Assessing Building vulnerability in 1% Flood in DC

Abstract

The Washington, DC, metropolitan area faces increasing flood risks, amplified by recent extreme weather events such as Hurricane Ida and severe storm surges along the Potomac River, which have caused significant infrastructure damage and economic losses. These events underscore the pressing need to assess building vulnerability to flooding and develop informed resilience strategies. This study evaluates the exposure of buildings in the DC area to 100-year flood events using spatial computing methods.

The research explores the question: How vulnerable are DC's buildings to extreme flooding, and what are the potential economic impacts on different building types. High-resolution datasets, including the National Structure Inventory (NSI) and FEMA flood hazard layer are used to identify exposed buildings and quantify potential property damage. Structural response evaluates susceptibility based on building materials and exposure to flood, while vulnerability analysis estimates economic losses of buildings in flood zone. Spatial computing methods, such as spatial overlay, vulnerability analysis, and heat maps for hotspot analysis, offer detailed insights into flood risk dynamics specific to the DC region.

The results reveal critical vulnerabilities, highlighting the spatial distribution of at-risk structures and the associated economic impacts. Findings indicate heightened exposure in low-lying areas near the Anacostia and Potomac Rivers, with compounded risks due to increasing flood depths and material-specific susceptibilities. These insights enhance the understanding of the DC area's flood risk and provide actionable recommendations for policymakers and urban planners to improve resilience and mitigate disaster impacts.

Introduction

The Washington, DC, metropolitan area, a critical political, economic, and cultural center, faces increasing threats from flooding due to its geographic and climatic conditions. Although not a coastal city, DC is particularly vulnerable to flooding from storm surges along the Potomac and Anacostia Rivers, heavy rainfall, and the compound effects of urbanization and climate change. Recent extreme weather events, such as Hurricane Ida in 2021, brought record-breaking rainfall and flash flooding to the region, causing significant damage to infrastructure and residential areas. In 2022 alone, flooding in the DC area resulted in damage estimated at over $1 billion, with disruptions to critical services and displacement of hundreds of residents (NOAA, 2022).

The National Oceanic and Atmospheric Administration (NOAA) reports that DC has experienced a relative sea level rise of 11 inches since 1924 due to a combination of global sea-level rise and local land subsidence, with projections indicating an additional rise of up to 2 feet by 2100 under high greenhouse gas emission scenarios (Sweet et al., 2022). The National Capital Planning Commission (NCPC) has identified over 15% of the district's land area as flood-prone, placing critical federal and local assets at risk. The First Street Foundation's 2023 report highlighted that nearly $4 billion worth of property in the DC area could be at risk from a single 100-year flood event, emphasizing the region's growing vulnerability.

Motivation for this study stems from the need to address DC's increasing exposure to flooding and its potential economic impacts. FEMA's National Risk Index ranks Washington, DC, among the top urban areas at risk of riverine and flash flooding in the United States. While significant federal assets like the National Mall and Capitol Hill have been considered in prior risk assessments, the structural resilience of the broader DC building stock has not been adequately analyzed, leaving gaps in understanding the region's vulnerability to extreme floods.

This research aims to address these gaps by answering the following question:
RQ1: Spatial Intersection and Join Foundations of Exposure Assessment
RQ2: Composite Vulnerability
RQ3: Hotspot Analysis to identify priority areas
RQ4: Property Loss and Vulnerability Correlation

The analysis evaluates the structural response of buildings and quantifies economic losses. High-resolution geospatial datasets, including the National Structure Inventory (NSI), FEMA flood hazard layers, and DC-specific floodplain maps, are employed to assess the exposure of building structures in the region. Spatial computing methods, such as spatial overlay analysis, vulnerability analysis and hotspot analysis, are integrated to comprehensively evaluate flood impacts.

By incorporating statistical models and spatial computing techniques, this study provides a robust framework to quantify building vulnerability and economic losses. The findings offer actionable insights for urban planners and policymakers, contributing to efforts such as DC's Flood Risk Management Plan and the Resilient DC initiative. This research builds on prior studies, such as those by Smith and Liu (2022), which emphasize the importance of tailored adaptation strategies for urban areas, and Johnson et al. (2023), who demonstrated the value of integrating geospatial tools for flood resilience planning. Ultimately, the study seeks to inform the development of resilient infrastructure and adaptive planning strategies for Washington, DC, ensuring that this vital region can withstand the increasing challenges posed by climate change. This paper is structured to include a comprehensive literature review, a detailed explanation of the methodology, an analysis of results, an in-depth discussion, and a concluding section summarizing the findings and implications.

Literature Review

Flood vulnerability analysis within 1% annual chance flood zones, often referred to as the "100-year floodplain," is a critical aspect of disaster risk management, particularly as the frequency of extreme flooding events increases due to climate change. The National Structure Inventory (NSI) dataset provides a robust foundation for assessing structural vulnerabilities within these flood zones, offering detailed data on building attributes, spatial location, and usage types. This literature review explores methodologies for utilizing NSI data in vulnerability analysis, focusing on structural characteristics, socioeconomic factors, and spatial techniques. Research has highlighted the increased vulnerability of structures located in 1% flood zones due to the combination of infrequent but high-impact flood events. Stein et al. (2018) evaluated NSI data to classify structural risks based on building materials and foundation types, finding that wood-framed buildings were disproportionately at risk due to their lower resistance to prolonged inundation. Similarly, Harper et al. (2021) applied NSI data to assess multi-story buildings and concluded that structures with elevated living areas showed significantly reduced vulnerabilities compared to single-story residences. The role of structural maintenance and retrofitting has also been explored. Perez et al. (2020) integrated NSI data with local inspection records to assess the resilience of aging infrastructure, revealing that older buildings within 1% flood zones are more prone to damage unless proactively maintained or retrofitted. Their findings emphasized the importance of considering construction age and repair history in vulnerability analyses.

The NSI dataset has been instrumental in linking building vulnerability to socioeconomic factors within 1% flood zones. Baker et al. (2019) employed NSI data in conjunction with census tract information to identify disparities in building exposure across income groups. Their study found that low-income neighborhoods often feature older, poorly maintained structures and face greater challenges in recovering from flood events. Further research by Thompson and Nguyen (2022) incorporated NSI data to analyze building ownership patterns, revealing that rental properties in 1% flood zones experienced higher levels of damage due to deferred maintenance. They also noted that these properties are less likely to be insured, exacerbating economic losses for both tenants and landlords. Similarly, Lewis et al. (2023) focused on community vulnerability, using NSI data to identify neighborhoods where flood risks overlap with limited access to resources for mitigation or recovery.

Advances in spatial analysis have enabled researchers to use NSI data to map vulnerabilities within 1% flood zones effectively. Collins et al. (2020) utilized spatial overlay techniques to identify clusters of high-risk structures, combining NSI building footprints with FEMA flood maps. Their study demonstrated that integrating spatial layers, such as land-use maps and critical infrastructure datasets, can enhance the accuracy of flood vulnerability assessments. Building on this, Patel et al. (2021) leveraged high-resolution flood hazard datasets alongside NSI data to model inundation scenarios for 1% flood events. They highlighted the importance of aligning NSI data with high-resolution flood maps to improve predictive accuracy. Miller and Zhang (2022) expanded this approach by using machine learning models trained on NSI attributes to predict building damage probabilities under varying flood conditions. While NSI data offers significant potential for flood vulnerability analysis, several gaps remain. For instance, Choi et al. (2022) identified challenges in accounting for temporal changes, such as urban development or changes in floodplain boundaries, which may alter the applicability of static NSI data. Furthermore, McAllister and Park (2023) noted that many studies fail to incorporate adaptation measures, such as levees or floodwalls, that may mitigate vulnerabilities within 1% flood zones. Integrating NSI data with real-time flood forecasting and climate projection datasets is a promising direction for future research.

This review highlights the versatility of the NSI dataset in assessing building vulnerabilities within 1% flood zones. Studies leveraging NSI data have contributed to our understanding of structural risks, socioeconomic disparities, and the benefits of spatial integration. However, addressing gaps in temporal dynamics and adaptation measures is critical for enhancing the practical application of these analyses. This study aims to build on existing research by integrating NSI data with high-resolution spatial datasets to develop a comprehensive framework for flood vulnerability assessment in 1% flood zones.

Methodology

This study integrates spatial datasets to analyze the vulnerability of building structures within the 100-year flood hazard zone in Washington, DC, with a focus on quantifying property loss, identifying hotspots of vulnerability, and visualizing results. The process includes data preparation, spatial overlay analysis, layer intersection, property loss calculation, and results visualization. The analysis utilizes three primary datasets: the National Structure Inventory (NSI), which offers detailed building attributes such as location, type, and value; the 100-year flood hazard layer, sourced from FEMA, depicting areas at risk of flooding during a 100-year event; and DC building footprints, which represent the spatial extent of individual structures. These datasets were imported into python and standardized to a common Coordinate Reference System (CRS) for spatial accuracy using shapely and geopandas library. Irrelevant attributes were removed to streamline data processing and reduce computational load. The 100-year flood hazard layer was overlaid on the building footprints to determine structures located within the flood zone. This spatial intersection generated a new layer of flood-exposed buildings. The intersected layer was further refined by integrating NSI data, adding essential structural and economic attributes. The resulting dataset provided a detailed framework for vulnerability analysis, capturing the number of structures at risk and their estimated values. To assess economic impacts, a property loss function was applied using current average property per square value of DC buildings. This function calculated potential financial losses for structures within the flood zone, enabling a quantitative assessment of the economic implications of flooding. Properties in high-risk flood zones often experience depreciation due to potential flood damage and associated costs. For example, data from the First Street Foundation indicates that homes near roads affected by tidal flooding lost approximately $3.70 per square foot annually between 2005 and 2016.

A heatmap analysis is conducted to identify hotspots of vulnerability. Using geopandas and matplotlib, the density of at-risk buildings and their associated losses are visualized, revealing areas with the greatest exposure and financial risk. These hotspots were further analyzed to prioritize regions requiring mitigation efforts or policy interventions. To communicate findings effectively, several visualizations, including heatmaps and statistical plots, were generated. These visualizations highlighted spatial patterns of flood exposure, the distribution of economic losses, and concentrated zones of high vulnerability. Summary statistics, such as the total number of vulnerable buildings, their cumulative area, and the estimated financial impact, were computed to provide a comprehensive overview of flood risk. This methodology not only quantifies flood vulnerability but also identifies spatial trends and high-risk areas, offering actionable insights for flood mitigation strategies and urban resilience planning in Washington, DC. By combining spatial analysis, economic modeling, and visualization techniques, this study establishes a robust framework for addressing the challenges posed by 100-year flood events in urban environments.

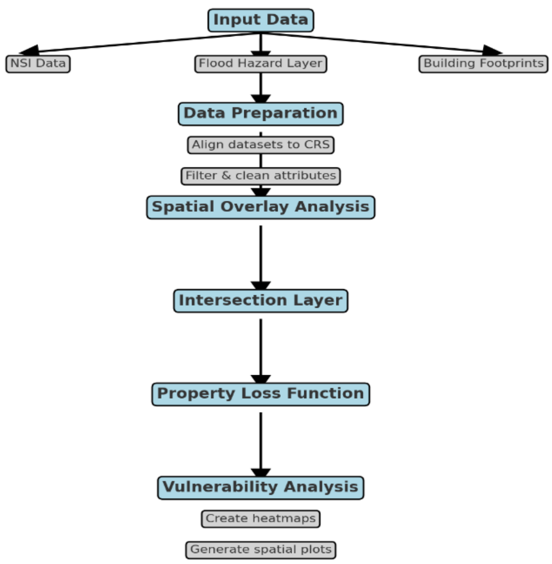

Fig 1. Box Diagram

Results

Spatial Intersection: This study utilizes a spatial computing method to quantify building exposure to the 100-year flood hazard layer. The initial analysis employed a two-step process involving spatial intersection and spatial join operations. First, the 100-year flood hazard layer, representing areas prone to inundation, was intersected with the building footprints of the Washington, DC area. This intersection identified the subset of buildings that fall within the flood hazard zone. Subsequently, the intersected dataset was spatially joined with the National Structure Inventory (NSI) database to enrich the results with detailed attribute information, such as building type, occupancy, and structure. This integrated dataset provides a comprehensive understanding of the vulnerability and potential impact of flood events on the built environment in the study area. The fig1. shows intersection layer on the left and spatial join on the right side.

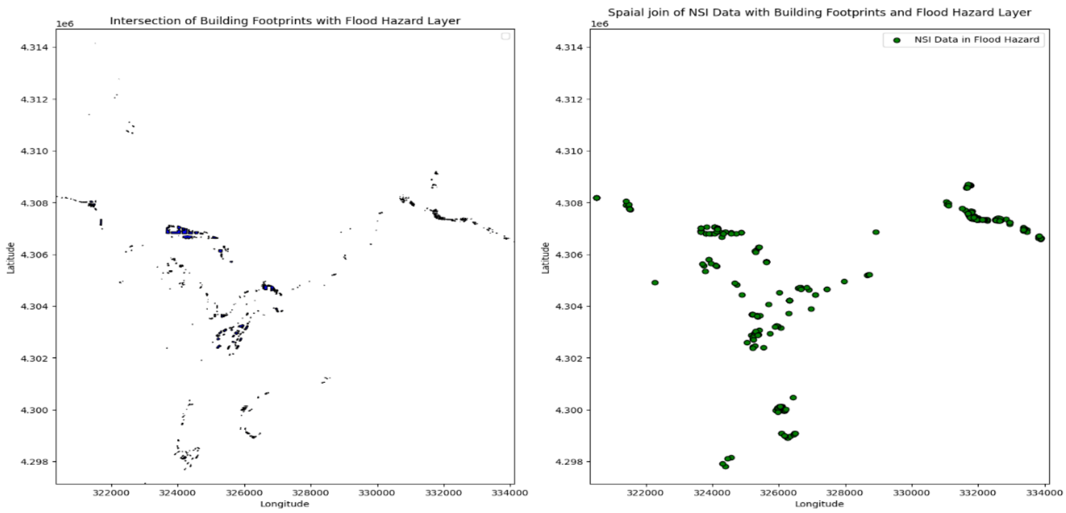

Fig 2: Spatial intersection and spatial join

Vulnerability Analysis: In this study, a comprehensive vulnerability analysis is conducted to assess the risk of building structures to hazards such as floods, utilizing the National Structure Inventory (NSI) dataset. The analysis was structured into three primary dimensions of vulnerability: structural, economic, and social, with the outputs synthesized into a Composite Vulnerability Index (CVI). Structures within high-risk flood zones, as identified by FEMA 100-year flood zone are prioritized for analysis.

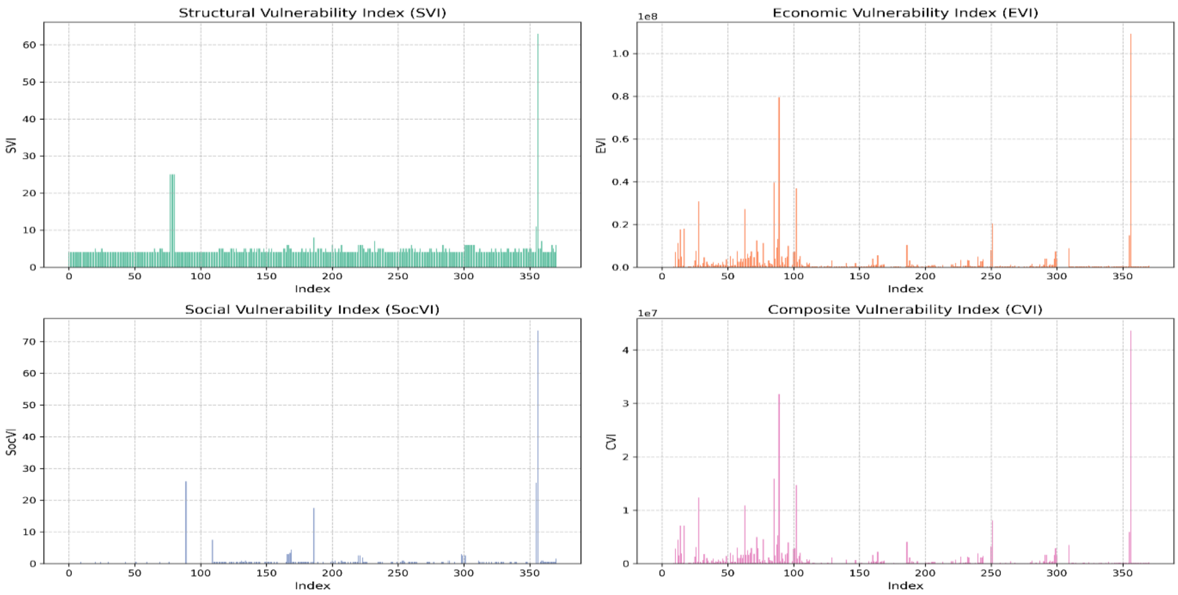

Fig 3: Vulnerability Analysis

The Structural Vulnerability Index (SVI) shown in fig 3 was developed to quantify the physical susceptibility of buildings to hazards. This index incorporated critical parameters such as building material type (bldgtype), foundation type (found_type), foundation height (found_ht), and the number of stories (num_story). For example, masonry structures with elevated foundations scored higher on resilience, whereas wood-framed buildings with low foundations were rated as more vulnerable. The spatial distribution of SVI revealed clusters of structurally vulnerable buildings, particularly in areas with low foundation heights and wind-exposed regions.

The Economic Vulnerability Index (EVI) shown in fig 3 quantified the potential financial impact of hazard exposure. The analysis considered building replacement values (val_struct), content values (val_cont), and the economic risk associated with vehicles (val_vehic). These components were aggregated to compute the Total Value at Risk (TVR) for each building. By overlaying hazard exposure probabilities, the model estimated potential economic losses under varying scenarios. The resulting economic vulnerability maps highlighted zones with significant financial exposure, particularly in areas with dense clusters of high-value properties.

The Social Vulnerability Index (SocVI) shown in fig 3 addressed the demographic and social aspects of vulnerability. The analysis emphasized populations with limited mobility and higher susceptibility to hazards, such as elderly individuals (pop2amo65), individuals with disabilities (u65disable), and school-aged children (students). Weighted factors were applied to these parameters, giving higher importance to elderly populations and moderate weights to disability metrics. The resulting maps identified socially vulnerable hotspots, where populations might face significant challenges during hazard events. The fig 4, shows the vulnerability indices of structural, economic and social which are spatially distributed.

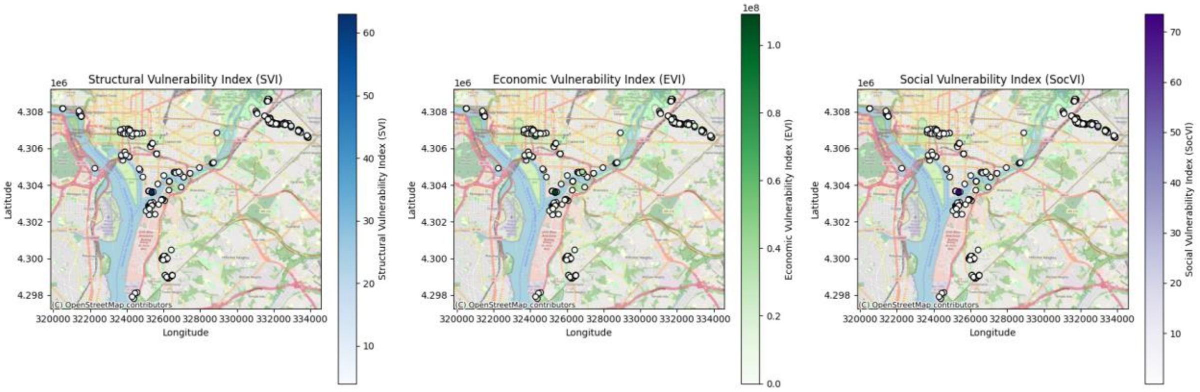

Fig 4: Vulnerability Indices

Hotspot Analysis: The Getis-Ord G statistic (G-star) * is a spatial statistic used to identify statistically significant hotspots (high-value clusters) and coldspots (low-value clusters) in geographic data. Hotspots (High Positive G-star Values) are areas where the Composite Vulnerability Index (CVI) is significantly higher than neighboring areas, indicating concentrations of high vulnerability. Coldspots (High Negative G-star Values) are areas with significantly lower CVI compared to their neighbors, suggesting relative safety or lower risk. Spatial Weights Matrix defines spatial relationships (e.g., Queen contiguity) to calculate the influence of neighboring features on each observation. The fig 5, shows the hotspot where composite vulnerable index is greater and lower.

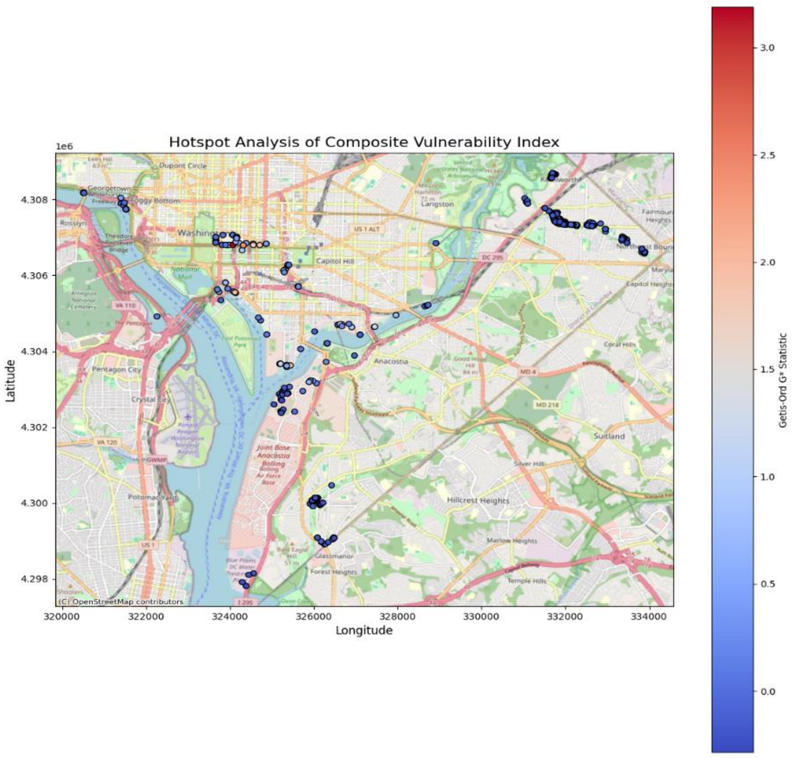

Fig 5: Hotspot Analysis

Property Loss Function: To estimate potential property loss within flood hazard zones, a custom function was developed to calculate losses based on structural characteristics. The calculate_property_loss function takes each row of the dataset as input and computes the property loss using the square footage (sqft) of a building and a fixed rate per square foot. In this study, the average cost was set at $506 per square foot, reflecting typical property valuation standards. The function was applied to the nsi_hazard GeoDataFrame, which combines the flood hazard data and enriched building attribute information from the National Structure Inventory (NSI). For each building, the property loss was calculated and stored in a new column, property_loss. This process provided a detailed estimation of potential financial impacts, considering the size and structural characteristics of buildings within the flood hazard zones. A preview of the results includes columns such as building type (bldgtype), the number of stories (num_story), square footage (sqft), and the calculated property loss, fig 6 shows property loss by building type.

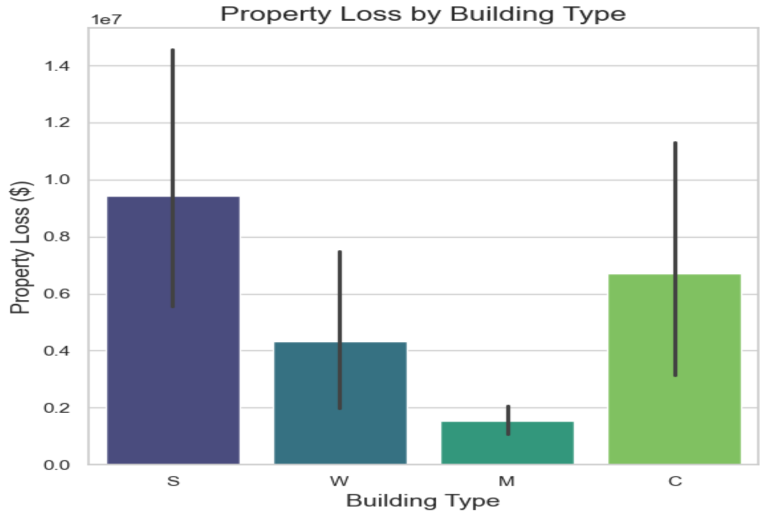

Fig 6: Property Loss Function

The scatter plot illustrates the relationship between the Composite Vulnerability Index (CVI) and property loss. Each point represents a building, with its position determined by its CVI value (x-axis) and the estimated property loss (y-axis). The regression line added to the plot shows the overall trend, indicating higher CVI values are associated with greater property loss. This relationship identifies how vulnerability levels influence potential financial impacts, providing valuable insights for prioritizing flood mitigation efforts in the most at-risk areas.

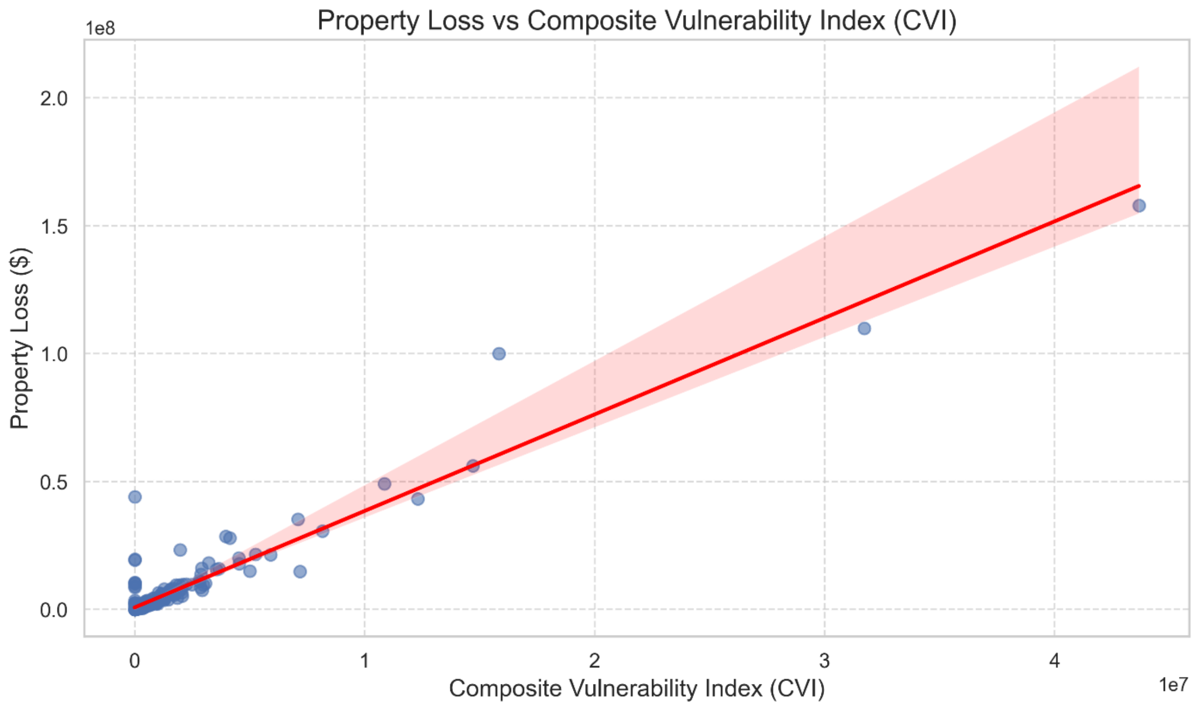

Fig 7: Property Loss with CVI

Discussion

This study presents a multi-faceted vulnerability analysis framework to assess the exposure of buildings within the Washington, DC area to 100-year flood hazards. By combining spatial computing techniques, vulnerability indices, hotspot analysis, and property loss estimation, the results provide a comprehensive understanding of structural, economic, and social vulnerabilities.

Foundations of Exposure Assessment the spatial intersection and join processes laid the groundwork for the analysis by identifying and enriching the subset of buildings within the flood hazard zones. By intersecting the 100-year flood hazard layer with building footprints and integrating the National Structure Inventory (NSI) data, the study established a robust dataset to analyze the physical and economic characteristics of at-risk structures. This step ensured a focused and data-rich foundation for vulnerability and loss analysis.

Unpacking Structural, Economic, and Social Dimensions the vulnerability analysis was conducted across three dimensions, each contributing to the composite vulnerability index (CVI) first structural sulnerability index (SVI) revealed clusters of physically susceptible buildings, particularly in areas with low foundation heights or less resilient materials. Insights from this index guide interventions like retrofitting and building code improvements. The economic vulnerability index (EVI) highlighted areas with significant financial exposure, focusing on high-value properties and their susceptibility to flood events. By overlaying hazard probabilities, this analysis identified economic hotspots where targeted insurance or funding could mitigate potential losses. The Social Vulnerability Index (SocVI) identified demographics at higher risk due to limited mobility or other challenges. Hotspots revealed by SocVI underscore the need for inclusive disaster planning, prioritizing resources for vulnerable populations. The spatial distribution of these indices, as shown in Fig. 4, underscores the diverse vulnerability landscape, where structural, economic, and social risks intersect and amplify each other.

The Getis-Ord G* statistic provided a powerful tool for identifying clusters of high and low vulnerability. Hotspots, as visualized in Fig. 5, represent areas requiring immediate attention due to concentrated high CVI values. Conversely, coldspots highlight regions with relatively lower risks, where current mitigation strategies may already be effective. This analysis helps prioritize resource allocation for resilience planning.

The property loss function quantified potential financial impacts by combining structural attributes and flood exposure data. Results indicated significant variability in property loss based on building characteristics, with higher losses observed in buildings with greater square footage or lower resilience. The scatter plot (Fig. 7) further revealed a positive correlation between CVI and property loss. Buildings with higher vulnerability scores consistently faced greater financial risks, emphasizing the compounded impact of structural, economic, and social vulnerabilities.

This study underscores the interconnectedness of structural, economic, and social vulnerabilities in determining flood risks and financial impacts. By leveraging spatial tools and quantitative methods, the findings contribute valuable insights for data-driven decision-making in urban flood resilience.

Conclusion

This study provides a comprehensive assessment of building vulnerability to 100-year flood hazards in Washington, DC, leveraging advanced spatial computing techniques and high-resolution datasets. By integrating the FEMA flood hazard layer, the National Structure Inventory (NSI), and local building data, the analysis quantified building exposure, identified vulnerability hotspots, and estimated potential economic losses. These findings emphasize the interconnected nature of structural, economic, and social dimensions of flood vulnerability and offer valuable insights for enhancing urban resilience.

The analysis revealed that a significant number of buildings in low-lying areas near the Potomac and Anacostia Rivers are at high risk of flooding, largely due to their proximity to water bodies and low elevation. The Composite Vulnerability Index (CVI), developed through this study, provided a robust measure of vulnerability by synthesizing structural, economic, and social factors. Structurally, the findings identified clusters of physically susceptible buildings, such as those with low foundations and less resilient materials. Economically, high-value properties concentrated in urban areas were shown to face significant financial risks, highlighting the need for targeted retrofitting and insurance strategies. Socially, the analysis identified vulnerable populations, including the elderly and individuals with limited mobility, in specific hotspots, underscoring the importance of inclusive disaster response and planning.

The hotspot analysis further identified areas of concentrated high vulnerability, enabling the prioritization of resources for regions with the greatest need. The custom property loss function revealed a strong correlation between higher CVI values and increased economic impacts, demonstrating how the combined effects of structural, economic, and social vulnerabilities amplify flood-related losses. These findings emphasize the compounded nature of risks and the need for integrated mitigation efforts.

While the study offers valuable insights, it is not without limitations. The reliance on static datasets, such as FEMA flood hazard layers and NSI, may not fully capture temporal changes in building stock or floodplain boundaries. Additionally, the economic loss estimation used a simplified property loss model that did not account for variability in building quality, age, or insurance coverage. The social vulnerability analysis, while comprehensive, did not include real-time mobility data or evacuation capacities, and the study did not simulate future flood scenarios under changing climate conditions. Addressing these limitations in future research can further refine the understanding of flood vulnerability.

Future studies should incorporate dynamic and real-time data to capture temporal changes and emerging risks, refine economic loss models by including more detailed building attributes, and expand social vulnerability analyses with real-time mobility and healthcare access metrics. Modeling future flood scenarios under climate change conditions will provide critical insights for long-term resilience planning. Moreover, exploring the impact of mitigation strategies, such as floodwalls, levees, and green infrastructure, will offer actionable recommendations for reducing vulnerabilities.

This study underscores the importance of integrating structural, economic, and social dimensions in flood vulnerability assessments. The findings highlight the urgent need for targeted interventions to address these vulnerabilities, particularly in high-risk areas near the Potomac and Anacostia Rivers. By advancing analytical frameworks and incorporating dynamic data, future research can further enhance urban resilience planning. These results provide a critical foundation for policymakers, urban planners, and stakeholders to develop adaptive strategies, ensuring that Washington, DC, and similar urban areas are better prepared for the increasing challenges posed by climate change.

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