Analyzing Post-Disaster Infrastructure Recovery Equity Using Remote Sensing Approaches - A Case Study Of Hurricane Ida

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Research Problem Statement

Damages to critical infrastructure as a result of climate-related risks are projected to increase across the world. Transportation networks are central to the post-disaster recovery and overall resilience of a community, as they determine access to other critical infrastructure, including medical services, food access and aid distribution[1]. Low-income and minoritized communities are more likely to be isolated from critical aid in the immediate aftermath of a disaster[1]. Additionally, infrastructure in these communities are more likely to experience more severe damages as a result of extreme weather events and are slower to recover[2].

Globally, infrastructure damage and service disruption data are inconsistently reported. Mmany post disaster needs assessments focus on physical damage, but do not quantify the degree and duration of service disruptions[3]. Although earth observation data have been utilized to categorize damage to critical infrastructure at different spatial scales, it remains underutilized to monitor the equity of post-flood outcomes and differing recovery rates among different communities[7,8].

Our study addresses this gap by proposing a computationally effective, geographically scalable remote sensing approach based on publicly accessible satellite data to measure the rate of recovery of road networks in the aftermath of a flooding disaster. Additionally, we analyze these disruptions in the context of socioeconomic factors. By modeling disaster recovery as a continuous process with variable trajectories based on human factors, as opposed to a point-in-time phenomenon, we contribute to emerging research that quantifies the societal impact of infrastructure disruptions on different communities[4].

As a pilot case study, we will implement this in the context of Hurricane Ida, a Category 4 hurricane that struck the coast of Louisiana on August 29, 2021, travelling 1,500 miles and impacting 22 states across the United States[5]. The event resulted in damages to infrastructure and housing costing approximately $9 billion[6]. We leverage Sentinel-1 Synthetic Aperture Radar (SAR) imagery to quantify surface flooding on road networks at the tract level, enabling the assessment of both immediate flood impacts and short-term recovery trends. By combining these remotely sensed observations with tract-level socioeconomic and land-use data, we aim to identify disparities in infrastructure recovery across communities (Figure 1). Preliminary analyses suggest that areas with higher fractions of high-intensity development experience lower peak flooding, likely reflecting differences in drainage infrastructure and built environment characteristics. This work will help inform decision-makers to quantify the human cost of inequitable infrastructure disruptions, thereby enabling targeted interventions for rebuilding in vulnerable areas.

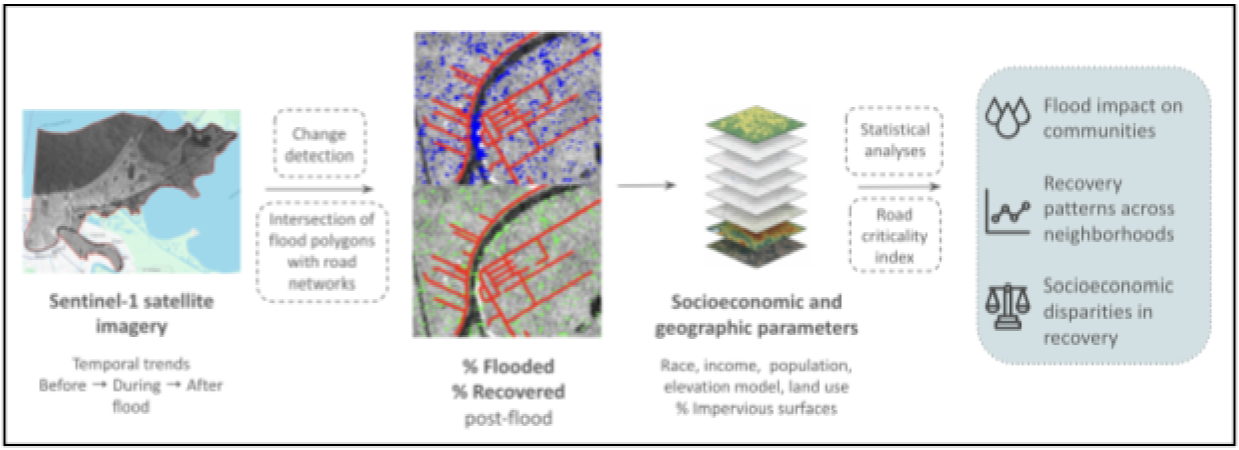

Figure 1: Remote sensing approach to monitoring road infrastructure recovery

Methods

Geographical focus

As a proof of concept, we focused on Orleans Parish in New Orleans, which has an area of 169.5 square miles, and a population of approximately 384,000. The county is highly racially diverse, with 54.7% of the population identifying as Black or African American, approximately 31% identifying as White, and growing Asian and Hispanic communities[9]. Orleans Parish was one of the worst affected areas during Hurricane Ida, with approximately 200,000 reported evacuations, and extensive infrastructural damage from street flooding, structural damage to buildings, and a 100% power outage[10].

Satellite data and flood detection

We utilized Sentinel-1 satellite imagery dating from July 20, 2021 to November 30, 2021, at a spatial resolution of 10 m. Radar-based imaging has been broadly used in flood mapping applications, owing to high image quality regardless of cloud cover or vegetation, and its applicability in larger geographical contexts[11]. The Sentinel 1 satellite constellation has a 6-day orbital repeat cycle, enabling long-term tracking of infrastructure recovery. Road networks were derived from OpenStreetMap data. This was used owing to the overall completeness of the dataset, measured at over 80% globally[12]. Road centerlines were buffered by 10 m and rasterized to create a binary road mask, approximating the spatial footprint of road infrastructure for intersection with flood extent maps.

Following SAR image pre-processing, we used a simple change detection approach to classify pixels as flooded, where the backscatter coefficient of both pre-flood and flooded imagery is calculated, and thresholding is applied to identify pixels that have reduced backscatter coefficients during the flooding period[11]. These values were then computed across available Sentinel 1 imagery during and post Hurricane Ida.

Socioeconomic and geographic parameters

For our initial regression, we used tract-level aggregations of percentage of non-White residents, total population, and median household income from the 2021 American Community Survey 5-Year Data[13]. We obtained land cover data from the National Land Cover Database, including percentage of areas with open water (i.e., less than 25% cover of vegetation or soil), and developed land of low (20% to 49% impervious), medium (50% to 79% impervious), and high (80% to 100% impervious) intensity to capture variation in surface permeability and built environment characteristics relevant to flood exposure.

We used FEMA's National Flood Hazard Layer (NFHL) to identify areas of high flood risk within Orleans Parish. We then computed the intersection between tract boundaries and the FEMA flood zones to calculate the area of each tract falling within a flood-prone region. From this, we extracted tracts that intersected Special Flood Hazard Areas, defined by FEMA as areas with a high probability of flooding, creating a tract-level indicator for high flood risk. This allowed us to include flood exposure as a covariate in our regression models.

For the proof of concept, we used a basic multivariate linear regression model to examine how tract-level socioeconomic composition (percent non-White residents, total population, median household income), land cover characteristics (open water, low/medium/high-intensity development), and flood risk designation (intersection with FEMA's National Flood Hazard Layer) predict peak and residual flooding following Hurricane Ida. All continuous variables were mean-centered to reduce multicollinearity, and robust standard errors (HC3) were used to account for heteroskedasticity. Interaction terms between socioeconomic variables and development intensity were tested to explore whether the association between community composition and flooding varied across different urban forms. In future work, we plan to extend these analyses using spatial regression models to account for potential spatial dependence in flooding outcomes across neighboring tracts.

Preliminary results and discussion

In the multivariate regression with the percent of road flooded during the peak of rainfall and a week after, we found that only the proportion of high intensity land-use was statistically significant, indicating that tracts with a higher fraction of this development type experienced lower peak flooding, while other socioeconomic and structural covariates were not significant. We found no significant covariates correlating with the rate of change of surface flooding between the two data points.

We hypothesize that this unintuitive finding can be attributed to several factors. Roads in areas with higher-intensity development are likely to have more impervious surfaces but also better engineered drainage systems, reducing surface water accumulation. In contrast, lower-intensity or sparsely developed areas may have poorer stormwater infrastructure or be located in lower-lying portions of the landscape, increasing susceptibility to surface flooding. Additionally, the limited temporal resolution of our flood measurements and the small number of post-event observations may obscure relationships between flooding and socioeconomic composition.

Limitations

This study was conducted as a proof of concept using one flooding incident in one high-risk, sociodemographically diverse county as a case study. As a result, several limitations should be noted.

First, we relied on a relatively simple radar backscatter change-detection approach to identify flooded regions using Sentinel-1 SAR imagery. While this method is computationally efficient and well suited for large-scale analysis, it is sensitive to well-known SAR artifacts such as layover, shadowing, and double-bounce effects, particularly in dense urban environments[14].

Second, the temporal resolution of Sentinel-1 imagery constrained our ability to isolate the impacts of a single flood event. In the case of Hurricane Ida, only one post-event image was available before a subsequent precipitation event, limiting our capacity to distinguish flood-related impacts from compounding hydrometeorological conditions.

Third, our analysis did not explicitly account for flood severity, depth, or duration. All detected flooded pixels were treated equivalently, despite evidence that infrastructure damage and recovery trajectories vary substantially with flood intensity and exposure time. This simplification may mask important heterogeneity in both physical impacts and recovery outcomes. We propose this method as a guiding framework that can help rapidly identify at-risk areas, as opposed to a substitute for holistic measures of damage and recovery that rely on ground observation and community input.

Finally, we treated infrastructure impacts uniformly, without differentiating between the relative criticality of different infrastructure types. Disruptions to highly critical networks, such as major arterial roads or emergency access routes, may have disproportionately larger social and economic consequences than impacts to less essential infrastructure, a distinction not captured in our current framework.

Conclusions and future work

This study presents a scalable, tract-level approach to monitoring disparities in road infrastructure recovery during and after flooding events, combining remotely sensed flood data with socioeconomic and land-use characteristics. By linking spatial patterns of surface flooding with community composition and built environment features, our approach enables the identification of areas where vulnerable populations may experience prolonged infrastructure disruptions. This framework provides a foundation for examining not only where flooding occurs, but also which communities are disproportionately affected and how recovery trajectories vary across urban landscapes. Although this study was limited to Orleans Parish, broadening the geographic and temporal scope of infrastructure monitoring will enable greater insights into gaps that exist in the aftermath of a flood event.

Future work will incorporate flood detection methods better suited to the complexities of urban environments, including deep learning–based change detection (e.g., U-Net or Mask R-CNN architectures for SAR or optical imagery) and interferometric SAR (InSAR) that can more effectively account for built-up surfaces and heterogeneous land cover. These approaches are expected to reduce misclassification arising from radar-specific artifacts and improve flood extent delineation in dense urban settings.

To better capture flooding severity, we plan to integrate simple flood depth estimation techniques, such as Height Above Nearest Drainage (HAND), enabling differentiation between shallow and severe inundation[15]. Accounting for flood depth will allow for more nuanced analyses of infrastructure damage and recovery trajectories. We also aim to integrate high–temporal resolution optical imagery, such as PlanetScope data, to improve the construction of continuous temporal profiles of flooding and recovery. Combining optical and SAR data will enable cross-validation of flood detection results and more accurate identification of recovery dynamics[11].

To better capture sociodemographic vulnerabilities, we plan to use additional metrics in our regression analysis such as road density and age to identify specific interventions that correlate with faster recovery. We will also quantify the functional impacts of flooding on access to essential services using a population-weighted travel-time surface. Furthermore, we will estimate the proportion of residents losing access to critical facilities, including hospitals and grocery stores, and the length of this service disruption for different populations. By estimating the human cost of inequitable infrastructure rebuilding, this study makes a case for policymakers to design recovery policies that account for differential vulnerability and ensure equitable restoration of essential services across all communities.

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