

ADVANCING DISASTER RESILIENCE AND SPATIAL ACCESSIBILITY ASSESSMENT USING MACHINE LEARNING AND GRAVITY-BASED MODELS

ABSTRACT

In the face of intensifying natural disasters, particularly hurricanes, the need for resilient infrastructure and equitable spatial accessibility to critical facilities is important. As such, this dissertation explores and integrates gravity-based spatial models and machine learning frameworks to assess and improve disaster resilience, with a focus on rural and coastal communities in Florida. The research is structured as a collection of four related studies that collectively advance knowledge on spatial accessibility before, during, and after hurricanes, emphasizing vulnerable populations and infrastructure under pressure.

The first study establishes a methodological foundation by evaluating the accessibility of public libraries, which serve as key community support services in Calhoun County, Florida. By employing the Enhanced Two-Step Floating Catchment Area (E2SFCA) and the Three-Step Floating Catchment Area (3SFCA) methods, the study moves beyond traditional travel time metrics to consider facility capacity and population demand. Results reveal significant accessibility disparities across census block groups, with higher population densities often correlating with lower accessibility. This work highlights the inadequacy of simple proximity-based models and underscores the importance of service capacity in rural planning. The study supports tailored service areas to ensure that essential services such as libraries, especially during disaster recovery phases, are equitably accessible to all, including older adults and other vulnerable groups.

Building on this foundation, the second study transitions to emergency-specific accessibility analysis using the Rational Agent Access Model (RAAM) within a geographic information system (GIS) framework. Focusing on hurricane shelters across Northwest Florida, the model incorporates real-world constraints such as congestion, changing road conditions, and travel behavior to evaluate shelter accessibility. The study finds that rural inland counties, including Liberty and Calhoun, face substantial accessibility deficits due to sparse transportation infrastructure, while

more urbanized and coastal counties exhibit better accessibility. This spatially explicit model helps emergency planners by identifying areas in need of infrastructural investments and optimizing shelter location and routing strategies to minimize travel time during evacuations. Findings support more data-driven, equity-centered disaster preparedness planning.

The third study shifts from preparedness to real-time disaster impact assessment, utilizing machine learning to evaluate roadway accessibility following Hurricanes Ian and Idalia. By integrating high-resolution satellite imagery with hurricane and demographic data, a machine learning model is trained to classify roadway segments as open, partially closed, or fully closed, achieving up to 89% accuracy. Findings show that densely populated coastal zones experience the greatest disruptions, demonstrating how hurricane intensity and land-use characteristics affect network vulnerability. This study underscores the role of machine learning in enhancing situational awareness during disasters, helping to direct resources to high-need areas and support sustainable post-disaster recovery.

The final study expands the proposed machine learning application by introducing a novel framework for quantifying roadway vulnerability and impact using aerial imagery. It develops two new indices, the Road Closure Impact Index (RCII) and the Roadway Vulnerability Index (RVI) to assess both immediate and recurring infrastructure risks across multiple hurricane events. Applied to Taylor County, Florida, the framework evaluates and compares the effects of Hurricanes Idalia and Debby. Results show differing impact profiles: Idalia caused wind-driven structural damage, while Debby resulted in prolonged flooding. These metrics enable local governments and planners to identify not just where roads fail, but how consistently they fail across events offering a powerful tool for prioritizing investments and improvements in transportation networks.

Taken together, these four studies represent a comprehensive approach to assessing and improving spatial accessibility and infrastructure resilience across the hurricane lifecycle before, during, and after the event. By combining spatial gravity-based models with advanced machine learning techniques and remote sensing data, this dissertation contributes scalable, data-driven methodologies for disaster preparedness, response, and recovery. The research offers actionable insights for emergency managers, transportation planners, and policymakers seeking to foster more

resilient, equitable, and informed infrastructure systems in hurricane-prone regions. Ultimately, this work demonstrates how integrating geospatial analysis with artificial intelligence can advance both theoretical understanding and practical decision-making in the era of climate-driven disasters.

Keywords: Spatial accessibility, Shelters, Roadway Vulnerability, Machine Learning, Hurricane Impact Assessment.