). In addition, the interactions between the built environment and population activities are nuanced and non-linear as a result of the different paces of the dynamic urban components including socio-economic activities of populations and the evolution of the infrastructure and the environment (J. Wang et al., 2019). To understand the inequality arising from intertwined urban features, it is critical to capture the variation and the non-linearity in the interactions between heterogeneous urban components.

Machine learning, a method that captures information from a portion of samples and predicts the labels of the rest, provides an effective way to assess the variation present in the data samples (Adeli & Hung, 1994; Rafiei & Adeli, 2016). Inequality, in the socio-economic context, could be well considered as the variations in the relationship between input features and output labels of data samples. Hence, machine learning could be very helpful to address inequality in cities (Zhou & Liu, 2019). On the other hand, machine learning models are created in the way the complex and non-linear interactions of the features are modeled in an automated manner, without theoretical assumptions for formulating the equations (Rafiei & Adeli, 2017). Such an automated learning process is promising to connect the interactions of urban features with the non-linear model structures of machine learning (Ahmadlou & Adeli, 2010). Considering these capabilities, we could claim the fundamental connection between the inequality of cities and the predictability of machine learning models to inspire the adoption of machine learning to assess inequality.

Examining socio-economic inequality as a phenomenon based on population activity and built environment features cannot be fully implemented without the support of sufficient fine-scale data. Prior to the age of smart devices and technologies, it was notoriously difficult to collect and analyze fine-grained data about urban components, such as facilities and population activities and their interactions (Esmalian et al., 2022). The digital footprints that accumulate and aggregate on smartphones provide an efficient and effective proxy for investigating issues of inequality, as the mobile phone data reveal patterns of human movements and activities at greater temporal and spatial granularity while ensuring anonymity and user privacy (Moro et al., 2021). In addition, the availability of place data that describe the location, category, and brand of a place enables specifying the distribution of urban facilitie and the development of the built environment, as well as population life activities. To harness the potential of these emerging location-based datasets, an increasing number of studies (Aleta et al., 2020) have employed these data in multiple research domains and have validated the scale and accuracy of these data. In particular, existing literature (F. Wang et al., 2019) has demonstrated that the location-based data could be highly demographically representative. Hence, the use of fine-scale location-based data can transform conventional measurement and understanding of inequality at a scale and in ways never attempted before (Milanovic, 2016).

More recently, benefiting from the explosion of urban data, data-driven inequality research (Fan et al., 2021b) has been growing significantly, and a transition from theoretical to data-driven inequality research has emerged (Mirza et al., 2021). One stream of work adopts and analyzes location-based data, such as mobile phone data and geotagged social media data. Researchers in this stream quantify the connection inequality of neighborhoods (Q. Wang et al., 2018), income inequality for resilience to natural disasters (Yabe & Ukkusuri, 2020), the racial inequality of probabilities of becoming infected in pandemics (Millett et al., 2020), and economic inequality of innovation activities and products (Balland et al., 2020) in cities. Another stream of research relies on public utility and empirical data, such as facility locations and survey data. These studies capture the inequality of facility distributions (Xu et al., 2020) and income inequality of hazard exposure (Rasch, 2017). These studies are largely based on datasets that document only single aspects of urban systems, such as social and physical connections (Dong et al., 2019), access to services (Johar et al., 2018), and interactions with the environment (Rao et al., 2017).

Cities, however, are complex systems involving a variety of interconnecting components, such as facilities, infrastructure, and populations (Pan et al., 2013). Devoting efforts to understanding and seeking equality based on individual components of cities is not nearly enough. An optimal socio-economic equality knowledge and solution require an integrative consideration of all urban components and their non-linear interactions. The question arises as to whether it is possible to predict the socio-demographic status of areas based on features related to population activities and the built environment and their interaction. This question is far from being answered by extant research due to the absence of consensus on ways of measuring inequality by concurrently incorporating features of the built environment and population activities, as well as the non-linear interactions among the features. Traditional linear mathematical models are insufficient to encode the non-linearity in urban systems in examining inequality.

Conventional mathematical models like multiple regression models have been widely adopted to examine the effect of independent variables on the dependent variable in the context of social science and urban development. In these complex study areas, independent variables also commonly interact with each other. That means, the relationship between an independent variable and the dependent variable changes when the independent variable interacts with another independent variable and the value of the third variable changes. This type of effect makes the underlying mechanism of variable relationships more complex. But this is, in fact, how the real world behaves, and it is critical to incorporate it into the model. Conventional mathematical models call it interaction effect.

The interaction effect in conventional mathematical models is examined in a couple of ways, such as incorporating the multiplication of two variables in the regression model to consider both the main effect and the interaction effect of the variables at the same time. This conventional method works well to consider the interaction effects, indicating that the relationship between an independent variable and the dependent variable depends on the value of another independent variable. The conventional methods, however, have two assumptions. First, the methods assume that the interaction effects of the variables follow the multiplication relationship. Second, the value of the dependent variable is a linear combination of the main effects of individual independent variables and the interaction effects of multiple independent variables. That is, conventional mathematical methods require that the relationship between the dependent variable and the independent variables and the interactions of independent variables need to be specified before testing the models on real-world data.

The interactions of urban environment features are particularly complex. Without fully understanding the mechanism of how these features are interacted and influence the dependent variable, it is challenging and problematic to specify the relationship in the mathematical model, especially in a case of a great number of independent variables. To overcome the limitations of these conventional mathematical models, here, we propose an interpretable machine learning model to automate the process of capturing the complex interactions of independent urban variables and the main and interaction effects on the dependent variable (socio-economic attributes). The proposed machine learning method can encode both the built environment and population activity features. The method advances our understanding of variable interactions, which releases the constraints of specifying the interaction terms and the linear combination of multiple effects in existing mathematical models, which will provide fundamental insights into interpreting the effects of urban development, human activities, and landscape change on socio-economic inequality in cities. With that, we claim that the proposed interpretable machine learning model outperforms conventional mathematical models.

The core idea of this study is that inequality can be identified and measured in cities using machine learning. Machine learning enables capturing various heterogeneous urban systems and population features and their interactions; if the socio-economic status of different areas could be predicted accurately by machine learning models using population activity and built-environment features and their non-linear interactions, then inequality exists. In other words, if equality is present, features of population activities and the built environment would not vary drastically across high-income versus low-income and minority versus non-minority areas. Hence, the prediction performance metrics of machine learning models could be used to measure the extent of inequality. The high predictability of models indicates greater socio-economic inequality in cities. Also, it could be evidence that inequality is a phenomenon that may not be attributed to individual features but rather to the complex interactions among various features in cities if individual features alone cannot explain the predictability of machine learning models.

We first created grid maps for 47 US Metropolitan Statistical Areas (MSAs), assigned socio-economic labels of census block groups (CBGs) to grid cells within block groups, and computed features for each grid cell. The considered features of urban components draw upon multiple sources of data, including 1 million points of interest (POIs) data, billions of anonymized mobile phone data, and more than 10,000 social-economic records for CBGs. The mobile phone data covers population activities during the first week of April 2019, which is considered a stable period, portraying regular human life activities. Two advanced machine learning (ML) models, XGBoost and neural network models, were trained and tested. We considered the predictability of the machine learning models, quantified by F1 scores, as a metric for evaluating models' prediction performance and, accordingly, as a measure of inequality in a city. To demonstrate the effectiveness and reliability of the metric, we investigated the tradeoff between grid size and accuracy and tested the influence of individual features on the predictability of the models. Furthermore, we demonstrated the cross-MSA generality of inequality patterns by training a model in one MSA and then applying it directly to other MSAs. The transferability of machine learning models can imply sharable inequality patterns and quantify variations across MSAs. We further examined the relationship between inequality metrics and urban characteristics, including road density and facility distribution in MSAs to explore potential solutions for alleviating inequalities. Finally, a conventional mathematical model, ridge regression model, is used to demonstrate the performance and capabilities of machine learning models in capturing the complex interactions of urban features. The study serves as an effort toward data-driven and ML-based scientific discovery to address urban policy challenges such as infrastructure planning to combat urban inequality.

2 | METHODS

2.1 | Data collection and processing

This study focuses on MSAs in the United States. We selected the MSAs based on three criteria. First, the population size of the MSA should be sufficiently large to serve as an object of study. Hence, the MSAs selected in this study are ranked in the top 50 in terms of the sizes of residential populations. Second, the selected MSAs should cover different regions of the United States, to consider the regional effects in concluding the general patterns of socio-economic inequality in cities. Finally, both public and private datasets should be available for the selected MSAs. Considering these criteria, we end up with 47 MSAs for analyses in this study. A complete list can be found in the Supplementary Information.

2.1.1 | Grid and label creation

To understand the fine-scale socio-economic disparities in cities, we divided the area of an MSA into grid cells of relatively equal size (see Figure 1). We considered one side of a grid cell as spanning a certain range of latitude or longitude. We started with 0.01 degree as the length of the side of grid cells and tested different values from 0.01 to 0.05 degrees with a step size of 0.01 degree. As the grid cells get larger, more facility and human activity information will be covered by a grid and integrated to represent the features of the grid cells. We used grid cells with a side of 0.01 for all analyses in this study and also showed that this is a proper selection for the size of grid cells.

To compare the features of different urban areas, we collected socio-economic public data including per capita income and race–ethnicity data from the US Census 2014–2018 (5 years) American Community Survey (ACS) at census tract level of spatial aggregation (United States Census Bureau, 2019). We focused on the three largest race–ethnicity groups as determined by self-identification in the Census: White, Black or African American, and Hispanic (Q. Wang et al., 2018). These three population

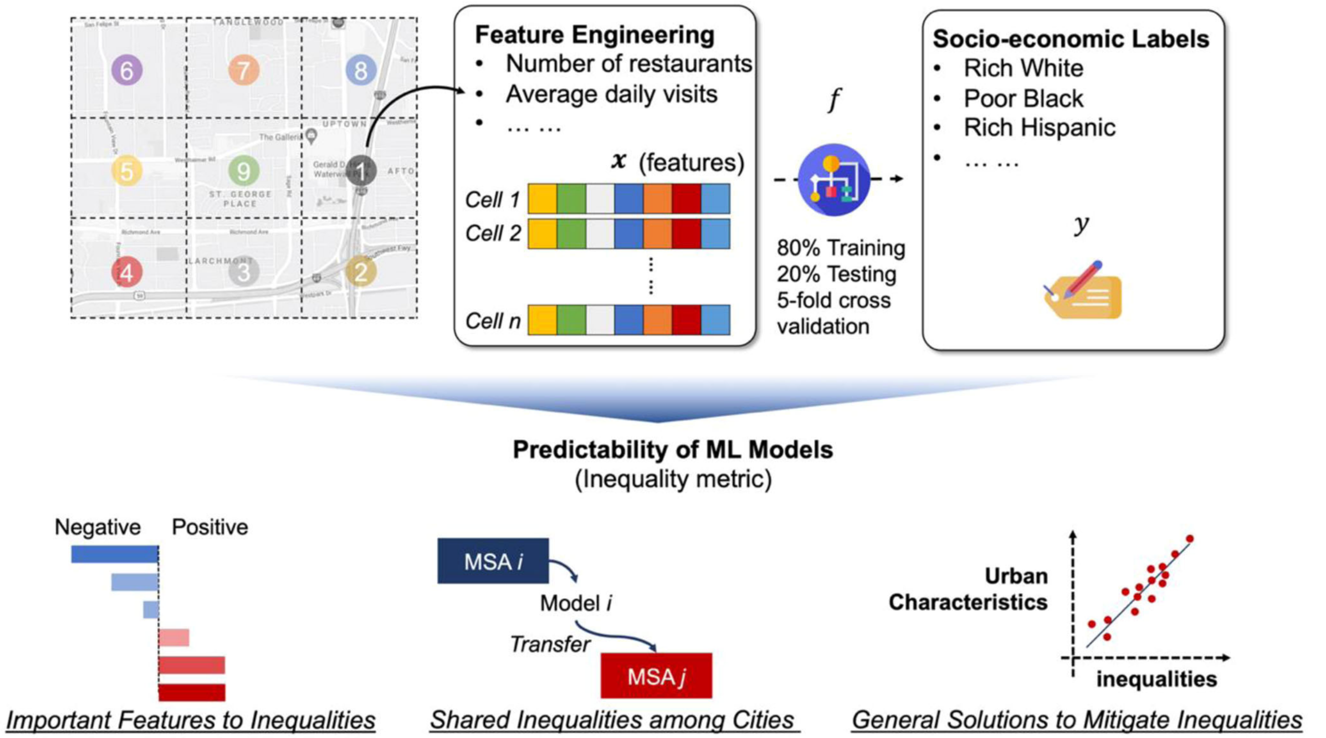


FIGURE 1 Illustration of the methodological framework. The upper panel shows a schematic of feature engineering, training, validation, and testing processes. We divide a metropolitan statistical area (MSA) into grid cells of equal size, extract the features related to facilities and human mobility, and convert the features into a vector for each grid cell. Each grid cell is labeled by one of the six labels related to income level and race. The lower panel of the figure shows three analyses using the F1 scores of the machine learning models as a metric of inequality. We interpret the importance of the features on the inequality of an MSA, evaluate the similarity of inequalities among MSAs, and identify general solutions for alleviating inequalities

subgroups are mutually exclusive: "Hispanic" including people of all races except White and Black, "Black" referring only to non-Hispanic Black people, and "White" including only non-Hispanic White people. The race that accounts for greater than 50% of people in a census tract reported in the Census data is considered the race label of this census tract. We similarly classified the census tracts as low-income or high-income based on whether the per capita income of the census tract is higher than the median of the MSA or not. We assign the label of a grid cell to the label of a census tract if the centroid of the grid cell falls into the polygon of the census tract. As such, the grid cells belonging to specific census tracts in an MSA are labeled by one of six socio-economic labels.

2.1.2 | Mobility data for activity features

Urban systems are spatially diverse in terms of population activities and facility distributions. Here, we characterize each grid cell based on these two dimensions. To understand the inequality of population activities, we employed mobile phone data from Cuebiq, a data intelligence company that collects location data from mobile phone users who opt in to share their data anonymously through a General Data Protection Regulation- and California Consumer Privacy Act-compliant frameworks. The current daily active user count collected by Cuebiq is roughly 15 million in the United States. The data sample has a wide set of attributes, including anonymized device identifier (ID), latitude, longitude, visited place ID (if the user visited a specific POI), UTC (coordinated universal time) time of observation, and the duration of each visit/stop (e.g., dwelling time). The data were shared under a strict contract with Cuebiq through their academic collaborative program in which they provide access to de-identified and privacy-enhanced mobility data for academic research. Cuebiq's responsible data-sharing framework enables us to query anonymized, aggregated, and privacy-enhanced data, by providing access to an auditable, on-premises sandbox environment (Moro et al., 2021). All researchers processed, aggregated, and analyzed the data under a nondisclosure agreement and were obligated not to share data further and not to attempt to re-identify data.

It is important to capture population activities in regular conditions when no external extreme events perturb human activities. Considering that we extracted the Cuebiq mobility data from April 1, 2019, to April 7, 2019 (7 days) for selected MSAs, there are no particular events for MSAs in this time period, to the best of our knowledge. Also, we took the data for 7 days in order to account for the variation of population activities on weekdays and weekends. Using these data, we first assigned each visit or stop point to a defined grid cell. Then, we calculated a vast number of features related to population activities, such as the mean daily number of visits to a grid cell, the average duration of each visit in a grid cell, and the maximum daily number of stops in a grid cell. In addition, Cuebiq provides an estimation of the residential areas of mobile devices, which allows us to estimate the number of residents in each grid cell. The complete list of population activity features is provided in the Supplementary Information. The representativeness of the Cuebiq mobility data has been demonstrated by multiple prior studies (Aleta et al., 2020; F. Wang et al., 2019). They found that Cuebiq data are valid to describe human activities as one of the urban components (Deng et al., 2021). Hence, the features generated using these datasets should be representative and valid for our analyses.

2.1.3 | POI data for facility-relevant features and metrics

To capture the distribution of facilities in urban areas, we adopted the 6.5 million active POI data in the United States from Cuebiq. The dataset includes basic information about the POIs, such as POI IDs, location names, geographical coordinates, address, brand, and North American Industry Classification System (NAICS) code to categorize the POIs. The NAICS code is the standard used by Federal statistical agencies in classifying business establishments, such as retail trade, health care facilities, education, and entertainment places (United States Census Bureau, 2017). In this study, we selected 10 important types of POIs that are closely relevant to human lives: restaurants, schools, grocery stores, churches, gas stations, pharmacies and drug stores, banks, hospitals, parks, and shopping malls. We counted the number of POIs in each grid cell as their facility features.

By knowing the grid cell location of each POI, we further adopted a metric, urban centrality index (UCI), to characterize the distribution of the facilities in an MSA. UCI is the product of the local coefficient and the proximity index (Pereira et al., 2013). The local coefficient is computed based on the number of POIs within each grid cell, and the proximity index is computed based on the number of POIs within each grid cell along with a distance matrix that considers the distance between grid cells. The indices are formulated as follows:

$$
\begin{aligned}
LC &= \frac{1}{2} \sum_{i=1}^{N} \left(k_i - \frac{1}{N} \right) \\
PI &= 1 - \frac{V}{V_{\max}} \\
V &= \mathcal{K}' \times D \times \mathcal{K}
\end{aligned}
\tag{1}
$$

where N is the total number of grid cells in an MSA; $\mathcal{K}$ is a vector of the number of POIs in each grid cell, and k_i is a component of the vector $\mathcal{K}$; D is the distance matrix between grid cells; $V_{\max}$ is calculated by assuming that the total POIs are uniformly settling on the boundary of the MSA. LC is the local coefficient, which measures the unequal distribution; PI is the proximity index, which solves the normalization issue; and V is the Venables index (Pereira et al., 2013). The value of UCI ranges from 0 to 1. The values close to 0 indicate polycentric distributions, while the values close to 1 indicate monocentric distributions.

2.1.4 | Other datasets and metric calculations

To calculate other metrics, we employed datasets from multiple commonly adopted platforms. In particular, we extracted data from Open Street Map (Open Street Map, 2021) to calculate the density of road segments in urban grid cells. We estimated complete road networks from the raw data by assembling road segments. Since the lengths of road segments created by the source are close to each other, we approached the road density by dividing the number of road segments by the areas of an MSA. To estimate the status of the economic development of the MSA, we adopted the 2018 data of gross domestic product (GDP) for each MSA (Bureau of Economic Analysis, 2018). The data are provided by the Bureau of Economic Analysis in the US Department of Commerce.

The socio-demographic data obtained from US Census 2014–2018 (5 years) ACS is also used to calculate the ethnicity entropy for an MSA. We first generated the distribution of population sizes for all race–ethnicity subgroups. Then, the Shannon entropy function is applied to calculate the ethnicity entropy $H(R)$:

$$
H(R) = -\sum_{i=1}^{n} P(r_j) \log P(r_j) \tag{2}
$$

where r_j is the race–ethnicity category, which occurs with probability $P(r_j)$ calculated by the proportion of people in the population of an MSA.

2.2 | Inequality characterization

The analyses employing the features and labels for urban grid cells consist of two components: (1) measuring inequality of each MSA using a quantitative metric, and (2) examining inequality within and across MSAs to explore potential inequality-alleviating solutions. This section provides an overview of the methods adopted to conduct experiments in these two components of analyses.

2.2.1 | Machine learning models

Machine learning models take as inputs the features of urban grid cells and learn the non-linear relationships among the features and the labels (Ramchandani et al., 2020). If the machine learning model in controlled experiments can reveal the socio-economic disparities of grid cells based on the input features and their non-linear relationships, it is an indicator of inequality in a city. In other words, in the presence of equality, the model should not be able to predict the socio-economic status of grid cells based on the input features. Accordingly, the predictability of socio-economic status based on the input features in the machine learning models is an indication of the existence of inequality, and thus the prediction performance measure could be a metric for measuring the inequality of the cities with regard to the complex interactions of the features. Hence, we consider the F1 score, which is a metric for the predictability of machine learning models, as the metric of inequality of the cities (see Figure 1).

In this study, the F1 scores in each socio-economic class are calculated individually first in a one-vs-rest manner. In each class, the positive label is the class label, and the negative label includes the rest socio-economic labels. Then, true positives are the ones where the model correctly predicts their real positive socio-economic label, and true negatives are the ones where the model correctly predicts a real negative label. False positives are the ones where the model incorrectly predicts the positive label, and false negatives are the ones where the model incorrectly predicts the negative label. Both false positives and false negatives indicate that the machine learning model cannot distinguish the socio-economic label well. True positives indicate a good performance of the model. Hence, both precision (considering true positives and false positives) and recall (considering true positives and false negatives) are equally important to the model. F1 score, the harmonic mean of precision and recall, conveys the balance between the precision and the recall of the machine learning models. In addition, data samples for different socio-economic labels are highly imbalanced. F1 score has been designed to work well on imbalanced data, compared to the accuracy of a machine learning model. The greater the F1 score in a model of a city, the greater the inequality.

To obtain valid and reliable results, this study adopts two widely used machine learning models: XGBoost and neural networks. The XGBoost model, a scalable tree boosting system, is an efficient and easy-to-use algorithm that delivers high performance and accuracy (Chen & Guestrin, 2016). We tend to have hundreds of thousands of samples (i.e., urban grid cells) in each MSA, leading to time-intensive model training processes. The XGBoost model could quickly execute and perform well in prediction tasks. Hence, this study mainly uses the results of XGBoost to characterize and understand the inequality in MSAs. Neural networks, composed of an input layer, a hidden layer, and an output layer, can efficiently identify important information from inputs leaving out redundant information. Through an embodied activation function, the neural networks are capable of capturing the non-linear relationship between the input features and output labels. Recognizing the benefits of the neural network model, we employed this model for validating the results generated from XGBoost, further enhancing the reliability of the findings and implications obtained from this study. The ridge regression model is a conventional mathematical model that is good at avoiding overfitting by regularizing the coefficient estimates (Hoerl & Kennard, 1970). The results of the ridge model help to demonstrate the performance and capabilities of the machine learning models in capturing complex urban feature interactions.

We implemented these machine learning models using an open-source Python package, scikit-learn (Pedregosa et al., 2011). We first randomly split the data into two sets, train and test; 80% of the samples are in the training set, and 20% of the samples are in the testing set. We further adopt the cross-fold validation to train the machine learning model and tune its hyperparameters. We divide the training set into five subsets of equal size. Four out of five subsets are used for training, and the remaining one is used for validation. With this process, the model would be further applied to the testing set and compute the F1 score for each city. In addition, the results of the machine learning model, especially the F1 scores for different MSAs, are validated through the training and testing of different machine learning models, neural networks and XGBoost.

The performance of a machine learning model may be influenced by many factors including the structure of the model, size of data, and so forth. The proposed method considers these uncertainties and controls them in generating the metric. We used the same model for learning the patterns of cities, the same size of grid cells in dividing urban spaces, and the same data sources for generating features. Each MSA has more than 1000 grid cells so that the model can have sufficient data for training and validation. Hence, we could expect that the method proposed in this study is capable of capturing the actual inequality phenomenon in cities.

2.2.2 | Understanding of inequalities

As explained earlier, in this study, the F1 score of machine learning models quantifies the degree of inequality of each MSA. The next step is to identify potential solutions to alleviate inequalities in urban areas, which requires a thorough understanding of the underlying mechanisms of inequality within and across MSAs. Here, we propose three experiments to understand inequality from three different aspects.

In an MSA, inequality is shaped by both static features of facilities and dynamic features related to human activities. Examining the contributions of each feature to the inequality of the MSA is necessary for identifying alleviation solutions. To this end, we conducted experiments to measure the importance of features to the F1 score of the machine learning models. In these experiments, based on the trained models with all parameters and hyperparameters fixed, we set the values of one input feature to be zero for all samples and measure the predictability of the model (Lundberg & Lee, 2017). The decrease in F1 scores, to some degree, can indicate the importance of the features to the inequality of the MSA. Transforming the distribution of the important feature in areas of MSA would contribute to reducing the inequalities.

In addition to MSA-specific strategies, policies that are effective in more than one MSA would be beneficial for reducing policy-making efforts and enhancing the execution of policies at scale. Capturing the similarities of MSAs based on their inequality characteristics allows us to understand the effectiveness of cross-MSA policies. To this end, we employed the method of transferring machine learning models to different MSA and quantifying the similarities of inequalities across MSAs by the metric of model transferability. Specifically, we train the machine learning model by feeding in the samples from an MSA. Once the training process is done and all parameters are fixed, we feed in the sample from other MSA and measure the predictability of the model. The obtained F1 score could indicate the extent to which the patterns of the MSA on which the model is trained share similarities with the patterns of the MSA that the model is predicting. This quantitative metric offers us a generic metric to capture similarities of features shaping inequality, which could inform us about policy generalization and execution.

Finally, inequalities are not uniform among MSAs. The variations of urban characteristics across MSAs may tell us general approaches to mitigate urban inequalities. As such, we extend our analysis to capture the relationships between urban characteristics and F1 scores across MSAs. Here, we primarily look into: (1) the status of economic development quantified by GDP; (2) the scale of urban development quantified by the number of POIs in the MSA; (3) the connectedness of urban areas quantified by road density; (4) the diversity of residents quantified by ethnicity entropy; and (5) the geometric distribution of facilities quantified by the UCI. The calculation of these metrics is as aforementioned in previous sections. With all these characteristics of MSAs, to capture the relationships between inequality and urban characteristics, we employ an ordinary least squares (OLS) regression model to incorporate the interactions among multiple independent variables:

$$y_i \sim \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \beta_3 x_{i,3} + \beta_4 x_{i,4} + \beta_5 x_{i,5} + \varepsilon_i \tag{3}$$

where y_i is the F1 score of MSA i; $x_{i,1}$ to $x_{i,5}$ are the variables of urban characteristics; β are coefficients; ϵ_i is the error term. In the regression, since the values of GDP, road density, and number of POIs have a much larger scale than other variables, we use logarithmic transformation of values.

3 | RESULTS

3.1 | Empirical statistics of features

The variety of datasets we gathered allowed us to capture different features of the cities. We first show examples of features mapped into the metropolitan area of Atlanta to gain a basic and empirical understanding of the distribution of facilities and human activities in an MSA. Figure 2 illustrates the extent to which densities of features vary across the areas of the Atlanta MSA. As we observed, the number of active residents varies across different regions of the MSA (Figure 2a). POIs are concentrated in the center of the MSA and expand like a tree from the center to the periphery of the MSA (Figure 2c). The main incentive for human movements is the visits to POIs, such as working and shopping, leading to agglomerated activities in the center of the MSAs with a high density of POIs (Figure 2b). Beyond activities in POIs, the footprints of people also include visits to friends and work commutes. Hence, the scale of population activities is broader than the locations of POIs. Finally, in Figure 2d, we show the residential areas labeled by socio-demographic groups. We find that White people account for the majority of the residential

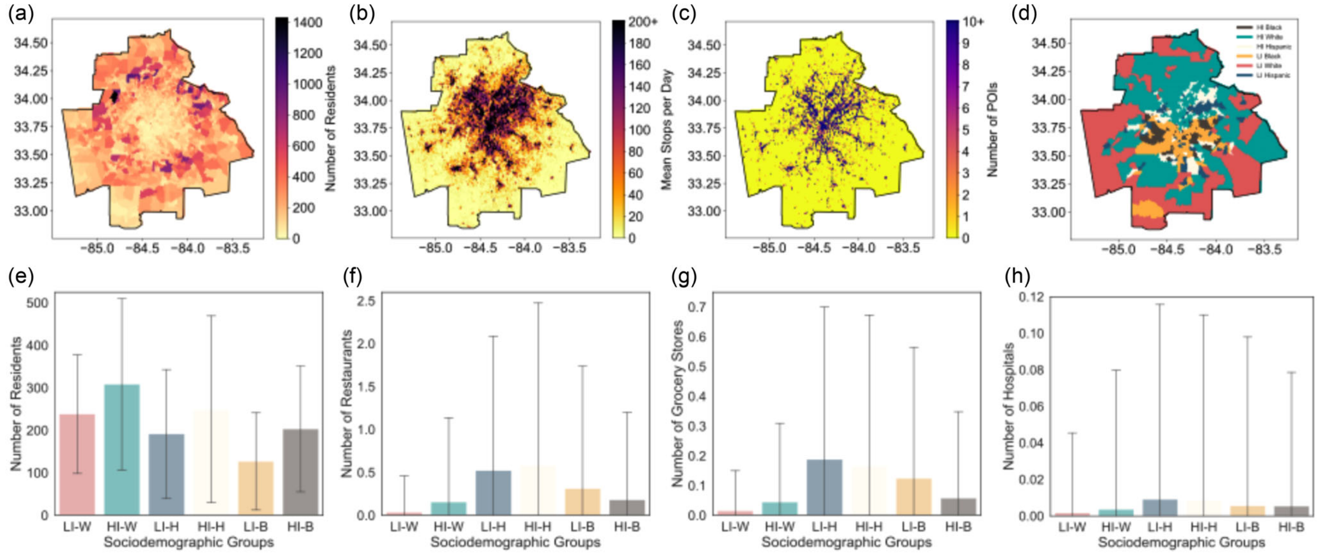


FIGURE 2 Spatial distribution of features and socio-economic characteristics of population groups in Atlanta MSA. (a) The distribution for the number of residents (mobile phone devices as a proxy) based on mobile phone data. The numbers of residents are aggregated at the census tract level. Because the areas of census tracts vary, the figure shows the only number of people in different regions of the MSA rather than the population density. (b) The distribution of the average number of stops per day in a grid cell. (c) The distribution of the number of points of interest in a grid cell. (d) The distribution of different income and race groups: HI represents high-income groups; LI represents low-income groups. (e–f) The distribution of some example features (i.e., number of residents (e), number of restaurants (f), number of grocery stores (g), and number of hospitals (h)) in each sociodemographic group: W represents White; H represents Hispanic, and B represents Black. The error bar represents the variance of samples.

area of the MSA. High-income White people are living in the North and close to the center of the MSA, while low-income White people tend to live on the periphery and the South of the MSA. Compared to the wide distribution of White people, the residential areas of Black people are more condensed, and high-income and low-income Black subgroups are intertwined in the center of the MSA. Hispanic subgroups occupy only a very small proportion of the area and are dispersed across the MSA. These observations inform us about the segregation and inequality of feature distributions and the complex association between urban features and socio-demographic groups.

In the next step, we first look at the features of facilities shared by different population groups. Figure 2e–h shows the differences in the number of example facilities in the grid cells occupied by different socio-demographic groups. We observe that the differences in facilities in residential areas of different socio-demographic people are not significant. Specifically, comparing the mean and variance in the average number of facilities in a grid cell, the differences may be present in the mean values. For example, grid cells of Hispanic people have more restaurants and grocery stores (Figure 2f,g). White people, high-income or low-income, have the minimum number of facilities in their residential grid cells. The variance across grid cells in a population group, however, is extremely large, making the differences in the number of facilities inconspicuous. This pattern is observed in all selected MSAs (more details can be found in the Supplementary Information). Such observation implies that inequality is not apparent and cannot be simply quantified through basic statistics and based on only one urban feature due to the complex interactions of urban features. Hidden and nonlinear mechanisms resulting in inequalities at the nexus of urban features and socio-demographic attributes exist and are underexplored without advanced methods capable of specifying the complex interactions of features.

3.2 | Measurement of inequality

To further decompose the inequality in cities, we trained three extensively adopted and technically mature models: two machine learning models, XGBoost and neural network models, and one conventional model, ridge regression model. The predictability of these models, given features in urban grid cells, is considered a metric of inequality in an MSA. The machine learning models are well-trained in the same way for different cities. All the metric values for evaluating the model performance are obtained when the models are optimized and convergent. We only compare the inequality metric of cities when all other influential factors, such as model types, grid size, and features, are controlled. Showing the influence of these factors on model performance is to help select the proper model, grid size, and features for this study. Under this context, the poor performance of the model can indicate less inequality since all other influential factors are controlled well. The results of F1 scores are based on the testing data for each city. The inequality is pronounced if the machine learning model can obtain high predictability, indicated by a great F1 score. That is, the interactions among urban features can distinguish the residential areas with different socio-demographic population groups, reflecting the fact that inequalities of urban features in serving residents of subgroups present. Using the F1 score as the metric of inequality, we quantify the inequality of all selected MSAs by considering the nuanced relationships of urban features. However, as aforementioned in the Methods section, the ability to capture the complex relationships among urban features and the algorithmic advantages varies among machine learning models. Here, by training and testing the models, we found that the ridge and neural network models have similar performance across all MSAs; and the XGBoost model outperforms conventional ridge models by about 25% in the majority of the selected MSAs (Figure 3a). The XGBoost models achieve an average of 0.8 for F1 scores among selected MSAs, meaning that the model can explain 80% of the variations of labels based on input variables. In view of the outstanding performance of the XGBoost models, we used the results of XGBoost to analyze the inequality of MSAs in this study, and the results of the other two models to validate the outcomes of XGBoost models.

The predictability of the machine learning models may be influenced by factors such as the size of grid cells or specific features that undermine the importance of the complex interactions of urban features. To examine the robustness of the models and the results, we applied the models to samples generated from different sizes of grid cells. Figure 3b displays the relationship between F1 scores and the size of grid cells for three examples of MSAs. We observe that the performance of the XGBoost model decreases when the size of the grid cell increases. There is a jump in performance at around the grid size of 0.02 and 0.03. Decreases in model performance could be attributed to the lack of grid cells (samples) to train the model and also the aggregation of features that reduces the disparities among grid cells. Such a negative correlation between model performance and grid size provides us with the rationale for selecting a proper grid size for measuring the inequality of MSAs. Based on the results, 0.01 and 0.02 would be proper grid sizes. Thus, for all the analyses in this study, we used 0.01 as the size of the grid cell so that the results generated from the machine learning models could be comparable and informative.

In addition, individual features may also influence the performance of the model due to the strong correlation between individual features and labels. Here, we examined the contributions of individual features while fixing the parameters of the well-trained model. The trained model preserves both the complex interactions of the features and the contributions of individual features. Figure 3e shows the decrease in model performance by removing specific features. The elimination of features related to general human activities, such as mean stops, mean visits, average visit time, and the number of residents, could lead to decreases in F1 scores. But the decreases do not significantly influence the performance of the model, compared to the high predictability of the model. For example, for the results of the XGBoost model, the average influence of the number of residents on F1 scores is below 0.3. In Figure S1a,b, we also plot the influences of the features on the F1 scores for the ridge and neural network models. The average influences of the features are even much lower than 0.2. Compared to the average F1 score of XGBoost, which is 0.81, we consider that urban features do not have a significant influence on the model performance. In addition, the specific types of POIs and visits to these types of POIs do not make too much difference to the F1 scores. In general, individual features cannot explain the inequality of each MSA well. This result implies that inequality is a phenomenon arising from non-linear interaction among various urban features. Hence, inequality should be attributed to hidden complex interactions of the urban features rather than individual attributes.

3.3 | Transferability of inequality

We mapped the F1 scores of the MSAs obtained from the XGBoost model in Figure 3c. There are 22 MSAs from the South, 12 MSAs from the West, nine MSAs from the Midwest, and six MSAs from the Northeast of the United States. We observed significant regional patterns from the map: MSAs in the US West tend to have higher F1 scores than MSAs from other regions, and Northeast MSAs tend to have lower F1 scores. That means, socio-economic inequality is greater in the MSAs in the US West, and socio-economic inequality is lesser in the MSAs in the Northeast, compared to the MSAs in other regions. To further explore this observation, we plotted the relationships among F1 scores, regions, and the GDP in Figure 3d. In addition to the regional patterns, we also find that lower GDP is correlated with higher F1 scores, while higher GDP is correlated with lower F1 scores. This association is not very strong since we selected MSAs with the largest populations. The weak negative correlation can still demonstrate the

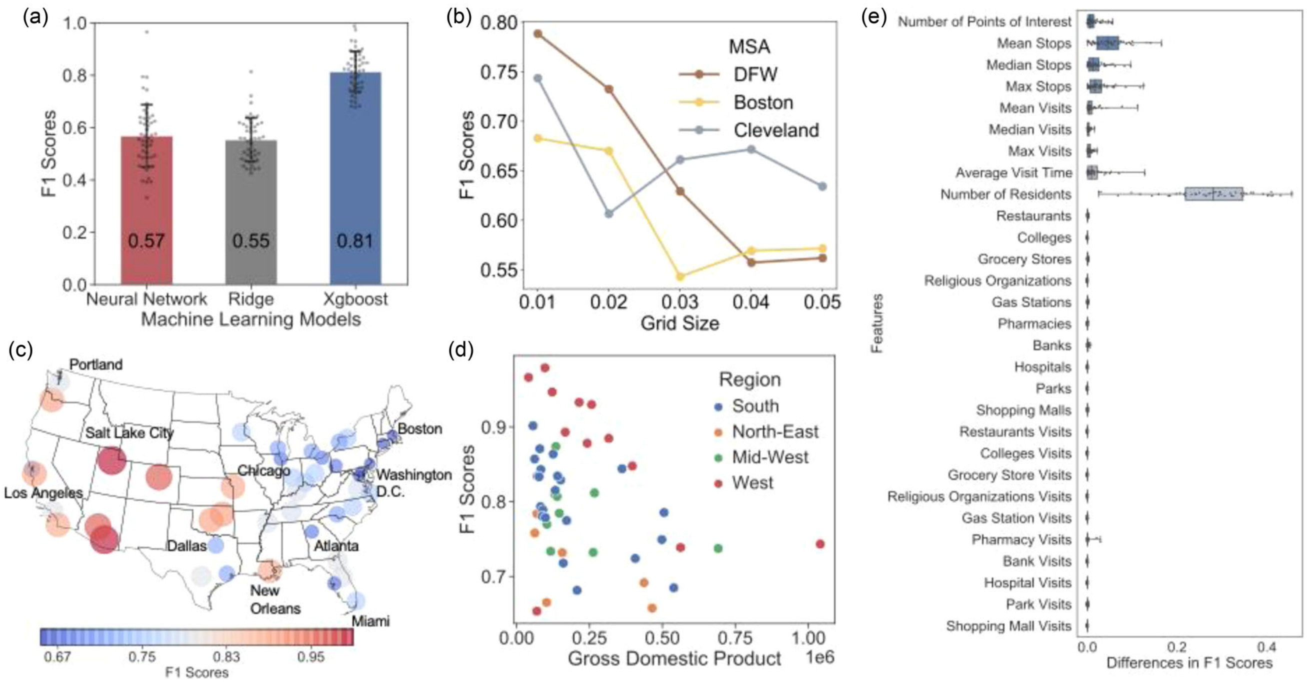


FIGURE 3 Results of model training and testing. (a) F1 scores of three models: neural networks, ridge classifier, and XGBoost for each MSA. The numbers on the bars are the mean values of the F1 scores for all selected MSAs. The dots on top of each bar represent the F1 scores of the MSAs. The error bars show the variance of the F1 scores. XGBoost achieves the best performance among the three models. (b) Results of testing the effect of grid size on the performance of the XGBoost model in three example MSAs: Dallas-Fort Worth MSA, Boston MSA, and Cleveland MSA. The sizes of the grid cells are measured by the differences in the longitude and latitude of the corner points on one side of a grid cell. Hence, the values on the x-axis represent the differences in degree in the geographical coordinate systems. (c) A geographical map shows the F1 scores for selected MSAs in the United States. (d) The relationships between F1 scores and gross domestic product of MSAs in four regions of the United States: South, Northeast, Midwest, and West. (e) Importance of features to the F1 score of the XGBoost models for each MSA. The x-axis is the difference between the original F1 scores and the F1 scores after dropping a specific feature from the input (decrease of predictability of the XGBoost model). The y-axis represents the features selected to be removed for understanding its contribution to the inequality of the MSAs.

association between the extent of socio-economic inequality and the GDP of the MSAs. These regional patterns of inequality motivate us to consider the common characteristics shared by MSAs.

To explore the similarities of inequality across a variety of MSAs, we conducted experiments on the transferability of the patterns. That is, to what extent the machine learning model trained with the samples of one MSA can predict the occupied population groups for grid cells in other MSAs. The transferability of the models helps us to understand the generalizability of the patterns across MSAs and regions. As most of the analyses and results are taken from the most populated MSAs, other MSAs can benefit from the identified and generalized patterns (Dong et al., 2019), if the shared inequality patterns can be captured. We trained the machine learning models using data samples from one MSA with both validation and testing processes. Then, we applied the fixed model to the data samples from another MSA. This process aims to address if the patterns from one MSA are transferrable to another MSA, which allows us to observe the variations of inequality in cities across the nation and motivates us to explore the factors related to variant inequalities. Hence, the results present in the paper are based on the performance of the models on the testing sets, either from the same MSA or a different MSA. Figure 4 summarizes the results obtained from cross-MSA experiments. As expected, all the models trained and tested on the same MSAs (diagonal) outperform models trained and tested in different MSAs. The performance of the models varies for different pairs of MSAs. The values on the upper left corner are closer to light blue, meaning that the F1 scores are close to 0.6 and the transferability is more evident, while most of the values on the right-hand side are dark red, meaning that the transferability is quite low (Figure 4a). These results imply that some MSAs share common characteristics shaping their inequalities, and thus the same inequality-alleviating measures could work across these MSAs. We also found that the transferability matrix is asymmetric. We show example MSAs that achieved the highest transferability and the

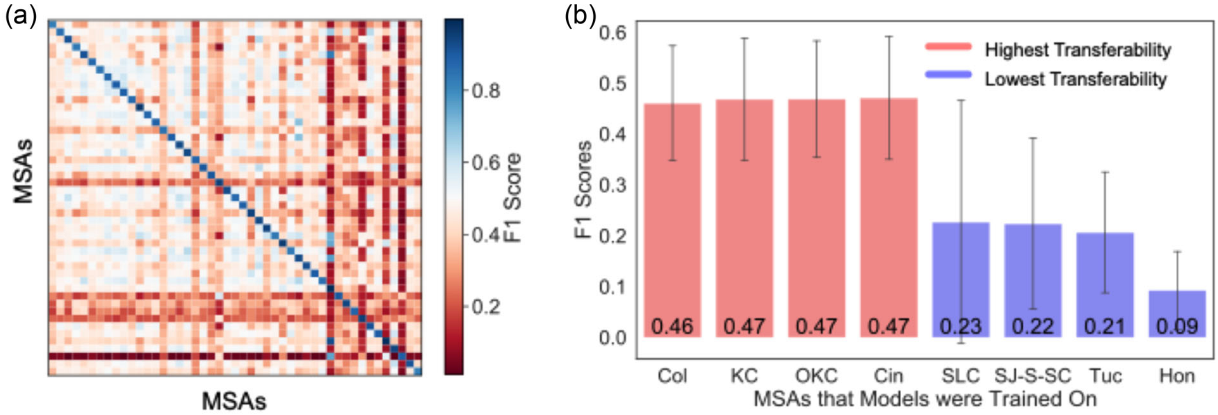
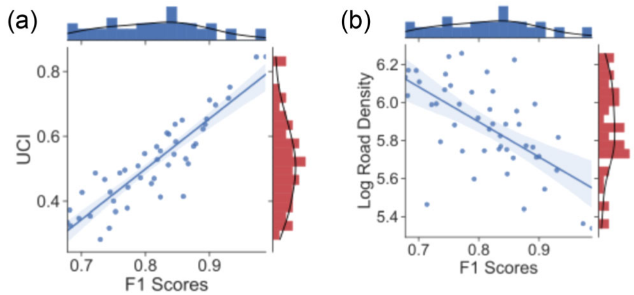


FIGURE 4 Shared inequality among selected MSAs measured by the transferability of machine learning models. (a) Pair-wise similarity of inequalities among MSAs. Each row represents the MSA where the model is trained, and each column represents the MSA where the trained model is adopted to make predictions. The color indicates the F1 scores. Here, the machine learning model is XGBoost. (b) Examples of transferability results for the top four and bottom four models for MSAs: Columbus (Col), Kansas City (KC), Oklahoma City (OKC), Cincinnati (Cin), Salt Lake City (SLC), SJ-Sunnyvale-SC (SJ-S-SC), Tucson (TC), and Urban Honolulu (Hon). The error bars show the variance of the F1 scores. The numbers attached at the bottom of the bars are the mean values of the F1 scores.

lowest transferability among the selected MSAs. Models trained on MSAs such as Columbus and Kansas City can learn the most common patterns of inequality, which could be applied to most of the other MSAs. However, models trained on MSAs such as Urban Honolulu are not able to capture the common inequality patterns of other MSAs since Urban Honolulu is in Hawaii, where the development and environment are different from cities in the US mainland.

3.4 | Relationship with urban characteristics

Considering the variety and transferability of models among MSAs, the next question is what inequality-alleviating strategies would be effective among MSAs consistent with their urban characteristics. To investigate this question, we computed the metrics of urban characteristics for MSAs, including the urban centrality index, road density, and ethnicity entropy, along with the number of POIs and GDP of the MSAs (more details can be found in the Methods section.) Results are summarized in Figure 5 and Table 1. The distributions of UCIs and the inequality extent measured by F1 scores are approximately normal, with histograms shown in Figure 5a. The Kendall rank correlation reaches 0.72, the Spearman rank correlation reaches 0.88, and the Pearson correlation coefficient approaches 0.89 for these 47 MSAs. All measures are statistically significant with $p < 0.01$, indicating a strong positive correlation between the UCI and the extent of inequality. UCI itself is not included in machine learning models. The strong correlation between UCI and the F1 score serves as an important interpretation of the presence of inequality in cities. That is, a pronounced concentration of POIs greatly contributes to inequality in MSAs. Analyses on road density reveal another significant relationship. The distribution of road density is close to log-normal, while the distribution of F1 scores is normal (histograms in Figure 5b). The Kendall rank correlation reaches −0.44, the Spearman rank correlation reaches −0.60, and the



Coefficients	P-value
Pearson $\rho = 0.89$	2.61×10^{-17}
Speaman $\rho = 0.88$	5.03×10^{-16}
Kendall $\tau = 0.72$	7.94×10^{-13}

Coefficients	P-value
Pearson $\rho = -0.62$	3.88×10^{-6}
Speaman $\rho = -0.60$	8.89×10^{-6}
Kendall $\tau = -0.44$	1.22×10^{-5}

FIGURE 5 The relationship between urban characteristics and inequality (F1 scores). (a) The values of urban centrality index (UCI) as a function of F1 scores obtained from XGBoost models. (b) The logarithmic values of road density in grid cells are a negative function of F1 scores obtained from XGBoost models. The correlation analysis under the plots shows the exact statistics and p-values. Three statistical tests were conducted for each of the correlation analyses. All measures are statistically significant with $p < 0.01$. The UCI is strongly positively correlated with inequality, and road density is moderately negatively correlated with inequality for the selected 47 MSAs.

TABLE 1 Ordinary least squares regression between metropolitan statistical area characteristics and F1 scores of XGBoost models

	Dependent variable: F1 Scores of XGBoost models						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Log GDP:				−0.004 (0.017)			0.033 (0.036)
Log POIs:			0.001 (0.020)			0.057 (0.044)	
Ethnicity Entropy:	0.031 (0.028)				0.020 (0.050)		
Log Road Density:		0.001 (0.031)			−0.209*** (0.040)	−0.249*** (0.051)	−0.237*** (0.052)
UCI:	0.521*** (0.039)	0.516*** (0.054)	0.515*** (0.041)	0.512*** (0.041)			
Constant:	0.509*** (0.040)	0.538** (0.204)	0.543*** (0.096)	0.568*** (0.097)	2.018*** (0.233)	2.034*** (0.229)	2.035*** (0.231)
Observations:	47	47	47	47	47	47	47
Adj. R^2:	0.796	0.79	0.79	0.791	0.355	0.377	0.364
F-stat:	90.77***	87.73***	87.73	87.87***	13.64***	14.9***	14.18***

Note: Standard errors are provided under coefficients in parentheses. All log values are log-based 10. GDP, gross domestic product; POIs, points of interest; UCI, coordinated universal time.

Significance Level

*$p < 0.1$

**$p < 0.05$

***$p < 0.01$.

Pearson correlation coefficient approaches −0.62, for 47 MSAs. These significant measures signify a moderate negative correlation between road density and inequality. That is, the increase in road density (as an indicator of urban development and connectivity) could contribute to alleviating socio-economic inequalities.

Coupled with other factors, we analyzed the extent to which urban characteristics can capture the inequality of MSAs. We examined the performance of multilinear models with different combinations of variables. Table 1 summarizes the results of the multilinear regression models using OLS. The first four models with the inclusion of UCI as a variable reach high-fitting performance with R^2 greater than 0.79, indicating that UCI can explain 79% of the inequality in MSAs. The coefficients for UCI are significant, showing a consistent result with the correlation analysis. Other variables, such as the number of POIs, GDP, and ethnicity entropy, are not significant, even though they may have positive and negative correlations with the inequality scores. The relationship between road density and inequality is not significant. This result implies that, although the correlation analysis finds the alleviating effect of road density on the inequality of MSAs, a polycentric distribution of POIs could moderate the effect of road density on inequality. The other three models exclude the UCI variable and examine the effects of road density coupling with other factors. In these models, the negative relationships between road density and inequality are significant, confirming our previous findings in the correlation analysis and making the road density weakly predictive of inequality. The R^2 of these models reaches more than 0.35, showing the moderate effect of expanding road density on the inequality of MSAs. Other factors, including GDP, and ethnicity entropy are still insignificant. To establish that the correlations between inequality and urban characteristics are sufficiently general, we tested these findings using the F1 scores obtained from neural networks and ridge models. The results are summarized in the Supplementary Information, Tables S1 and S2. These findings inform us about the potential of enhancing road density and POI distribution for inequality alleviation, which will be discussed in detail in the discussion section.

3.5 | Model comparison

The machine learning models that this study focuses on are the neural network model and the XGBoost model. The ridge regression model is a conventional mathematical model because it is a type of linear regression technique used to solve some of the problems of OLS by imposing a penalty on regression. The form of the ridge model is clearly defined. Solving the ridge model is equivalent to solving the coefficient for each independent variable. The results in Figure 3a show the lowest predictive performance of the ridge model, compared to the machine learning models like neural network and XGBoost models. In addition, comparing the results in Figures 3c,d and S2, we find that the ridge regression model cannot distinguish the degrees of inequality across US cities. Finally, based on the poor performance in Table S1, compared to the results in Tables 1 and S2, we find that the ridge regression model is limited in interpreting the factors influencing inequality in cities. Therefore, we prove that conventional regression models are not capable of capturing the complex interactions among the inputs. The proposed machine learning models outperform conventional mathematical models to measure and explain inequality in cities.

4 | DISCUSSION AND CONCLUDING REMARKS

Measuring and understanding the socio-economic inequality in cities is of great importance to policymaking, planning, and design toward equitable urban systems of facility services and life opportunities. When equality exists, people of different income levels and racial groups would have similar interactions with facilities and infrastructure to meet their life needs. In this study, we present a new computational method that leverages the interpretability of machine learning models to encode the high-dimensional and complex interactions of urban features to quantify and understand socio-economic inequality in 47 US metropolitan areas. Inequality is a multifaceted phenomenon that arises from the complex interactions among heterogeneous urban features. Different from existing works, the method proposed in this study allow us to integrate heterogeneous urban features and their complex interactions into a comprehensive and quantitative metric. The metric is capable of providing a holistic view of the inequality of intertwined urban components in a city and also allowing to transfer insights across cities.

We show that being able to predict the income and race label of an area based on population and the built environment features is an indicator of inequality. Accordingly, we demonstrate the effectiveness of using the predictability of machine learning models as a metric of inequality to integrate the non-linear relationships among urban components. We also examine the tradeoff between grid size and model accuracy and find regional patterns of inequality of MSAs. The results show that the predictability of machine learning models does not decline drastically if individual features are removed. This result provides evidence that inequality is a phenomenon influenced by the intertwined urban features rather than a consequence of individual features.

We conducted validation on different parts of the method to enhance the validity of the findings. First, the validation of the machine learning models has been conducted using five-fold cross-validation in training the models. Second, the results of the machine learning model, especially the F1 scores for different MSAs, are validated through the training and testing of different machine learning models such as neural networks and XGBoost and the comparison with the results of conventional mathematical models like the ridge regression model. Third, the strong correlations between F1 scores and facility distributions, and road density, which align with existing social science literature, could also support the validity of the method and findings in this study.

The objective of the proposed machine learning method for urban inequality is not to improve the prediction accuracy or other quantitative metrics of model performance. The proposed machine learning model overcomes the limitations of the conventional mathematical models that require specifying the form of feature interactions and compound effects on the dependent variable. In fact, it is improper to specify the forms of feature interactions and compound effects before being aware of the underlying mechanisms of these interactions. As such, existing mathematical models based on assumed formulae are not comparable with our model because the complex interactions of urban features are unknown.

The finding helps us rethink how inequality should be examined in cities. The transferability analyses of the models show that MSAs indeed share common patterns of inequality, implying that urban characteristics may influence the inequality of cities. Variations of inequality patterns, however, still exist because the models are not completely transferable. By examining the relationships between urban characteristics and the inequality metric, we develop a deeper understanding of inequality and identify general solutions for inequality mitigation. The results and findings of this study have notable implications that contribute to decision-making in various research and practical domains such as urban planning, infrastructure development, economic promotion, and government regulation.

With the growing availability of urban big data and the amplified complexity of urban systems, learning how urban components interact with and understanding the consequent impacts of complex interactions are particularly critical for optimizing the operations of urban systems and the decision-making of urban development. Our results suggest individual features cannot reveal the complexity of the urban systems and how inequalities emerge, and thus are not capable of quantifying the inequality of cities properly. The inequality metric proposed in this study further understanding of the non-linear interaction of population activities and facility distributions and the effects on social-economic inequality of cities. The proposed metric provides a new perspective on evaluating the complex relationships of urban components and a novel approach to deriving knowledge of urban systems from large-scale multisource granular data. In particular, overcoming city-scale challenges such as inequality issues, a holistic perspective to think about the underlying mechanisms and solutions is required, as the interdependencies of the urban components are making a difference in the socio-economic outcomes of the whole city.

Another implication of our work is helping city planners and governments evaluate strategies for alleviating socio-economic inequalities in MSAs with the inferred relationship between urban characteristics and the inequality metric. Our study shows that better urban development and dispersed distribution of facilities could alleviate inequality of cities significantly. Changing the facility distribution from mono-centricity to poly-centricity could narrow the service gap between different areas of the cities and could intertwine with the regular life activities of the population. Increasing road density (as an indicator of urban development) could improve the accessibility of public services. On the other hand, the effects of facilities distribution may moderate the effects of road density on inequality. This finding raises a more practical way for alleviating and mitigating inequalities as dramatically changing the distribution of facilities in a city would lead to a worse impact on the economy than the benefits of mitigating inequality. Hence, given limited resources, policies that could increase road density and slightly change facility distribution at the same time may end up being cost-effective solutions, as these actions could reshape the mobility flows and visit patterns of the population. In addition, localized actions for each MSA are still needed since variations of inequality patterns are also observed in our study.

This study also has some limitations that need future research to overcome. First, human activities are not static features. Activities in different scenarios, such as gathering events, commuting peaks, and natural disasters could show a more comprehensive profile of population patterns and further make a difference in measuring socio-economic inequality. Future research could build upon our framework and extend the machine learning models to incorporate dynamic population activities. For example, the long short-term memory model could be adopted to encode time-series information on human activities (Alam et al., 2020). The understanding of inequality could be deepened by capturing more features about urban systems and populations. Second, this study considers each area of a city as independent. The physical adjacencies and social dependencies are not computed and included in our models, although these features are of importance to understanding the spillover effect of inequality. Future research could develop new computational models (Martins et al., 2020), such as graph neural networks to encode such relational information quantifying the inequality of cities.

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SUPPORTING INFORMATION

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Anatomy of perturbed traffic networks during urban flooding

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A R T I C L E I N F O

Dataset link: https://inrix.com/products/speed/

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A B S T R A C T

Urban flooding disrupts traffic networks, affecting mobility and disrupting residents' access. Flooding events are predicted to increase due to climate change; therefore, understanding traffic network's flood-caused disruption is critical to improving emergency planning and city resilience. This study reveals the anatomy of perturbed traffic networks by leveraging high-resolution traffic network data from a major flood event and advanced high-order network analysis. We evaluate travel times between every pairwise junction in the city and assess higher-order network geometry changes in the network to determine flood impacts. The findings show network-wide persistent increased travel times could last for weeks after the flood water has receded, even after modest flood failure. A modest flooding of 1.3% road segments caused 8% temporal expansion of the entire traffic network. The results also show that distant trips would experience a greater percentage increase in travel time. Also, the extent of the increase in travel time does not decay with distance from inundated areas, suggesting that the spatial reach of flood impacts extends beyond flooded areas. The findings of this study provide an important novel understanding of floods' impacts on the functioning of traffic networks in terms of travel time and traffic network geometry.

1. Introduction

Transportation networks connect populations and services (FEMA, 2020). The stability of a transportation network is challenged by flood hazards (Pregnolato, Ford, Wilkinson, & Dawson, 2017), which can trigger compound physical and functional failure that results in network connectivity loss (Dong, Gao, Mostafavi, & Gao, 2022). Community recovery is further impacted when access to critical facilities such as fire stations, shelters and hospitals is disrupted (Fan, Jiang, Lee, & Mostafavi, 2022; Yuan, Xu, Li, & Mostafavi, 2022). The extent of impact is expected to increase due to climate change (Ghanbari, Arabi, Kao, Obeysekera, & Sweet, 2021; Wasko, Nathan, Stein, & O'Shea, 2021). Researchers have sought to understand how floods disrupt transportation networks (Dong et al., 2022; Wang, Yang, Stanley, & Gao, 2019) to improve infrastructure resilience planning (Esmalian et al., 2022). Existing studies, however, focus mainly on either physical road network topology during disruptions (Bagloee, Sarvi, Wolshon, & Dixit, 2017; Mattsson & Jenelius, 2015; Wang et al., 2019) or on transportation functionality in normal conditions without disruption (Hamedmoghadam, Jalili, Vu, & Stone, 2021; Li et al., 2015). Little attention is devoted to the time-varying link functionality in transportation networks. The flow of traffic through the network, as well as network connectivity, is essential to functioning of a community. But the flood impact on traffic networks is not yet fully understood.

The use of percolation methods (Stauffer & Aharony, 2018) to analyze physical road networks provides limited insights regarding floods' impacts on transportation systems. Although such measures adequately quantify the extent of the impact on road networks, they give little to no insights into how travel is impacted in the city. Percolation-based analysis informs about the physical vulnerability of networks but does not inform about impacts on transportation system functioning. One key indicator of the functioning of traffic networks is travel time. Some studies have tried to address this using the percolation approach (Ganin et al., 2017; Sohouenou, Neves, Christodoulou, Christidis, & Lo Presti, 2021) but there is limited research on the understanding of traffic networks under natural disasters such as flooding. However, little is known about the extent to which floods perturb travel time in traffic networks and whether the impacts on traffic networks would be local to flooded areas or affect the more significant part of the network. Or how long would the travel time impacts persist in the network after the flood recedes? Therefore, percolation analysis does not fully capture real-world networks' temporal dynamics and spatiality. Recent studies have shown the significance of understanding the geometric

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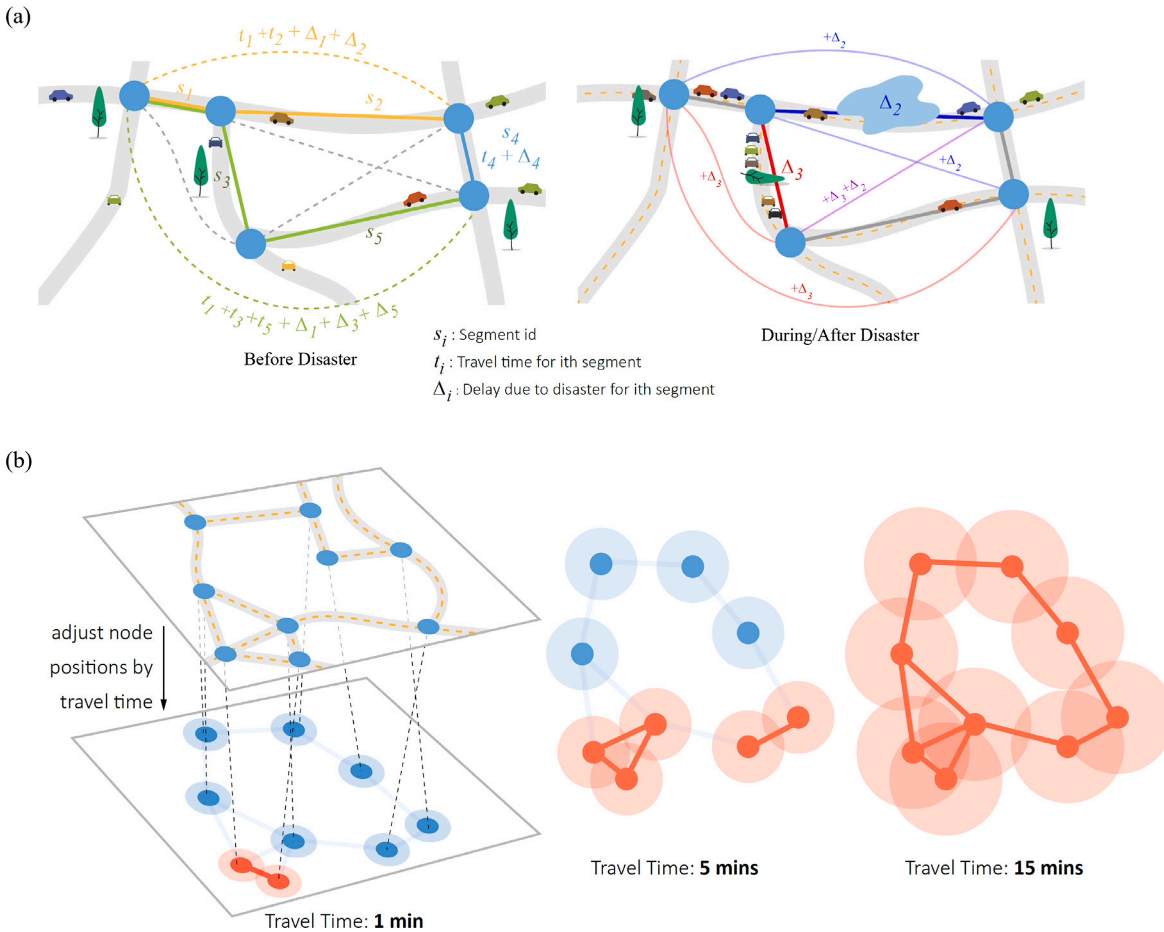

Fig. 1. Conceptual illustration of the analysis performed. (a) Illustration of pair wise travel time and changes in temporal links due to perturbations. (b) Connected component framework at different Filtration levels. Each filtration level corresponds to a travel time, within which the nodes (road junctions) in the network are connected, although they may not have a direct link connectivity. Metric for the number of connected components at each filtration level represents the most basic higher order network analysis metric.

properties of spatial infrastructure networks such as road networks (Badhrudeen, Derrible, Verma, Kermanshah, & Furno, 2022; Dumedah & Garsonu, 2021; Liu & Li, 2019). However, when the flow dynamics on the network are involved, we need to derive new metrics to understand the network resilience properties. Traffic networks are spatially embedded in cities and communities, and their link dynamic varies temporally (Batty et al., 2012; Serok, Levy, Havlin, & Blumenfeld-Lieberthal, 2019). We have learned the impact of floods on the spatial geometry of the physical road network, but how the geometry of the traffic network changes in the time domain has yet to be fully understood. For example, when road inundations and heavy congestion increase the travel time between two spatial nodes (i.e., road junction), this is equivalent to the two spatial nodes becoming more distant from each other. Hence, the temporal geometry of spatially-embedded traffic networks would change.

To this end, the goals of this research are to assess (1) the extent to which floods perturb travel time in traffic networks, (2) whether the impacts on traffic networks would be isolated to flooded areas or would affect a larger part of the network, and (3) length of time that the impacts on travel time persist in the network after the flood recedes. Traffic networks are defined as representations of a network of roads with time-varying functionality. To characterize the anatomy of perturbed traffic networks during floods, we adopted two novel geometric properties of the dynamic traffic network (Fig. 1): (1) network expansion and (2) simplicial complex change. Network expansion refers to the extent to which travel time between the node pairs (road junction pairs) in the networks increases due to perturbations. In flooding, road inundations and congestion would increase travel time between node pairs and hence, cause a virtual expansion in traffic network topology. Simplicial complexes represent the topological geometry of networks (Torres & Bianconi, 2020). They capture higher-order topological changes in traffic networks during flooding. Hence, the examination of changes in the higher-order traffic networks with time-varying link functionality can provide a better understanding of the perturbed traffic networks during floods. Both network expansion and simplicial complex change simultaneously capture the effects of road inundations and congestion caused by flooding, providing a more complete understanding and quantification of flood impact on traffic networks.

Using high-resolution empirical traffic data from Harris County, Texas, collected during Hurricane Harvey (2017), We first examined the average shortest travel time between node pairs (road intersections) during normal status and during flood-disrupted states to quantify the extent to which flooding expands travel time between node pairs, and to infer the virtual expansion of the traffic network. Second, we examined the Betti number at different filtration levels in traffic networks, as fluctuations in the Betti number reflect the traffic network simplicial complex change. Fluctuations in the Betti number expose the characteristics of higher-order network changes and reveal the extent of changes in traffic network topological features when flooding causes direct (road inundation) and indirect (congestion) perturbations. Using this travel time-based characterization of the traffic network, the findings of this study move us closer to a complete understanding of the impacts of flooding on transportation systems and the functioning of cities. Fig. 1 shows the conceptual illustration of the idea of the paper. More about it will be discussed in detail in the methods section.

The study's contribution lies in several aspects; for instance, as per our knowledge, no prior studies have examined the impact of flooding on traffic networks based on observational data and also from the perspective of higher-order networks. Moreover, our study captures the impact of both functional and physical failure simultaneously, which traditional methods such as percolation analysis are not able to do. The functioning of the road transportation system cannot be evaluated only based on knowledge of road closures in a particular location. Since traffic network's role is to provide access to critical infrastructure at the time of need and facilitate evacuation, understanding the travel times from every part of the city to another is an important attribute, which to our knowledge, had not been considered by any previous studies. This study also evaluates the pair-wise travel time from every junction in the road network to another to assess the impact of local flood-related failures in the road network on the entire traffic system. The results of this study have significant implications for city managers, transportation planners, and emergency managers for better evaluating network performance and recovery levels during disasters

The outline of the remaining sections is as follows. Section 2 discusses the review of past literature in the domain of city vulnerability and infrastructure codependency, and resilience assessment using complex networks. Section 3 discusses data, pre-processing steps, and novel methodology implemented in this study. The results are discussed in Section 4, and key results and their significance are highlighted in discussion Section 5. We conclude this work by summarizing key findings in Section 6.

2. Related work

2.1. City vulnerability based on infrastructure interdependence

A disaster's impact and recovery time can be dramatically impacted by how people, businesses, and governmental organizations behave before, during, and just after the disaster (Aerts et al., 2018). Aerts et al. (2018) explain why this is a problem and show that, despite the inevitability of the initial efforts' limited representation of human behavior, innovations in flood-risk assessment that incorporate societal behavior and behavioral adaptation dynamics into such quantifications may result in more accurate risk characterization and improved evaluation of the effectiveness of risk-management strategies and investments. Existing research mainly focus on the link-node representation without taking into account important system features, such as hydraulic features/structures for water distribution networks and traffic flow characteristics for transportation networks (Mohebbi et al., 2020). Cariolet, Vuillet, and Diab (2019) reviewed recent literature and identified that methods for mapping hazard, vulnerability and risk are well established. But for mapping resilience in urban areas poses a challenge as there are no agreed-on methodological approaches for doing so. Moreover, they identified that very few methods have been used to identify inherent resilience at city scale. Serdar, Koç, and Al-Ghamdi (2022) reviewed resilience assessment methods for transportation networks, indicators, and disturbance categories. They recommend a new representation for the relationships between performance, time, and resilience, emphasizing other network characteristics and their association with resilience.

Mohebbi et al. (2020) used an infrastructure oriented approach to examine system interdependence and quantification of resilience for different infrastructure networks. In order to examine the combined impact of integrated infrastructure disruptions and socioeconomic factors on household vulnerability during disasters, Dargin, Berk, and Mostafavi (2020) suggests a novel paradigm based on disaster risk theory and Food–Energy–Water (FEW) Nexus systems thinking. They evaluate disaster impact at household level. Utilizing extensive mobility data gathered from Puerto Rico during Hurricane Maria, Yabe, Rao, and Ukkusuri (2021) evaluated the socio-physical interdependencies in urban systems and their impacts on disaster recovery and resilience. They showed that as cities get bigger and their centralized infrastructure systems get more extensive, key services recover more quickly, but socioeconomic systems' ability to rely on themselves in times of crisis is reduced. Yang, Ng, Zhou, Xu, and Li (2019) propose a synthetic physics-based framework for resilience analysis of interdependent infrastructure systems. They investigate the pre-event resilience of interdependent stormwater drainage system and road transport system to model the functional behaviors of diverse infrastructure systems at the component level and capture the effects of interdependencies across various systems. Yang, Ng, Zhou, Xu, and Li (2020) developed a synthetic physics-driven framework for system-wide infrastructure resilience analysis which takes into account the interdependence of infrastructure systems.

2.2. City infrastructure resilience assessment using complex networks

Considering the geographic exposure of infrastructure to natural hazards, Dong, Wang, Mostafavi, and Gao (2019) evaluated network robustness by considering the post-disaster network access to important critical facilities such as emergency services. Mostafavi (2017) provided a System-of-Systems (SoS) methodology for a comprehensive evaluation of resilience in US civil transportation infrastructure. To determine how vulnerable the metropolitan road system is to flooding, Singh, Sinha, Vijhani, and Pahuja (2018) developed an integrated framework relating flood depth to speed reduction and assess the vulnerability of the road network, connecting meteorological data, land use functions, and hydrodynamic model with safety speed function. They discovered that during a 100 year return period rainstorm event in India, more than 40% of the network's route length becomes impassable.

Morelli and Cunha (2021) discusses methods for measuring transportation vulnerability to extreme events in urban road networks based on travel distribution in a city in Brazil as a case study. They found that shorter trips are more robust to these extreme events. Fan, Jiang, and Mostafavi (2021) used adaptive reinforcement learning to evaluate perturbations on urban mobility in disasters. Dong, Yu, Farahmand and Mostafavi (2020) presented a probabilistic model based on the Bayesian framework to assess risk of cascading failures on co-located road and channel networks. Goldbeck, Angeloudis, and Ochieng (2019) developed an integrated, dynamic modeling and simulation framework that combines network and asset representations of infrastructure systems and models the optimal response to disruptions. Their framework takes into account resources needed for operating and maintaining assets, failure propagation dependencies, and system-of-systems architecture.

Erath, Birdsall, Axhausen, and Hajdin (2009) analyzes the effects of network-wide congestion on the transport-related implications of link failures. They identify detours, mode shifts, destination shifts, and trip-activity suppression as four potential demand shifts brought on by single link failures. Their study shows that detours are the most common demand response. Abenayake, Jayasinghe, Kalpana, Wijegunarathna, and Mahanama (2022) used a network measure-based method such as betweenness centrality and closeness centrality network metrics for evaluating the failure of the entire transportation system as a result of urban floods. As a result, they evaluate the effect of urban floods on patterns of human migration.

3. Data and methods

To evaluate the dynamics of change in the geometry of traffic networks, we employed the framework shown in Fig. 2. First, we processed the raw data to correct any rounding errors and obtained the required temporal resolution. Then we form a spatio-temporal network where edge attributes change with time. Creating a network model is the first step in the methodology. We then obtained a pair-wise node distance matrix which were used in the two main approaches used in this study to examine effects of disaster in spatio-temporal traffic networks. Both shortest path analysis and higher network dimension analysis are independently analyzed but they both rely on the distance matrix. Each step in the method is explained below.

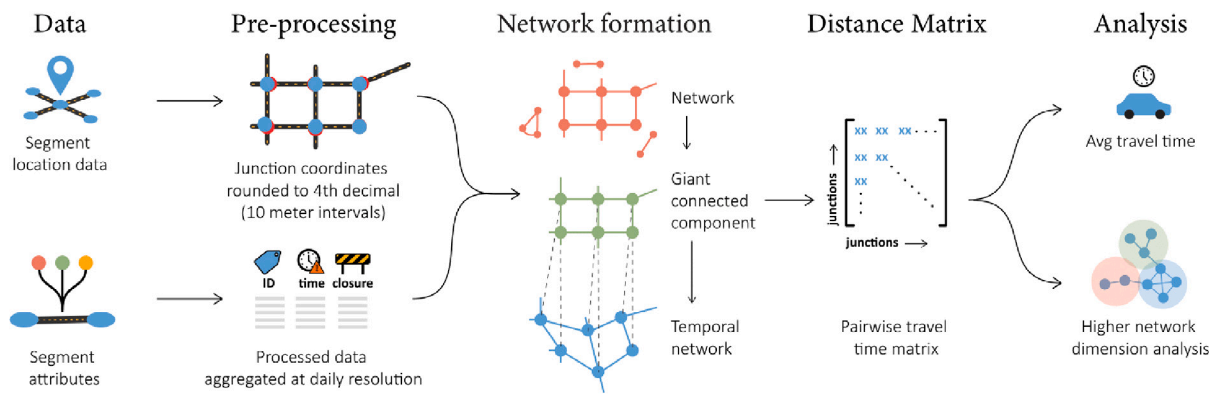

Fig. 2. Framework used in this study to evaluate the dynamics of change in spatio-temporal traffic network.

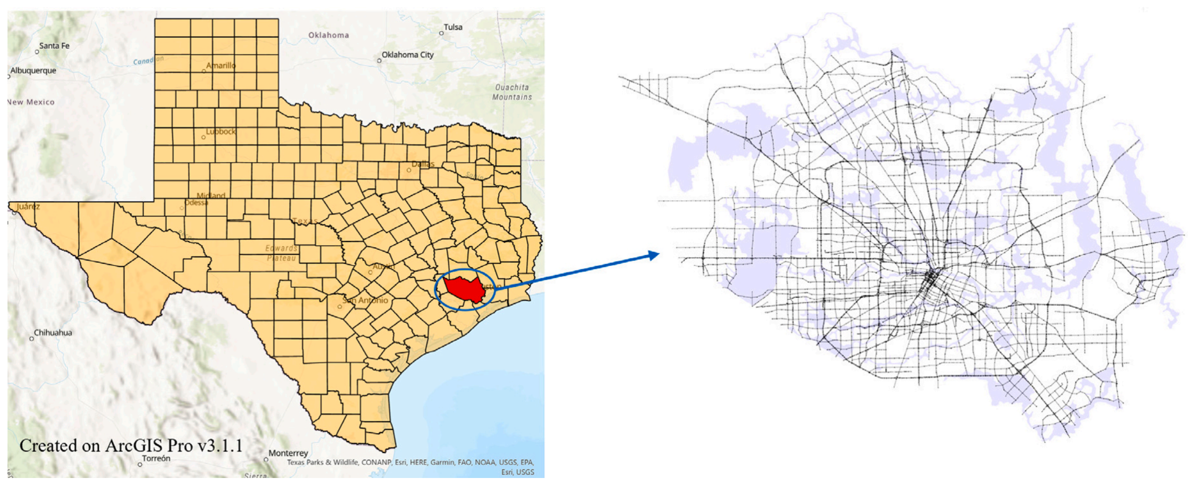

Fig. 3. Study region. Harris county is the most populous county in Texas state and includes the city of Houston. Due to its proximity to the coast and climate change, it is susceptible to flooding-related events. The figure on the right shows the road network along with the flood-inundated areas during the peak of Hurricane Harvey.

3.1. Data and pre-processing

We used a weighted road transportation network of Harris County, Texas, a period before and after Hurricane Harvey flooding (August 1 through September 30, 2017) for this analysis. Fig. 3 shows the study region along with the road network on which we evaluate the travel times. In 2017, Hurricane Harvey hit Houston, the fourth-largest city in the United States. Houston suffered an estimated $125 billion loss, mainly from the flooding triggered by the rainfall and the release of the Addicks and Barker reservoirs (Costliest, 2018). A major flood occurs somewhere in Harris County about every two years (Blackburn, 2021). Due to the high risk of Harris County to flood-related events and data availability, we chose this city for this analysis. The findings from this study will provide valuable insights for city managers, decision makers, and transportation planners in the region, enabling them to better prepare for and respond to future flooding events. From INRIX, a private analytics company, we acquired two components of traffic data: road segment location data and segment attributes. The dataset includes the travel time value for each major road segment in Harris County, within which is located the city of Houston. INRIX collects location-based data from both sensors and vehicles. INRIX traffic data contains the average traffic speed of each road segment at 5-min intervals and their corresponding historical average traffic speed. Each road segment's geometric information, such as name, geographic locations defining its start and end coordinates, and length, is also available from the INRIX data set. Aggregating these two datasets yields a dataset that has location information of all the road segments and their corresponding travel times and information on road closure.

Location attributes of some of the road segments varied at the fifth decimal level when taken in degree decimal format. This resulted in some of the road segments being disconnected from the main network, although they were physically connected. To address this, coordinates were rounded off to the fourth decimal to ensure that road segments connect entirely when a network is formed. We then aggregated the attribute information of the road segments at a daily resolution to reduce computational effort and provided an overall travel characteristic for the entire day that may differ during rush hours and early morning. Travel time for a road segment was calculated by taking the mean value for all 15-min intervals for an entire day.

3.2. Network construction

We constructed a network from the processed road segment data that contains 17,089 edges and 13,550 nodes. Where edges correspond to road segments and nodes correspond to road junctions. We map each of the road segments based on their location attributes to form this network. The original network consisted of 19712 edges and 15390 nodes but we filtered the nodes and edges from the largest connected component in the network and removed some of the nodes that had no data even during non impact days. This step ensured that shortest paths exist between every pairwise junction in the network as it is a primary step in data processing in this paper. Having disconnected nodes or clusters would lead to non-reachable junctions which are not desirable for this analysis. The resulting giant component (largest connected component) accounted for 88% of the nodes and 87% of the edges from the original network.

We use this network as a skeleton and construct weighted temporal traffic networks for each of the days from August 1, 2017 through September 30, 2017. We use travel time in minutes as edge weight in the network that represents the time for a vehicle passing through an edge (road segment) to traverse through it.

3.3. Distance matrix

After obtaining temporal networks with travel time as edge attributes, we computed a matrix $A_{13500\times13500}$ where A_{ij} corresponds to the shortest travel time from road junction i to road junction j in minutes. Since we treat the transportation network as an undirected graph, travel time from $i \leftarrow j$ is the same as from $j \leftarrow i$, thus yielding a symmetric matrix, where $A_{ij} = A_{ji}$. This distance matrix, where distance between junctions i and j (or j and i), is evaluated in time domain. This matrix contains information about the travel time between any junction pairs in the network and collectively represents the travel characteristics of the Harris County traffic network. We use the Bellman-Ford algorithm (Bellman, 1958) to compute the travel time for the shortest paths between every pairwise junction. Since, our network has roughly 13,500 nodes and 17,000 edges, it is computationally expensive to compute the shortest paths between every pairwise node in the network. Python natively uses single core for computation so Python libraries such as *swifter, dask*, and native libraries that allow multi-core processing were adopted to speed the computation.

3.4. Shortest paths analysis

We use the distance matrix to evaluate the effective spatial transformation of traffic network in Harris County. As the travel time changes for each road segment, the shortest paths between pairwise junctions (nodes) denote the spatial proximity of these junctions in the time domain. Fig. 1(a) illustrates a sample traffic network showing pairwise travel time with impact on delays due to disasters. Each road segment undergoes a change in travel time during disruption. This could be both positive or negative. If a road segment experiences disruption due to inundation, debris, or other disaster-related obstruction, it would experience increased travel time. This would have a compounding effect on travel times between different junctions, as multiple road segments in the path experience disruptions. Other road segments that are not in proximity to damaged areas may experience higher than usual travel times, as they absorb additional traffic routed through them.

To assess the impact of urban flooding on the entire traffic network, we compute two parameters: the impact of flooding on the average travel time between every pairwise road junction and the impact of Harvey on different travel time ranges of 15-min intervals. For both these parameters, the first two weeks of August 2017 were used as a baseline to compute change during Harvey. The same days of the week are compared to one another to account for different mobility patterns during different days, such as the weekday-weekend effect (Siła-Nowicka et al., 2016; Xia et al., 2018). The first parameter provides an idea on the extent of the impact of flooded roads on the average state of the entire network. The second parameter informs us about the disproportionate impacts on different travel time ranges.

3.5. Higher network dimension analysis

The simple network based measures, such as average path length, giant component size in the disrupted network, and other network-related measures are not able to fully capture the underlying changes in the network geometry (Dey, Gel, & Poor, 2019). The study of interactions between higher-order network features gives a more thorough understanding of topological changes in the network that may uncover important roles that higher-order networks might play in the understanding of dynamics of network topology during disruptions. We capture these hidden dynamics by considering the most basic higher-order feature computed using Betti number of zeroth order (Betti-0) that gives a count of the number of connected components at different distance thresholds (Islambekov, Kumer Dey, Gel, & Poor, 2018; Torres & Bianconi, 2020). The Betti numbers are fundamental topological invariants that characterize higher-order networks represented by simplicial complexes (Bianconi, 2021).

Mathematically we can represent it as following: Let $G = (V, E, \omega)$, an (edge)-weighted graph, be a representation of a temporal traffic network. If we select a certain threshold (or scale) $\epsilon_j > 0$ and keep only edges with weights between nodes u and v, ω_{uv}, is less than ϵ_j, we obtain a graph G_j with an associated adjacency matrix $A_{uv} = \mathbb{1}_{\omega_{uv}\leq\epsilon_j}$. Now, changing the threshold values, $\epsilon_1 < \epsilon_2 < \cdots < \epsilon_n$, results in a hierarchically nested sequence of graphs $G_1 \subseteq G_2 \subseteq \ldots \subseteq G_n$ that is called as a *network filtration*. These filtration levels are depicted in Fig. 1(b) for a sample network. Each sequence of graphs represents a list of junctions that fall within a specific threshold, where threshold represents travel time. Intuitively, each threshold of travel time indicates road junctions that are accessible within a temporal distance of threshold. At the lowest threshold (0 min), no other junction is accessible, so we have the same number of components as nodes or junctions in the network. As the threshold increases, more junctions become reachable to these individual junctions; these are connected to form clusters. As the travel time threshold is increased again, these clusters slowly start merging with other clusters to form a single connected component. When the accessibility to a junction is not broken, the last threshold yields just one large connected component, as all junctions are reachable by one another within this time period.

During non-impact days, the composition of the number of clusters that get formed at different travel time thresholds changes and may show certain characteristics in network geometry indicating higher order dynamics of traffic networks. These changes may not be apparent with basic network measures. Using Vietoris–Rips (VR) complex (Carlsson, 2009; Otter, Porter, Tillmann, Grindrod, & Harrington, 2017; Zomorodian, 2010), one of the most popular Topological Data Analysis filtration methods, we track evolution of topological features such as connected components using Betti numbers at different filtration levels. In our case, the distance measure corresponding to travel time in minutes was for a graph, $G = (V, E, \omega)$; the vertices correspond to road junctions, edges correspond to a link between every junction, and weights account for the travel time between the vertices.

3.6. Spatial dependence

To determine if flood impacts show spatial decay, spatial patterns of travel time change with respect to proximity to inundated areas were evaluated for each road junction in the traffic network. To compute this, we calculate the median change in the travel time at every junction, considering travel to every other junction. This was done to obtain an overall measure of the travel time change for each junction. Next, we computed the distance from the flooded region for each road junction to investigate if there was any spatial dependence on the impact of flooding on the travel time change. To visually observe the spatial dependence of flooded roads with travel times in every junction, the junctions that exhibited an overall magnitude of change of more than 15% were spatially visualized along with the traffic change in each road segment. This allowed for a better understanding of the spatial patterns of travel time change with respect to proximity to inundated areas.

4. Results

4.1. Persistent travel time increase and temporal expansion in the entire traffic network

Hurricane Harvey made landfall in Harris County on August 25, 2017, and significantly disturbed the traffic network. To evaluate the

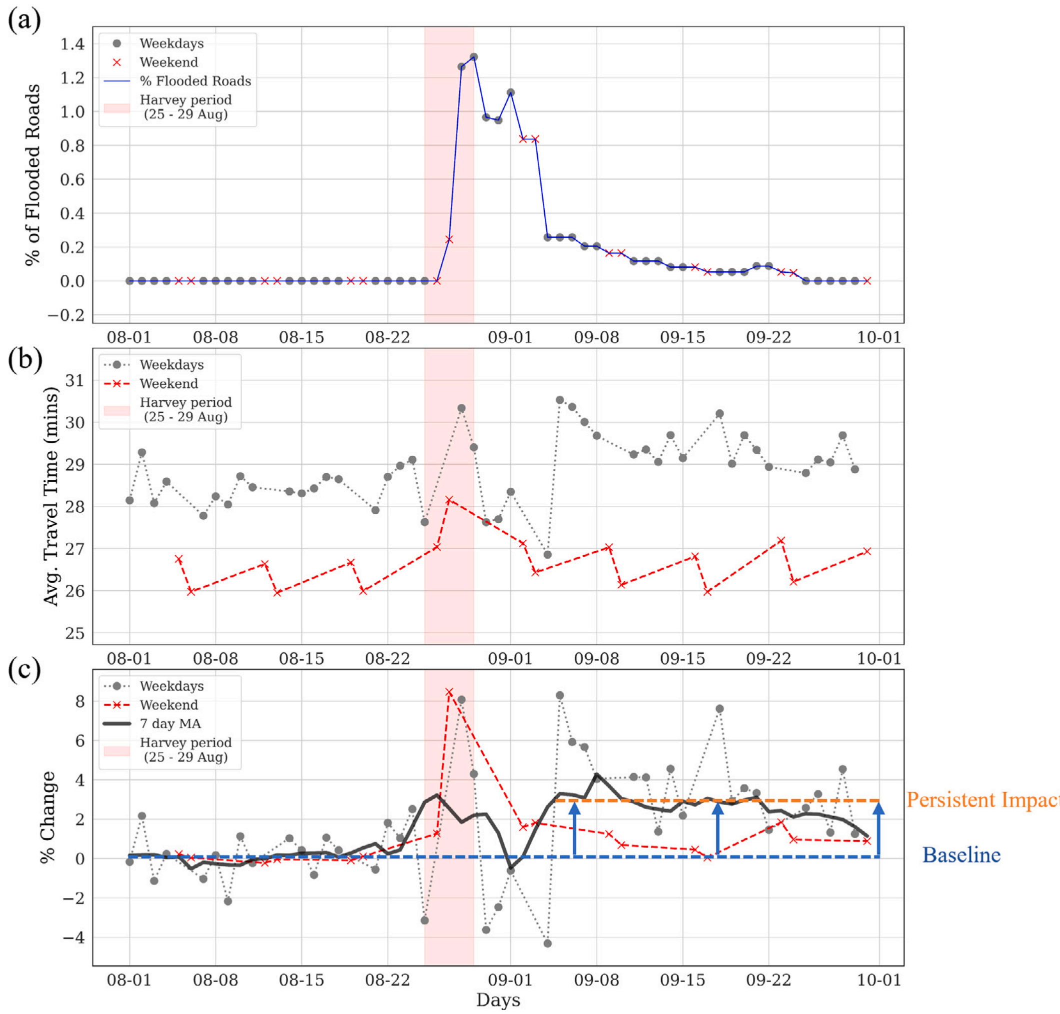

Fig. 4. Percentage change in travel time between every pair of road junctions in Harris county during, before and after Harvey. (a) Percentage of flooded edges as a function of time. After Harvey leaves Houston, further flooding happens due to reservoir water release leading to addition road closures immediately after Harvey period. (b) Average daily travel time between pairwise junctions in minutes. Weekdays and weekends show distinct trip patterns due to differences in lifestyle and lack of work-related trips on weekends. Work-related trips increase average traffic and lead to higher travel times compared to weekends. (c) Change in the pairwise travel time compared to the baseline values. The same day of the week is compared across weeks to account for differences in movements for different days of the week. For a modest 1.3% of flooded roads, 8% increase in travel time is observed for the entire network on August 27 and 28. After roads recover from inundations, with only 0.25% of roads remaining perturbed, sustained impact is observed for travel times. The entire network experiences an average of 3% increase in travel time among node pairs even a month after Harvey landfall.

impact of flooding in the traffic network, we look at the changes in the pairwise travel time in the network obtained from computing the shortest paths between every road junction in the traffic network. In the average network-wide pairwise travel time at different phases of the Harvey (Fig. 4), we see that the travel time first decreased at the time of Harvey's landfall (August 25) due to residents sheltering in place, thus reducing travel demand, in anticipation of Harvey's landing. Travel time then increases (August 28) due to the increase in flooding-induced road closures. The travel time drops again between August 28 through 30, as flooding is receding but residents still have not started traveling. By September (Fig. 4a), the number of flooded/perturbed road segments decreased from 1.3% (August 28 and 29) to 0.25%. The travel time slowly recovers as flooded roads become available and debris is removed. By September 5, road conditions are largely improved and travel demand is headed towards normalcy. Longer travel times due to congestion have a persistent impact on the travel time for the entire network for perturbed road segments that account for less than 0.25% of road segments.

A small fraction of road closures impacts the entire traffic network. According to Fig. 4(a), at peak inundation, 1.3% of perturbed roads contribute to an average of 8% of increases in travel time in the entire network, which is equivalent to the network being expanded by 8% (every junction pair gets more distant from each other by 8% travel time). However, it is interesting to note that both 1.3% (August 28 and 29) and 0.25% (Sep 4) of flooding-induced road closure can result in an 8% of increase in travel time. This affirms two findings: (1) the location of flooding is important. When a small number of critical roads are perturbed, the impact is as extensive as the disruption of multiple ordinary roads; (2) accounting for disturbed travel demand due to flooding is a factor in assessing the impacts on the traffic network in terms of travel time. During Hurricane Harvey, many roads were closed, thus increasing overall travel time. In the post-Harvey period, travel demand picked up, and thus more congestion on the road (while fewer road segments were perturbed). With a small proportion of road closure remaining, the compound flooding and congestion impacts led to an increase in the travel time of 8% on September 4 (Dong et al., 2022).

Flooding affects traffic networks differently during weekdays and weekends. As shown in Fig. 4(b and c), Travel times during weekdays and weekends were both disturbed by the flooding; however, weekend travel time quickly recovered to the pre-Harvey level, while weekday travel sustained the average 3% of travel time increase even one month after the Harvey. This persistent travel time increase during weekdays can be attributed to the weekday commute demand change in the aftermath of flooding. Weekend travel needs and schedules tend to be flexible, thus travel time returned to normal during weekends more quickly. The 3% persistent travel time increase in the entire network during weekdays can translate to significant social and economic impacts in terms of user costs, additional CO_2 emissions, and lost productivity.

4.2. Flooding disproportionately prolongs long-duration travel

For the shortest path between pair-wise road junctions (also called node pairs), travel time is computed by summing the time contribution of perturbations or disturbances in each road segment. This method has a compounding effect on the overall time for movement from one location to another. We evaluated the impact of flooding on trip ranges by segregating trips into 15-min intervals: trips of less than 15 min, between 15 up to 30 min, 30 up to 45 min and so on, the last interval being 60 to 75 min. We then count the number of junction pairs that fall within each travel time range and compare them with baseline. This parameter provides insights about the disproportionate impact on junctions within different temporal proximity. This interval classification accounts for more than 99.9% of the trips on non-impact days; therefore, represents the entire traffic network reliably. The distribution of travel time versus fraction of node pairs (Fig. 5(a)) suggests that, during peak inundation, travel time follows long-tailed distribution. Changes in travel time of pairwise junctions on August 29 (Fig. 5b) suggest that while peak inundation induces an overall increase in travel time, due to disconnection of some junctions from main network due to closure related to inundation and road damage. Nevertheless, a large proportion of road segments show a decrease in travel time.

The results shown in Fig. 5(c–g) provide insights on the extent of change and impact for travel time ranges. On average, trips with a mean travel time of less than 30 min show a decrease of about 5 to 10%. This is because trips of shorter travel time, thus fewer road segments, are less subject to compounding effects. On the other hand, the extent of increase in trips of greater than 60 min is about 50% on average and increases to about 140% during peak impact day. On average, the extent of impact increases as travel times increase between road junctions. Thus, the impact on travel times due to urban flooding is directly proportional to the distance between the places.

We also see a sharp decline in shorter travel times immediately after Harvey, as there is less traffic on road. As evacuated residents return and city recovers to normalcy, travel times increase exponentially, reaching the same level as that during Hurricane Harvey. This is due to the fact that some road segments are still littered with debris or closures, but still must cater to high demand. It is worth noting that the average levels of change for all time intervals reach almost the same level as that observed during Harvey. This indicates that although the actual landfall lasted only for a couple of days, its impact was observed at virtually the same intensity on average until the end of September.

To examine the impact of flooding on higher-order network measures, we use a topology based measure, Betti-0, that computes the number of connected components in a network at different travel time thresholds. In the context of a traffic network, Betti number at a threshold of 15 min ($\epsilon_1 = 15$) would look at the number of connected network components when road junctions within a 15-min proximity are merged and considered as one component. At the initial thresholds of travel time, there are multiple pockets of such connected components, since not all junctions are reachable by one another given the threshold. Hence, a number of clusters get formed. These clusters represent places of closest proximity in terms of travel time. For simplicity, we focus only on five thresholds, $\epsilon_i, i = 15, 30, 45, 60, 75$. The results of the percentage change in Betti numbers on different days for these five filtration values are shown in Fig. 5(h–l).

The results indicate that changes in the topological features in the network follow distinct patterns. For features within 15- and 30-min thresholds, we first see a decrease in the number of such connected components, then an increase, followed by a slight decrease before reaching at equilibrium. For other filtration levels, we see an increasing trend till the second day of Harvey (August 26) and then a decreasing trend till immediately after Harvey (September 1). There is then an increase in the connected components at the respective travel time thresholds that stagnates at a higher or similar level, as observed during Harvey. The percentage change in the number of connected components within different time intervals is less than the changes observed in the variation in the number of junctions connected at different thresholds (Fig. 5h–l). This result indicates that higher filtration levels (associated with connectivity of junctions with longer travel times) show more sensitivity to changes in the network due to flooding. This result confirms the earlier results regarding the greater sensitivity of longer travels to flooding impacts.

The reduced number of the connected components during Harvey for shorter trips is a result of decreased travel time due to less traffic, making a greater number of nodes reachable within a time threshold as compared to pre-Harvey conditions. In contrast, there was an increase in the number of connected components for longer trips during Harvey, implying lower reachability given the same time window, as if flooding caused an invisible temporal expansion of the entire road network of the city. This temporal expansion of the traffic network influences the higher-order structures in the network and makes more junctions reachable for shorter trips in terms of travel time and fewer junctions for longer duration trips. The differences in travel time change for various filtration levels reveals that floods affect travel durations disproportionately, putting longer-distance travels in jeopardy. Coupled with critical service needs and accessibility, such impact disparity can further exacerbate the community vulnerability (Dong, Esmalian, Farahmand and Mostafavi, 2020).

4.3. The extent of travel time change does not decay with distance from inundated areas

We evaluated the spatial patterns of travel time changes with respect to proximity to inundated areas. We spatially visualized the junctions that show an overall magnitude of change of more than 15%. Here we assess the impact by aggregating the travel times from one junction to every other junction and calculate the average change in travel time at a junction. We compared this result with road segments having an average travel time change of more than 15% to evaluate if they exhibit spatial colocation. Fig. 6(a) and (b) show spatial occurrence of the specified junctions and road segment, respectively, on peak flooding day, August 29. The effect of perturbation in the filtered road segments can be seen in Fig. 7(c), which corresponds to August 27, two days after the landfall of Harvey in Harris County; Fig. 7(d) shows the road segments that experienced an increase in travel times due to flooding for the same day. Although the road segments on the major highways show increased travel times, the effect can be seen over the entire network. Most of the junctions show an increase in travel time of more than 15%, with some showing more than a 50% increase. Similar insights can be obtained by comparing the results for August 28 and 29.

When Harvey dissipated in the Houston area on August 30 and 31, the majority of junctions experienced a reduction in travel time, consistent with the results obtained from comparing average travel times in the overall network. Although some regions, such as southwest Harris County, retained road segments with increased travel times, the effect cannot be seen locally or throughout the entire network. But a week later, the increase in travel time resolved in Southwest area, despite roads unaffected by flooding showing increased travel time. This result provides evidence that, although flood-related impacts on the road network are local, the spatial reach of flooding on the overall travel time and connectivity is extended beyond inundated areas. This spatial reach does not decay with distance from inundated areas.

Further investigation of the absence of spatial decay evaluated the change in travel time with distance from flooding (Fig. 6c). The median

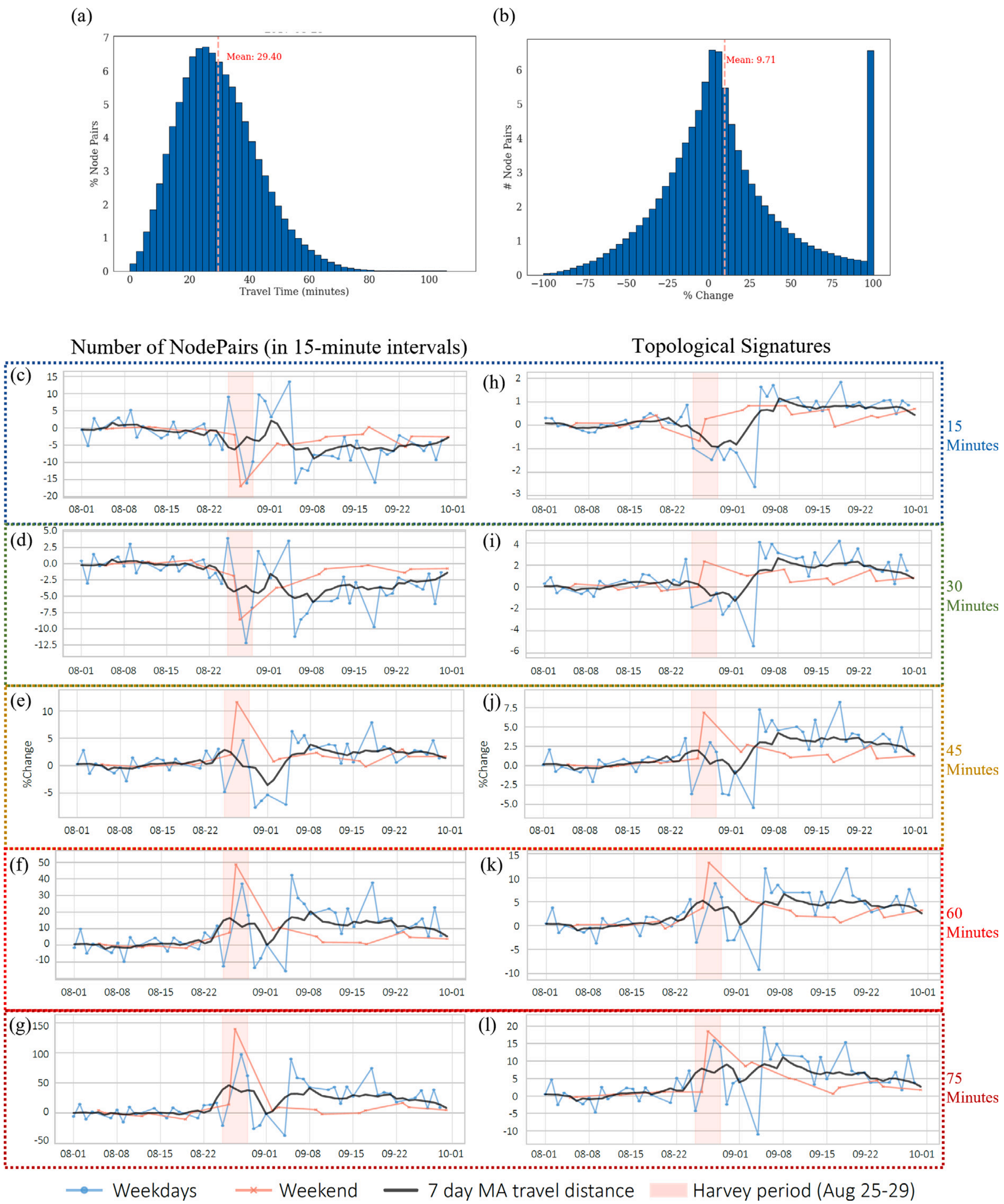

Fig. 5. Perturbation characteristics of long and short trips in traffic network. (a) Distribution of the number of node pairs (junction-to junction-travel pairs) versus travel time for August 29. Distribution for all days follows a bell curve for and has a mean value of around 30 min. (b) Proportion of the number of node pairs corresponding to travel time percent change due to Harvey on August 29. Change of more than 100% was considered as 100% for better visual clarity. (c–g) shows the change in the trips for intervals of 0–15, 15–30, 30–45, 45–60, 60–75 min intervals respectively. (h–l) shows change in the number of connected components at thresholds of 15, 30, 45, 60 and 75 min, respectively. Longer trips show higher impact due to traffic disruptions as impacts compound for longer commutes. Travel time and topology-based impact assessment show different characteristics of disruption and recovery for different time intervals. Post-disaster sustained impact is seen in every time range in both assessments.

Fig. 6. Spatial impact of floods on traffic network on August 29. (a) Percent change in travel time for each road segment along with flooded regions for that day. (b) Average impact in terms of percent change in travel time at each node (road junction) when trips are considered to every other node. (c) Changes in travel time as a function of distance from flooded region. Change for regions within inundated region is shown by Violin plot at 0 distance; plot at 5.5 km distance presents the aggregated changes for all road junctions more than 5 km away, which accounts for less than 1% of the road junctions. There is no decay in change of travel time with respect to distance to inundated areas. Areas far from the flooded regions also show same extent of travel time change on an average.

change in the travel time at every junction, considering travel to every other junction, shows a similar pattern irrespective of the distance from flooded region. Additionally, junctions in flooded areas have the same change as those outside inundated areas, demonstrating that flooding affects the entire traffic network irrespective of direct proximity to flooded regions. We do not, therefore, observe any decay in flooding impact on travel time with distance from flooded regions. While Li, Wang, Liu, Small, and Gao (2022) show that mobility exhibits spatio-temporal decay from crisis locations when observed at county, state, and country resolution, our analysis at a much finer resolution does not indicate the presence of spatial decay in the impacts flood on traffic networks.

5. Discussion

This study examines the virtual expansion of traffic networks during flooding by considering flood impact on travel time. The results reveal three novel properties of perturbed traffic networks caused by urban flooding: (1) persistent entire network travel time increase, (2) long-tail effects on long-travel distance travels, and (3) absence of spatial decay in travel time changes with distance from inundated areas. Specifically, the results show that 1.3% of flooded roads during Hurricane Harvey in 2017 were responsible for an 8% increase in overall travel time throughout the network. The impacts of flooding on traffic networks persisted for several weeks after inundation receded. Furthermore, such impact on travel time is not homogeneous but affects longer trips (i.e., 45–60 min) more strongly than shorter ones (i.e., less than 15 min). Such a heterogeneous impact of flooding on travel times is a factor to be considered in disaster traffic management to maintain a community's access to critical services. Investigation of high-dimensional features using the Betti number reveals that flooding imposes an impact on traffic congestion post-disaster, which can be as high as that observed during peak inundations. Although flood disruption on road segments is localized, the generated impact is diffused throughout the network, suggesting that the impact on the travel time in a city is invariant of the location of disruption. Moreover, the impact is sustained even one month after flooding and causes a 3% expansion of the traffic network for a fraction of unrestored road segments.

The findings of this study had important implications: first, the findings reveal the impact of floods on travel times in urban traffic networks. Prior studies focused on vulnerability of physical roads (Bagloee et al., 2017; El-Maissi, Argyroudis, Kassem, & Mohamed Nazri, 2023; Mattsson & Jenelius, 2015; Wang et al., 2019); our understanding of the perturbed functioning of traffic networks during floods was limited. Second, we found that the impacts of the flood are not local but affect the entire network disproportionately when travel times are considered. So even if flooding is localized in a city, the infrastructure impact will be local and considered contained, but our study reveals that the impact on travel time will be seen in the entire city. A percolation-based approach is less equipped to provide these insights. Third, unlike the majority of studies that use location-based human mobility data for analyzing origin–destination trip fluctuations in floods and other crises, this study dissected fine-resolution link-level travel time data to analyze the perturbed dynamics of traffic networks. The fluctuations in human mobility do not fully capture the functionality of traffic networks in terms of travel time (the primary function of transportation networks). The number of trips might return to normal, but the travel time between junctions may stay elevated for a longer duration.

This study employed topological network measures and higher-order network analysis to capture both temporal dynamics and spatiality of traffic networks. The prior studies on urban networks were primarily based on percolation analysis (Stauffer & Aharony, 2018) and were not able to capture temporal dynamics of links functionality as well as the spatiality of real world networks, so new metrics were needed to understand the network resilience properties, that we presented in this paper. Hence, the novel insights obtained from this study move us closer to a better understanding of the impacts of floods on urban traffic networks. Results from this study can be used to evaluate the impact of floods on communities better. As multiple studies have focused on aspects such as income, distance from the city center, elevation, and accessibility to the road network, the results of this study have implications for the community's well-being. If travel times increase, commuters' quality of life will be impacted. Moreover, it will have an additional cost for both individuals and businesses. Not only will the communities and companies be impacted, but it will lead to an increase in carbon emissions and other pollutants. The study provides a more comprehensive way of understanding transportation vulnerability which has potential implications for infrastructure planning in different cities.

6. Concluding remarks

Urban flooding is a threat to large metropolitan cities, and the frequency of floods is expected to increase with climate change. The study revealed persistent and network-wide impact of floods and their heterogeneous impacts on trips of varying lengths, providing evidence for planners and emergency officials to effectively manage the city traffic during urban floods to ensure proper functioning of cities. The pairwise junction travel assessment method and higher order analysis employed in this study capture both temporal dynamics and spatiality of traffic networks. The findings of this study would be generalizable to other cities, and flood events since traffic and mobility networks show similar characteristics in cities thought the world (Chan, Donner, & Lämmer, 2011; Noulas, Scellato, Lambiotte, Pontil, & Mascolo, 2012). Therefore, they are likely to exhibit similar patterns of disruptions and recovery during disasters. Moreover, This method can be transferred to other spatially embedded and dynamic temporal networks and disaster scenarios, such as the power grid during storm events. Application of these methods on traffic networks showed that on average, localized impact has same effect on travel times away from disrupted regions as those within and in the nearest proximity to disruptions locations.

This study complements existing location-based human mobility studies by dissecting fine-resolution link-level travel time data to analyze the anatomy of flood-perturbed traffic networks. We reveal that although the total number of trips might return to normal after flooding, the travel time between junctions can persist for a longer duration. The approach used in this study can be employed for assessing the resilience of other spatially embedded and temporally dynamic networks, such as power grid networks. Given the importance of traffic network function in terms of travel time, the findings of this study can inform city managers, transportation planners, and emergency responders about the persistent and entire network impacts of local floods, which are expected to grow with climate change impacts. The persistent travel time increase in the entire network can translate to significant social and economic impacts in terms of user costs, additional CO_2 emissions, and lost productivity.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share the data due to the legal restrictions of the data provider. Interested readers can request it from INRIX, provided here (https://inrix.com/products/speed/).

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Code availability

The code that supports the findings of this study is available from the corresponding author upon request.

Appendix

See Figs. 7 and 8.

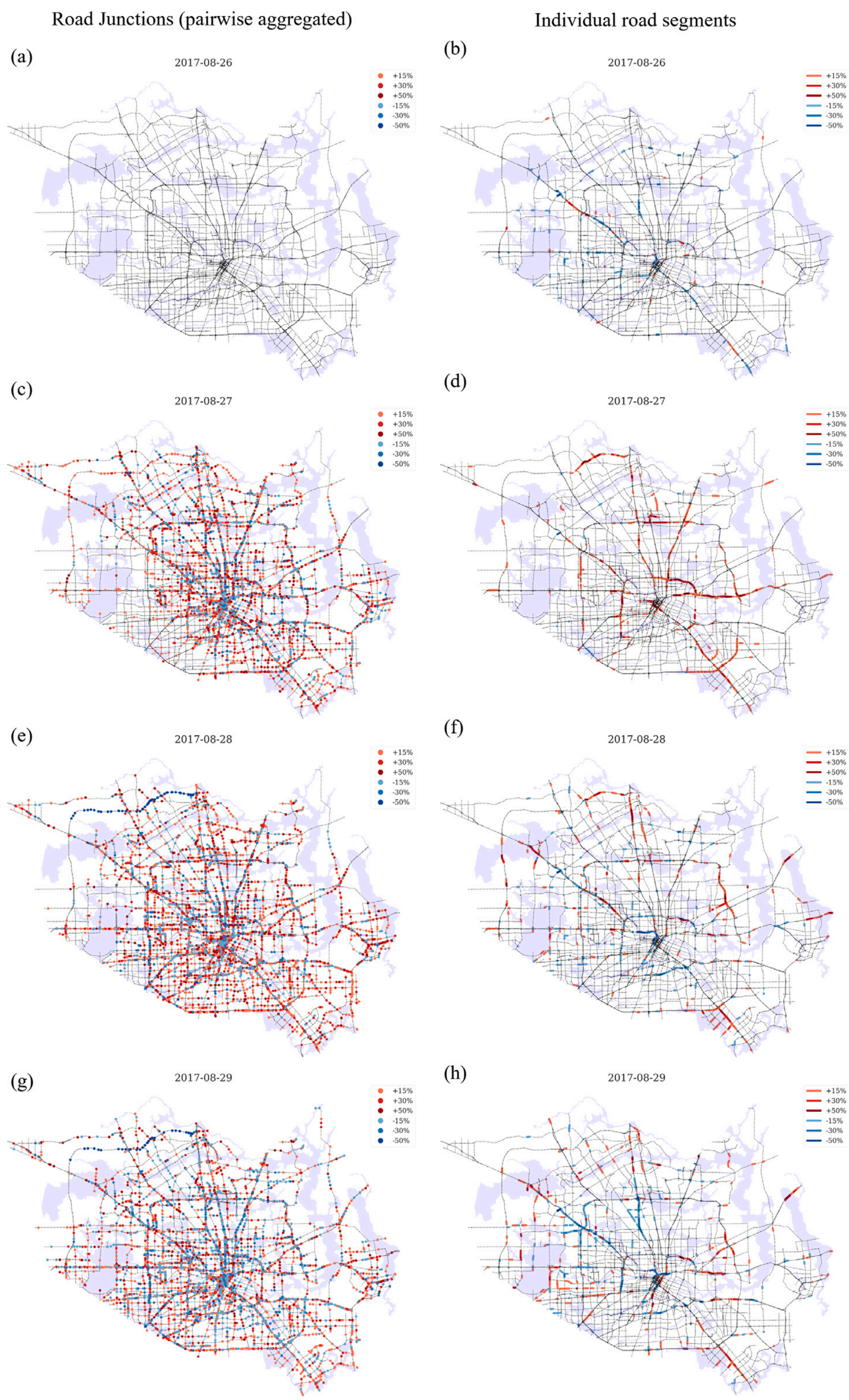

Fig. 7. Average change of travel time observed in road junctions in comparison to change in travel time for road segments during Harvey. (a), (c), (e) and (d) show the change in travel time for road junctions, and (b), (d), (f) and (h) show the change in travel time for edges for the respective days.

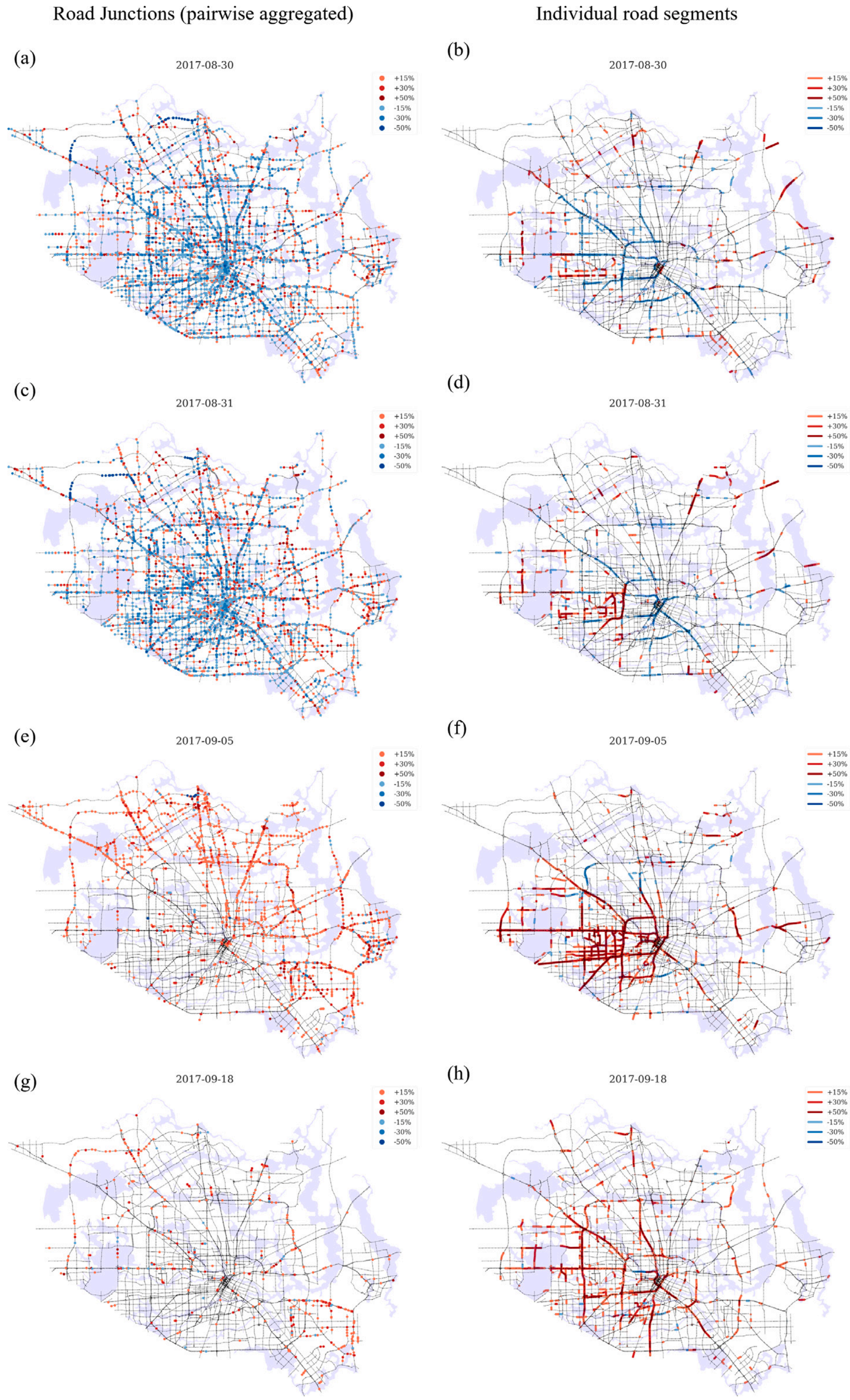

Fig. 8. Average change of travel time observed in road junctions in comparison to change in travel time for road segments after Harvey. (a), (c), (e) and (g) show the change in travel time for road junctions, and (b), (d), (f) and (h) show the change in travel time for edges for the respective days.

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