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Uneven Exposure and Unequal Capacity: Spatial Patterns of Riverine Flood Vulnerability in Vietnam

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Research Article

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Abstract

Vietnam is a country where suffers highly riverine flooding. However, comprehensive vulnerability assessments should distinguish between natural hazards exposure and socio-economic susceptibility for a more effective adaptation effort. The research provides a national level assessment of flood vulnerability across Vietnamese provinces. A 100-year return period riverine flood is extracted from WRI Aqueduct and integrated with socio-economic data from the General Statistic Office of Viet Nam (GSO). The analysis follows the widely accepted framework comprising of exposure, sensitivity, and adaptive capacity. Spatial indicators are constructed and mapped using QGIS to examine the geographic distribution of exposure, sensitivity, and overall flood vulnerability across the country. The results reveal a pronounced spatial mismatch between physical hazards and structural vulnerability. By utilizing bivariate spatial cross-classification, the paper identifies three distinct typologies of risk: "exposure-driven" vulnerability in deltaic and coastal provinces where hazard intensity dominates; "capacity-driven" vulnerability in the uplands, where limited infrastructure and digital connectivity constrain adaptation despite lower hazard exposure; and "compound injustice hotspots" (e.g., Quang Tri, Hue, An Giang, Soc Trang), where severe flood exposure intersects with critically low coping capacity. The evidence highlights the need for place-based adaptation policies that concern both structural flood protection in high-exposure deltas with urgent, and targeted capacity-building investments in mountainous regions.

Keywords

Flood vulnerability, Exposure – Sensitivity - Adaptive capacity, Spatial inequality, Social vulnerability, Vietnam

1. Introduction

Flooding constitutes one of the most significant natural hazards in Vietnam and has attracted growing scholar attention. It poses substantial threats to socio-economic development, infrastructure, and human well-being. Floods account for approximately 97% of the country's average annual losses from natural hazards (World Bank Group & Asian Development Bank, 2021). Flood vulnerability varies considerably across provinces, with particularly high concentrations in the Red River and Mekong River deltas. The research of Phung et al., (2016) has found vulnerability indices ranged substantially. Notably, upstream provinces near rivers exhibited higher vulnerability indices than coastal provinces. Additional evidence from Phuong et al., (2023) in Thua Thien Hue province found coastal fishery communities highly vulnerable due to high exposure and sensitivity, while the results from Tran et al., (2022) in Da Nang identified flood depth, land-use conditions, and drainage systems as key differentiating factors.

Most of the previous research approach employed popular framework of exposure – sensitivity – and adaptation (*IPCC*, 2014; Leon & Pittock, 2017) and has focused on evaluating how community were exposed to flood, how they lost and how they overcome. To decompose and understand underlying factors of vulnerability, different indicators have been employed to construct each vulnerability component of exposure, sensitivity and adaptive capacity. These indicators derive from physical conditions to socio-economic status, such as access to critical infrastructure and facilities, dependent demographic groups, livelihood dependence, healthy population, economic resources, unemployment rate, income, etc. (Nguyen et al., 2022; Pathak et al., 2020; Phung et al., 2016; Weis et al., 2016). Most of studies integrate exposure, sensitivity, and adaptive capacity into a single composite index, called vulnerability index (Pathak et al., 2020; Weis et al., 2016). Their findings implicitly interpret vulnerability as an absolute condition of places under specific flood scenarios (Cutter et al., 2003; Tate, 2012). While such aggregation is useful for identifying areas of overall high vulnerability, it may reduce the richness of the information and can obscure the underlying spatial dynamics. Specifically, it can mask how physical flood hazards spatially align with pre-existing social and adaptive conditions. Moreover, since the systematic vulnerability index is the research goal, it remains an open question whether extreme flood hazards spatially coincide with low adaptive capacity and high sensitivity? In different research scenarios, the findings preliminarily show evidence suggests the partial but imperfect spatial coincidence between extreme flood hazards and low adaptive capacity (Giriraj Amarnath et al., 2017; Nguyen et al., 2022).

Additionally, previous flood vulnerability assessments in Vietnam have largely focused on specific geographic areas, basins, or cities, such as Hoi An (Nguyen et al., 2022), Da Nang (Tran et al., 2022), Thua Thien Hue (Phuong et al., 2023). Some of studies have successfully developed detailed local flood vulnerability maps using remote sensing and GIS techniques (Bangalore et al., 2019; Phung et al., 2016; Phuong et al., 2023). In many cases, indicators, particularly those related to sensitivity and adaptive capacity are derived from household survey, focus group discussion (Dinh et al., 2021; Ha et al., 2025; Pathak et al., 2020; Phuong et al., 2023; Tran et al., 2022). Such approaches provide rich, context-specific insights into local conditions and help explain households' coping capacities, motivations, and behavioral responses to flood-related losses. However, because these methods are highly localized and resource-intensive, their findings are difficult to generalize or apply broader scales.

In 2025, Vietnam experienced severe floods that extended beyond traditionally affected regions and caused substantial economic losses and disruptions (United Nations, 2025). The concentration of previous studies on historically flood-prone locations may overlook emerging vulnerabilities in provinces that typically face limited flood exposure (McDonald, 2025). In many areas, preparedness measures and institutional responses remain limited. This situation highlights the need for a systematic, nationwide assessment capable of identifying spatial variations in flood vulnerability and revealing potential risk hotspots beyond well-known flood - prone zones. The existing studies on flood in Vietnam, therefore, have not yet provided comprehensive assessment that enables systematic comparison of flood vulnerability across provinces nationwide.

This paper adopts a two-step approach. First, exposure, sensitivity, and adaptive capacity are constructed and examined as analytically distinct dimensions. In this stage, flood exposure to be considered as an external hazard process derived from spatial datasets rather than as constructed indicator integrated with other variables. The other indicators used to construct sensitivity and adaptive capacity are compiled entirely from nationally available secondary data sources. The use of this standardized secondary data enables consistent measurement across provinces. Second, a composite vulnerability index is computed to provide an overview of vulnerability patterns. Crucially, the analysis intends to go beyond composite scores, when explicitly focusing spatial match and mismatch between flood exposure and adaptive capacity. This approach allows the identification of provinces where high level of exposure coincides with limited coping capacity. The study shifts the analytical focus from simply ranking vulnerability levels alone to identifying patterns of climate-related spatial injustice, where flood risks disproportionately burden socially disadvantaged regions (de Sherbinin, Alex et al., 2019).

Additionally, the methods to statistically construct indices are diverse among growing literature (Becker et al., 2017). According to de Sherbinin et al., (2019), there have been around 42% research applying AHP to quantify vulnerability of the complex human-environment system under hazards. Particularly, previous flood vulnerability studies in Vietnam frequently rely on the Analytic Hierarchy Process (AHP) to derive indicator weights, reflecting expert judgments on the relative importance of physical, built environment, and socioeconomic factors (Nguyen et al., 2022; Tran et al., 2022). While this method can be useful and widely applied for site-specific decision support, its results are inherently sensitive to expert selection, subjective pairwise comparisons, and context-dependent assumptions. This study, therefore, adopts an equal-weight aggregation strategy as a transparent and theory-consistent baseline, allowing multiple dimensions of vulnerability to interact without imposing hierarchies among them. Additionally, by treating factors as distinct but equally important mechanisms, we are able to build a single pathway that enhances comparability across provinces. Importantly, this equal-weight approach will subsequently be assessed through PCA - based sensitivity analysis to emphasize transparency, reproducibility, and reduced subjectivity.

To address these empirical and methodological gaps, this study conducts a comprehensive nationwide assessment of flood vulnerability and provides a spatial diagnostic of flood vulnerability by mapping exposure, sensitivity, and adaptive capacity across provinces. This allows the study to explicitly identify spatial matches and mismatches. The research does not assess development directly. Instead, its results serve as a screening framework, which helps to identify provinces where high flood exposure and low adaptive capacity coincide. The findings serve as the foundation and motivate future research into the mechanisms of spatial development, injustice and long-term welfare outcomes.

For this purpose, the research intends to answer the following questions:

- RQ1: How do flood exposure, sensitivity, and adaptive capacity vary across provinces in Vietnam? Which dimensions dominate high-risk provinces?

- RQ2: Do extreme flood hazards spatially coincide with low adaptive capacity? Where do "exposure-capacity mismatches" emerge?

2. Data and Method

All spatial analysis is conducted using Vietnam's pre-administrative-reform provincial boundaries (63 provinces). This ensures temporal consistency between flood hazard, population, and socioeconomic data. Provincial boundaries are obtained from *geoBoundaries* (2017), accessed via Humanitarian Data Exchange (*Viet Nam - Subnational Administrative Boundaries | Humanitarian Dataset | HDX*, 2022)

2.1. Exposure indicators – The flood hazard data and processing

The exposure is constructed based on the level of flood exposing to people and assets. It will be estimated by overlaying gridded flood hazard maps with population raster and aggregating exposed population to the provincial level. By this approach, exposure is measured as the share of provincial population located within the extent of flood inundation.

Flood hazard data was obtained from the World Resources Institute – Aqueduct Floods dataset (*Aqueduct Floods Hazard Maps | World Resources Institute*, 2020). The datset provides global gridded flood inundation depth maps derived from hydrological and hydraulic modeling. The research employs the 100-year return period riverine flood (*rp0100),* which represents a 1-in-100-year return period flood with a minimum inundation depth threshold of 0.1m. This kind of flood information 100 represents a low-probability but high-impact event that is more likely to overwhelm local coping mechanisms and expose structural weaknesses in adaptive capacity. While previous studies examining population exposure employ multiple return periods to assess sensitivity (Bangalore et al., 2019), the focus here is on identifying spatial mismatches between extreme flood hazard and adaptive capacity. To ensure conceptual consistency, we only use the riverine floods and exclude coastal flooding which is driven by different physical mechanism (i.e., storm surge, sea level rise).

The *rp0100* riverine flood raster is processed using QGIS. The raster is first clipped to the national boundary of Vietnam and reprojected to the coordinate reference system of WGS 84. Flood hazard indicators are then aggregated to the provincial level using zonal statistics. Especially, the mean flood inundation depth within each province is calculated to represent overall flood hazard exposure. This approach helps to capture spatial heterogeneity in flood intensity across provinces.

Population distribution was derived from the WorldPop 2020 gridded population dataset at 1km spatial resolution (Bondarenko et al., 2020). To estimate exposed population, the binary flood hazard mask (threshold 0.1m) overlaid with the population raster through cell-by-cell multiplication. The resulting raster represents the number of people exposed to flood hazard at each pixel level. Exposed population was then aggregated to the provincial scale using zonal statistics. Two exposure indicators are derived: (i) total exposed population and (ii)

the proportion of the provincial population exposed to flooding. This normalized indicator allows consistent comparison of flood exposure across provinces of different population sizes.

$$exp_sum_i = \sum_{c \in i} Pop_c \cdot I\ (flood\ depth_c\ \geq 0.1m)$$

where c is grid cell; i is province, and $I(.)$ is flood indicator (0/1)

3.2. Sensitivity and adaptive capacity: standardization, aggregation, and weighting scheme

Sensitivity indicators are selected to capture demographic, socioeconomic, and livelihood conditions (*IPCC*, 2014; Cutter et al., 2003). They are the intrinsic characteristics of each region that affect the magnitude of flood impacts. Particularly, the paper constructs sensitivity dimensions using four indicators that capture poverty, land-based dependence, livelihood fragility, and dependence ratio. Data are primarily drawn from the General Statistics Office of Vietnam (GSO) (*GSO*, 2022) and Results of the Vietnam Population and Housing Census (*UNFPA Vietnam*, 2020). Specifically, poverty rate (%) proxies limited economic buffers and recovery capacity at the household level. Cropland share (%) is calculated as the proportion of agricultural land relative to total land area of provinces. This captures land-based livelihood sensitivity and potential losses in flood-prone agricultural systems. Low-skill labor share (%) is measured as the proportion of workers engaged in elementary or simple occupations. The metric reflects employment with limited income stability and high disruption risk during flood. Housing fragility rate measures the proportion of structurally vulnerable dwellings, derived from the share of "simple permanent house", which are more susceptible to flood damage. Lastly, dependency ratio (non-working age population relatives to working-age population) reflects demographic vulnerability as dependency burdens.

Turning to adaptive capacity , the concept is conceptualized as the ability of regions to cope with and recover from flood impacts through available resources, services, and capabilities (Brooks et al., 2005; *IPCC*, 2014). In contrast to sensitivity, which captures inherent susceptibility, adaptive capacity emphasizes endowments and enabling conditions that moderate flood damage. Accordingly, the study will include indicators of human development, health system capacity, and access to essential services and information to represent adaptive capacity. First, we employ the Human Development Index (HDI) as a composite measure of education, health, and income, to captures broad human capital and long-term development foundations relevant for adaptation (United Nations, 2022). Health system capacity is proxied by the number of hospital beds per 10,000 population and doctors per 10,000 population, reflecting the ability to provide medical care and respond to flood-related health shocks. Next, access to hygienic water is used to capture basic service provision. Also, internet use and social media use are included to represent information access and communication capacity, which are important for early warning dissemination, and recovery support.

To construct the sensitivity and adaptive capacity index, all variables were first transformed to a common scale using z-score standardization to ensure comparability across different measurement units. Indicators with higher values consistently denote higher sensitivity or greater adaptive capacity. The standardized indicators were then aggregated using equal weights to construct composite indices at the provincial level. This choice is guided by conceptual considerations rather than statistical optimization, reflecting the multidimensional nature of sensitivity and adaptive capacity as two main components of the vulnerability concept. Equal weighting provides

a transparent and easily interpretable baseline, reducing the risk of implicit value judgments embedded in data-driven weighting schemes (OECD et al., 2008; Yusuf & Francisco, 2009).

Formally, sensitivity for province *i* is computed as:

$$S_i = \frac{1}{K}\sum_{k=1}^{K} Z_{ik}$$

where Z_{ik}denotes the standardized value of sensitivity indicator k in province i, and K is the total number of indicators. The resulting index is rescaled to a 0–100 range for mapping and comparison.

And adaptive capacity for province *i* is computed as:

$$AC_i = \frac{1}{M}\sum_{m=1}^{M} Z_{im}$$

where Z_{im}denotes the standardized value of adaptive capacity indicator m in province i, and M is the total number of adaptive capacity indicators. Finally, for visualization and interpretability purposes, the resulting indices are rescaled to a 0–100 range as well.

3.3. Vulnerability construction

The composite vulnerability is constructed by integrating exposure, sensitivity, and adaptive capacity (Cutter et al., 2003). Exposure and sensitivity are treated as risk-enhancing components, while adaptive capacity acts as a buffering factor (Pathak et al., 2020). All component indices are first standardized to a common scale to ensure comparability, after which vulnerability for province i is computed as:

$$V_i = E_i + S_i - AC_i$$

where higher values indicate greater relative vulnerability. Like other metrics, the vulnerability scores are linearly rescaled to a 0-100 range for a better cartographic presentation and spatial comparison.

3.5. Robustness checks

To assess whether the resulting indices are sensitive to this weighting assumption, a robustness check is conducted for the multi-indicator components that include sensitivity and adaptive capacity. We compare the baseline equal-weight indices with alternative indices derived from principal component analysis (PCA). Specifically, PCA-based indices are constructed using the first principal component as an alternative aggregation scheme, capturing the dominant variance structure in the data (OECD et al., 2008).

Robustness is evaluated using Spearman rank correlations between equal-weight and PCA-based indices, together with an overlap analysis of high-ranked provinces. This combined approach assesses whether key spatial patterns and hotspot identification remain stable under alternative weighting schemes. The approach focuses on the stability of policy relevant spatial patterns, rather than exact index values. Such rank-stability checks are commonly used in vulnerability and composite-index research (Tate, 2012).

This two-step approach: first, conceptually grounded construction, then followed by statistical robustness testing helps to enhance the credibility of the composite vulnerability assessment.

Table 1. Methodological Flow and Analysis Framework

Stage	Process & Analytical Steps	Data Sources & Indicators
Stage 1: Selection	**Conceptual Framework**: Analytical separation of Hazard (E) from Social Dimensions of Sensitivity (S) and Adaptive Capacity (C)	- GSO Vietnam / Census - WRI Aqueduct Floods
Stage 2: Data Processing	**Exposure (E)** - Riverine Flood (100-year RP). Calculated as % Population exposed via raster overlay. **Sensitivity (S)** - Cropland share - Poverty rate - Housing fragility rate - Dependency ratio - Low-skill labor share **Adaptive Capacity (AC)**: - HDI - Health system - Clean water access - Internet use - Social media use	- Exposure: WRI Aqueduct (rp0100) + WorldPop (Zonal Stats) - geoBoundaries (Vietnam 63 Provinces) - Sensitivity and Adaptive Capacity: General Statistics Office (63 provinces)
Stage 3: Normalization	**Z-Score Standardization**: Transforming multidimensional indicators to a common scale ($z = (x-\mu)/\sigma$).	
Stage 4: Aggregation	**Equal-Weight Strategy**: Transparent baseline aggregation for S and C indices. **Robustness Check:** PCA-based sensitivity analysis (replacing AHP) to test rank stability.	- Principal Component Analysis (PCA) - Spearman Rank Correlation
Stage 5: Synthesis	**Composite Vulnerability Index** (VI): $VI = (E + S) - C$ **Mapping** E, S, C and Vulnerability **Spatial Injustice Analysis**: Bivariate mapping to identify matching and mismatch between E and C.	- GIS mapping - Bivariate Spatial Analysis

3. Results

To effectively visualize the spatial distribution of flood risk components and facilitate comparative analysis, the provincial indices for exposure, sensitivity, adaptive capacity, and composite vulnerability were categorized into five distinct categories from very low to very high. Consistently, this study utilized an equal quantile classification method to established cartographic practices in regional vulnerability mapping (Hussain et al., 2021). This approach distributes an equal number of provinces into each of the five classes, ensures that the resulting maps highlight relative geographic disparities and structural gradients across the country.

3.1. Spatial patterns: Exposed population under rp0100 riverine flooding

Flood hazard exposure is mapped using graduated symbology based on the proportion of the population at each province who exposed to a 100-year return period riverine flood. Provincial exposure indicator is exported for subsequent analysis.

The flood exposure map reveals pronounced spatial heterogeneity in flood-exposed populations across Vietnamese provinces. The exposure rate map (percentage of provincial population exposed) captures exposure intensity, highlighting provinces where flooding affects a large share of residents. Meanwhile, the absolute exposure map (total exposed population) captures the magnitude of exposed population contributed by each province to the national burden. The distinguishing between these two critically presents that the same hazard footprint generates very different risk outcomes depending on population concentration and settlement patterns.

Several provinces display high relative exposure but only moderate absolute exposed population, examples include Quang Tri in Northern Central area and Central coastal area, Ninh Binh in Red River Delta. This pattern is typical of sparsely populated or medium-density provinces where flood-prone areas overlap with a large share of residents. Conversely, some provinces - such as Bac Lieu, Soc Trang in the Mekong River Delta - show very high absolute exposure without falling into the highest class of relative flood exposed, (see Figure 1a, 1b). This distinction is critical for policy: provinces with high exposure rates may require targeted local measures, whereas those with high exposure sums are essential for national prioritization because the interventions in these areas can significantly reduce total exposed population.

Generally, both maps suggest non-random spatial clustering of high exposure. The hotspots tend to appear in provinces that are plausibly associated with low-lying terrain and floodplain systems and/or dense settlement corridors. Such clustering is a typical feature of flood exposure in deltaic and coastal settings, where water-related livelihoods and urbanization co-evolve, concentrating people and assets in hazard-prone zones.

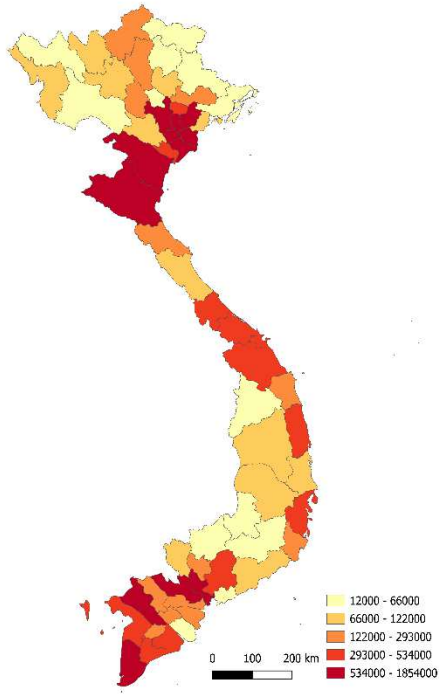


Fig 1a. Total population exposed to extreme flooding across Vietnamese provinces

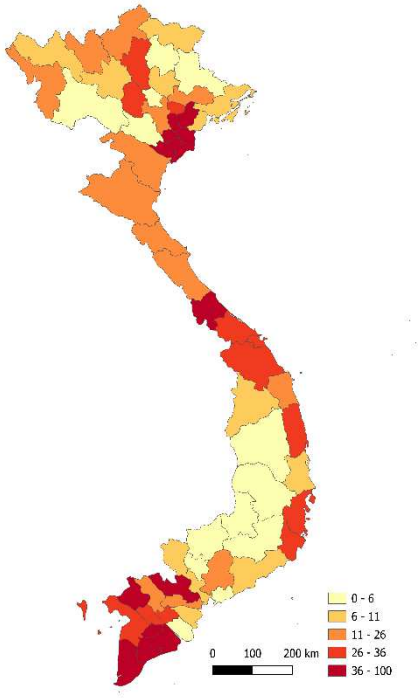


Fig 1b. Population exposure rate to extreme flooding across Vietnamese province

When considering regional level, the largest totals are observed in Red River Delta and the Mekong River Delta, followed by North Central and Central Coastal area. Together, these regions account for the majority of the national exposed population. By contrast, the Central Highlands and the Northern midlands and mountain areas contribute relatively little to the national total of exposed population (see Figure 4). This does not only imply low flood hazard per se but also reflects lower population densities and a more dispersed settlement structure in these regions. Taking regional exposure intensity into account, Mekong River Delta exhibits the highest level, and higher than Red River Delta. In contrast, exposure rates are markedly lower in the Southeast and Central Highlands.

The evidence from exposure maps of floods share similar patterns have been reported in earlier studies (Bangalore et al., 2019). Delta regions dominate both measures of exposure intensity and absolute exposure. These spatial patterns provide a baseline for further analysis determining vulnerability. Provinces with moderate exposure may nonetheless experience disproportionate impacts if high exposure coincides with socioeconomic disadvantage or limited adaptive capacity.

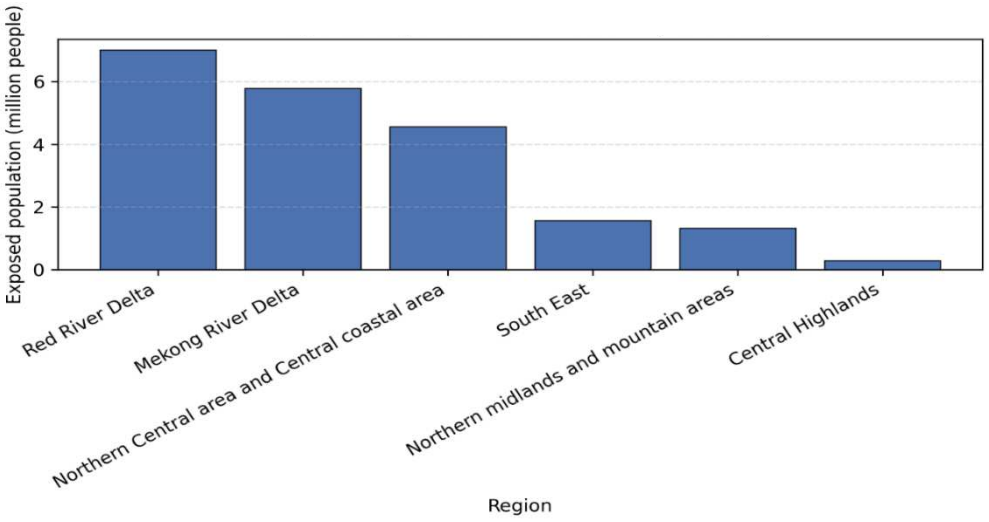


Fig 2. Regional exposure concentration

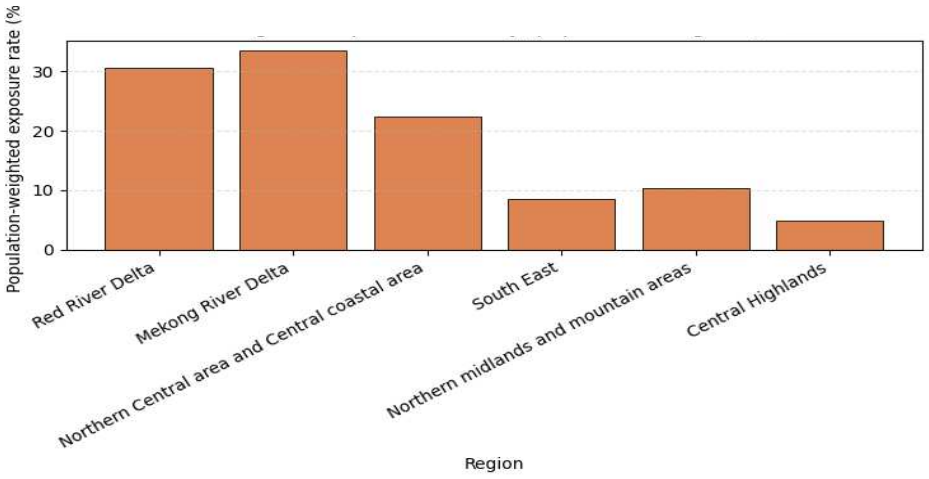


Fig 3. Regional exposure intensity (population-weighted)

3.2. Sensitivity map

Beyond physical exposure, the sensitivity map reveals a clear and structured spatial pattern dictated by socio-economic realities. Provinces in the northern uplands display consistently high sensitivity levels. These areas are typically characterized by a convergence of high cropland dependence, elevated poverty rates, fragile housing conditions, a large share of low-skill labor, and unfavorable dependency ratios. These conditions jointly make flood exposure likely translate into adverse social and economic outcomes. In contrast, provinces with lower sensitivity values – predominantly located in more urbanized or economically diversified regions – exhibit greater internal buffering capacity. That helps to reduce their propensity to experience severe impacts under similar exposure conditions. This gradient echoes findings in comparable mountainous geographies like Nepal, where

socioeconomic disadvantages were found to drive vulnerability regardless of hazard proximity (Pathak et al., 2020).

The sensitivity pattern underscores that flood risk in Vietnam is diverse strongly shaped by socially differentiated susceptibility, consistent with social vulnerability frameworks that emphasizing demographic and livelihood characteristics as key determinants of hazard impacts (Birkmann, 2013; Cutter et al., 2003).

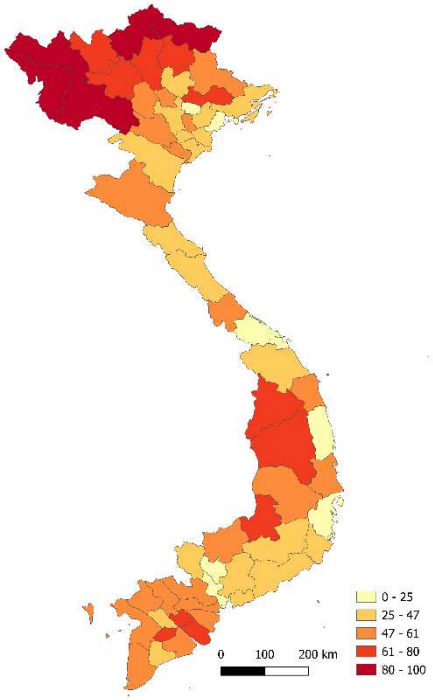


Fig 4. Social sensitivity to flood impacts across Vietnamese provinces

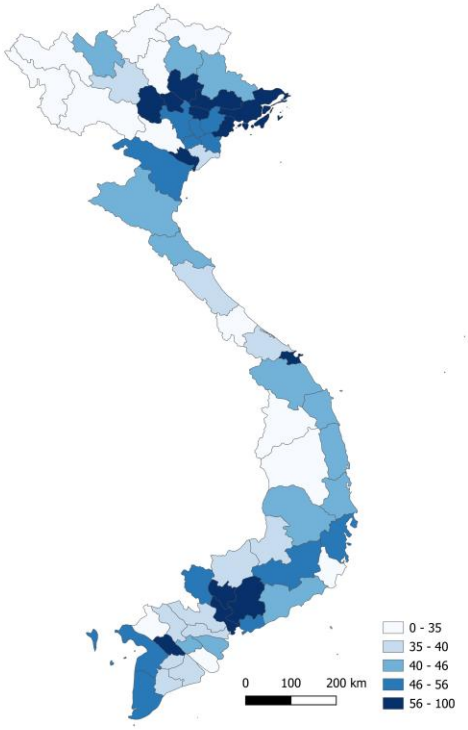


Fig 5. Adaptive capacity to flood risk across Vietnamese provinces

3.3. Adaptive capacity map

Likewise, the adaptive capacity map also displays contrasting spatial configuration. Provinces at the top of the adaptive capacity distribution are characterized by high HDI levels, greater availability of medical personnel and hospital beds, access to clean water, internet and social media use. All of these help to enhance information access, early warning dissemination, and post - disaster response. Conversely, provinces with the lowest adaptive capacity are largely concentrated in structurally disadvantaged regions, where is attributed by limited health - care resources, weaker digital and service infrastructure. The conditions constrain the ability to anticipate, cope with, and recover from flood events.

Importantly, an initial inspection reveals that several provinces exhibit only moderate sensitivity and nonetheless fall within the low adaptive capacity category, including Tuyen Quang, Quang Tri, Kon Tum, Gia Lai, An Giang, Tra Vinh, etc. (see Figure 6 and Figure 7). This spatial pattern indicates that inadequate provision of

health, infrastructure, and basic services can amplify vulnerability even where social susceptibility is not pronounced. The observed pattern underscores the heterogeneous and non-linear interaction between sensitivity and adaptive capacity across space. Simultaneously, this pattern highlights that vulnerability is shaped not only by the magnitude of each component but also by their spatial concurrence and combination across provinces.

3.4 Composite vulnerability hotspot

3.4.1. Spatial distribution of vulnerability

The vulnerability map indicates pronounced regional clustering and a clear structural gradient. The highest vulnerability class (74-100) concentrates in the northwestern mountainous provinces, including Lai Chau, Dien Bien, Ha Giang, and Cao Bang. Elevated vulnerability also appears in the Central Highlands, notably Gia Lai, and in the southern Mekong Delta, particularly Ca Mau. The high vulnerability category (57-74) extends this pattern across adjacent upland and central provinces such as Lao Cai, Son La, Quang Binh, and Kon Tum, as well as parts of the lower delta. In contrast, lower vulnerability levels (0-49) are concentrated in economically dynamic regions, including provinces in the Red River Delta (e.g., Hung Yen, Hai Duong) and the Southeast (e.g., Binh Duong, Dong Nai) (see Figure 9).

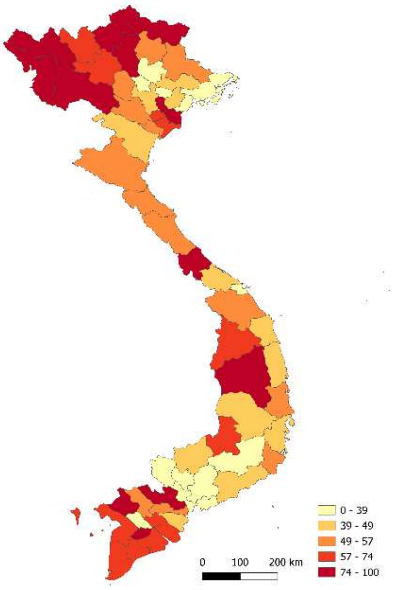


Fig 6. Composite vulnerability index map

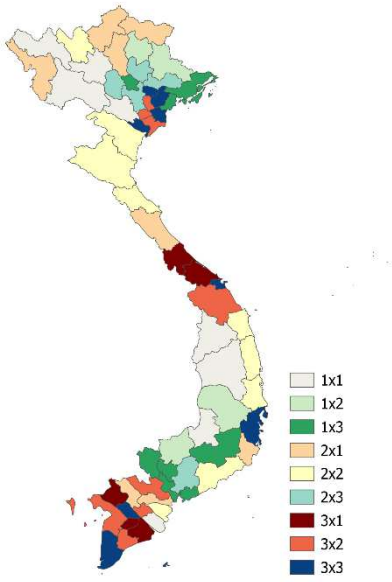


Fig 7. Bivariate exposure and Adaptive capacity map

This pattern suggests that structural socioeconomic disparities, rather than exposure alone, underpin the observed spatial differentiation. Sensitivity and adaptive capacity play the dominant role in shaping overall vulnerability outcomes. The results agree with previous studies indicating that high vulnerability does not necessarily coincide with substantial exposure to flooding (Nguyen et al., 2022). A distinct group of provinces – predominantly mountainous and socio-economically disadvantage areas - display high vulnerability despite relatively low exposure levels. Vulnerability is primarily driven by high socio-economic sensitivity, characterized by elevated poverty rates, high dependency ratios, and a large share of low-skilled labor. This situation is combined

with very low adaptive capacity, as indicated by poor human development outcomes, limited healthcare availability, weak digital connectivity, and restricted access to basic service. In these contexts, even infrequent or localized flood events may translate into disproportionately severe impact.

To identify which dimensions, dominate high-risk provinces, we examine the sensitivity and adaptive capacity profiles and identify the main drivers among the indicators. The results show that the sensitivity of the most vulnerable provinces is primarily driven more by socio-economic factors. Poverty exhibits the highest standardized value (mean z-score = 1.18), followed by dependency ratio (0.75) and the share of low-skilled labor (0.67). In contrast, structural indicators such as cropland share contribute comparatively less to sensitivity. These results suggest that socio-demographic fragility, rather than agricultural exposure alone, constitutes dominant mechanism of sensitivity for the highest vulnerable provinces (see Figure 10).

Applying similar approach, the adaptive capacity profile of top high-risk provinces reveals a clear pattern of deficits concentrated in basic service provision and digital connectivity. The most pronounced constraints are observed in access to clean water (mean z-score = -1.20), internet access (-0.97) and social media usage (-0.96). These indicators, followed by levels of human development (HDI = -0.94) form the primary cluster of structural limitations. This suggests that deficiencies in basic services and digital connectivity, rather than healthcare-related infrastructure constitute the dominant constraints on adaptive capacity in high-risk provinces.

Together, the results suggest that vulnerability differences across provinces largely reflect the contrast between socio-economic fragility in high-risk areas and stronger development capacity in more resilient regions (see figure 10).

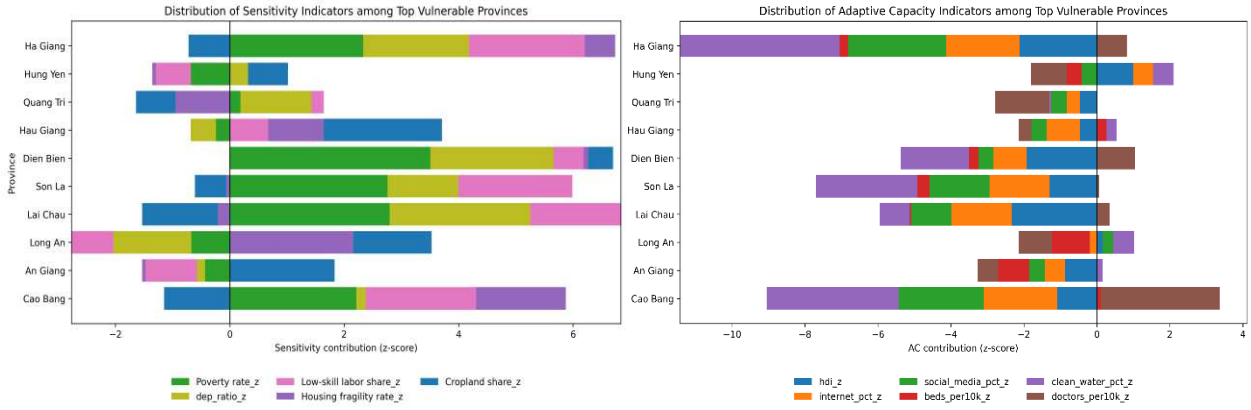


Fig 8. Structural Drivers of Vulnerability: Sensitivity and Adaptive Capacity Profiles

3.4.2. Bivariate Exposure and Capacity map

To diagnose the structural drivers of vulnerability, we constructed a bivariate Exposure and Adaptive Capacity map using a percentile-based classification approach. First, the normalized exposure index (0-100) was divided into three ordinal classes (E3) using tercile thresholds. They represent low, medium, and high exposure. Similarly, an identical procedure was applied to the adaptive capacity index (0-100) to generate three capacity classes (C3), ranging from low to high capacity. Second, the exposure and capacity classes were combined through a categorical cross-classification (E3 x C3) and producing nine distinct exposure-capacity states. This binary

coding preserves the relative ranking of provinces. Then, each category was assigned to an interpret label and symbolized using a diverging bivariate color scheme. This approach allows the map to convey hazard pressure and adaptive capacity at the same time.

Exposure-driven vulnerability

Provinces classified as high exposure (level 3) with medium or high capacity (from 2 to 3) indicate vulnerability that is primarily exposure driven. These provinces concentrated along parts of delta and coastal areas, for example Nam Dinh, Hung Yen, Quang Nam, Long An, Kien Giang, Bac Lieu (3x2); Ninh Binh, Thai Binh, Hung Yen, Hai Duong, Da Nang, Khanh Hoa, Can Tho, Ca Mau (3×3). In these provinces, vulnerability primarily reflects elevated hazard pressure likely associated with coastal and deltaic exposure while institutional and socioeconomic capacity partially buffers impacts. Risk here is driven more by hazard intensity than by structural fragility.

Capacity-driven vulnerability

A second group consists of provinces with low or moderate exposure (level 1 and 2) but low adaptive capacity (level 1), where vulnerability is capacity driven. This pattern is evident in parts of the uplands and mountainous areas, including Lai Chau and Son La, Yen Bai, Hoa Binh, Kon Tum, Gia Lai, Dak Nong (1×1) or Ha Giang, Cao Bang, Tuyen Quang, Quang Binh, Ninh Thuan, Dong Thap, Tien Giang (2×1). In these areas, limited access to healthcare, infrastructure, and social services constrains adaptive responses even under less extreme exposure conditions. These provinces demonstrate that vulnerability can be high even when hazard pressure is not maximal, underscoring the role of long-standing development constraints.

Compound injustice hotspot

The most critical pattern corresponds to provinces characterized by high exposure (level 3) and low adaptive capacity (level 1), which emerge as compound injustice hotspots. These areas are in parts of the Central region and Mekong Delta, notably Quang Tri, Hue, An Giang and Soc Trang. These provinces face simultaneous hazard pressure and limited coping capacity, producing structurally entrenched vulnerability. This pattern reflects spatial climate injustice, where populations most exposed are also least equipped to adapt. In contrast, other provinces where they are highly exposed, but exhibit relatively strong adaptive capacity that makes them to be more resilient. By systematically cross-classifying comprehensive adaptive capacity against raw exposure, the result proves that ultimate vulnerability hotspots are predominantly located in structurally marginalized regions rather than solely in the highly inundated deltas.

3.5 Robustness check

Robustness checks indicate that the main spatial patterns of sensitivity and adaptive capacity are not driven by weighting assumptions. Principle Component Analysis (PCA) was utilized as an alternative aggregation method. For sensitivity, the first principal component explains 49.3% of the total variance across indicators. Different from observable variables, social vulnerability is a multidimensional indices (Tate, 2012), approximately half of the total variance across indicators is acceptable. This suggests a moderately strong common dimension but still retains meaningful multidimensionality. Rank-based comparison between the equal-weight and PCA-based sensitivity indices has a Spearman correlation of 0.67, indicating moderate-to-strong agreement.

Importantly, 7 out of the top 10 high sensitivity provinces are consistently identified under both approaches, demonstrating substantial stability in the identification of policy relevant, especially for high-sensitivity areas.

Adaptive capacity exhibits even stronger robustness. The first principal component explains 52.1% of the variance, reflecting a more coherent structure among indicators. The rank correlation between equal-weight and PCA-based adaptive capacity indices is high (Spearman $\rho = 0.88$). This indicates very strong consistency across weighting schemes. Lastly, 7 of the top 10 high-capacity provinces overlap between methods, confirming that key spatial contrasts in adaptive capacity are stable.

Table 2. Robustness summary of composite indices

Index	PC1 variance (%)	Spearman ρ	Top-10 overlap
Sensitivity	49.3	0.67	7/10
Adaptive Capacity	52.1	0.88	7/11

4. Discussion

This study adopts the widely accepted framework of flood vulnerability—comprising exposure, sensitivity, and adaptive capacity—which has been extensively applied in recent assessments. However, distinct from previous indicator-based approaches that calculate exposure through determinant factors such as average elevation, distance to rivers, or land use metrics, this research directly extracts exposure data from flood hazard maps to calculate the population potential in flooded areas. By decoupling the calculation of exposure from its physical determinants, this study isolates the spatial interaction between physical hazard and social susceptibility. This approach avoids multicollinearity often found in studies where physical determinants are conflated with exposure outcomes. The study focuses on a more rigorous examination of the "matching" or "mismatching" of exposure, sensitivity, and adaptive capacity across provinces. Furthermore, regarding the aggregation of vulnerability indices, while many studies such as Nguyen et al. (2022) utilize the Analytic Hierarchy Process (AHP) reliant on expert opinion, and others rely on variable-specific weighting, this study applies equal weighting to socio-economic factors and validated it by robustness checks. By validating our equal-weighting approach against Principal Component Analysis (PCA) achieving Spearman correlations of 0.67 for sensitivity and 0.88 for adaptive capacity, the research confirms that the identified spatial patterns are structurally robust and not artifacts of subjective preference in vulnerability mapping.

The mapping reveals a critical spatial divergence: while the deltas exhibit "exposure-driven" vulnerability, the most structurally vulnerable provinces are actually the mountainous regions (Northwest and Central Highlands) which display "capacity-driven" vulnerability. This finding challenges the assumption that hazard hotspots are synonymous with vulnerability hotspots. The sensitivity profile of the most vulnerable provinces is primarily driven by socio-economic factors, particularly poverty, dependency ratio, and share of low-skilled labor rather than the dependence of agricultural livelihood. Additionally, the deficiencies in basic services such as the access to clean water, digital connectivity, rather than healthcare availability, constitute dominant constraints on adaptive capacity in high-risk provinces. This mirrors findings by Pathak et al. (2020) in Nepal,

where socio-economic constraints and lack of adaptive resources were found to be decisive drivers of vulnerability independent of physical proximity to water bodies.

Especially, the bivariate mapping of exposure and capacity highlights distinct typologies of risk that require differentiated policy responses. Exposure-driven vulnerability**:** Provinces in delta and coastal areas face high hazard burdens but possess moderate-to-high adaptive capacities. Capacity-driven vulnerability: provinces with low or moderate exposure but low adaptive capacity; vulnerability is entrenched by structural disadvantages rather than extreme hazard intensity. Compound Injustice: The identification of "compound injustice hotspots" in provinces like Quang Tri, Hue, Soc Trang and An Giang highlights areas where high exposure intersects with low capacity. This supports the observation that climate impacts often exacerbate existing inequalities, disproportionately affecting regions with the least resources to cope.

5. Conclusion

This study provides a comprehensive national-level assessment of flood vulnerability in Vietnam shaped by three interacting dimensions of exposure, sensitivity, and adaptive capacity. The study distinguishes itself through a methodological reliance on direct hazard extraction and robust, equal-weighting aggregation rather than subjective expert scoring. By expanding the analysis beyond poverty to encompass broader socio-economic sensitivity and adaptive capacity, the research uncovers a significant spatial mismatch: the areas of highest physical exposure are not necessarily the regions of highest composite vulnerability

The analysis confirms that flood risk in Vietnam is co-produced by socially differentiated susceptibility and uneven development pathways. Therefore, national adaptation policies must move beyond a "one-size-fits-all" engineering approach. Effective risk reduction should be a dual strategy: targeted structural protection and land-use planning for the high-exposure deltaic provinces, and urgent investments in basic services, healthcare, and livelihood diversification for the high-sensitivity mountainous regions. This nuanced spatial understanding is essential for prioritizing limited adaptation resources to address not just the physical floodwater, but the underlying inequalities that turn hazards into disasters.

While this study offers a rigorous national-level assessment of flood vulnerability in Vietnam through a spatially explicit exposure – sensitivity – adaptive capacity framework, several limitations inherent to the methodological design and data constraints must be acknowledged. First, the assessment of physical exposure likely represents an upper bound estimate. Consistent with the limitations identified in Bangalore et al. (2019), the flood hazard maps utilized in this study do not fully account for flood protection infrastructure, such as the extensive dike system in the Red River Delta. In well-protected regions, this omission may lead to an overestimation of the exposure. Second, while the scale of analysis at the provincial level is necessary for national strategic prioritization, it masks intra-provincial heterogeneity. Pathak et al. (2020) argue that national-scale research inevitably obscures location-specific issues that are critical for micro-level policy.

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532 **Appendix**

533 **Table 3**. Descriptive statistics of variables used in the flood vulnerability assessment (N = 63 provinces)

Variable	Mean	Std. Dev.	Min	Median	Max
Sensitivity indicators					
Scropland share (%)	40.51	21.14	6.45	37.78	83.84
Poverty rate (%)	7.60	8.38	0.12	4.96	36.74
Housing fragility rate (%)	13.41	6.81	0.00	15.00	28.00
Low-skill labor share (%)	39.90	19.26	5.70	36.50	78.60
Dependency ratio	0.48	0.07	0.29	0.48	0.64
Adaptive capacity indicators					
Human Development Index (HDI)	0.69	0.05	0.58	0.69	0.80
Hospital beds (per 10,000 people)	34.55	10.01	15.39	32.63	72.20
Physicians (per 10,000 people)	8.68	2.91	4.15	8.32	18.06
Population with access to clean water (%)	95.14	8.37	58.80	98.70	100.00
Internet users (%)	82.05	5.54	71.00	82.00	94.00
Social media users (%)	74.38	5.77	59.00	74.00	90.00

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535 **Table 4.** Standardized sensitivity indicators of top vulnerable provinces (N = 10 provinces)

Province	Cropland Share (z-score)	Poverty Rate (z-score)	Housing Fragility Rate (z-score)	Low-Skill Labor Share (z-score)	Dependency Ratio (z-score)	Sensitivity Index	Sensitivity Score (0-100)	Vulnerability Score (0-100)
Ha Giang	-0.72	2.33	0.53	2.02	1.85	1.2	95.04	100
Hung Yen	0.7	-0.68	-0.06	-0.61	0.32	-0.07	49.05	96.46
Quang Tri	-0.69	0.19	-0.95	0.22	1.24	0	51.53	93.46
Hau Giang	2.07	-0.24	0.97	0.67	-0.44	0.61	73.41	92.43
Dien Bien	0.43	3.51	0.09	0.52	2.15	1.34	100	87.67
Son La	-0.55	2.76	-0.06	1.99	1.24	1.08	90.43	83.18
Lai Chau	-1.32	2.79	-0.21	1.58	2.46	1.06	89.89	81.22
Long An	1.37	-0.67	2.16	-0.73	-1.36	0.15	57.02	80.16
An Giang	1.83	-0.43	-0.06	-0.9	-0.14	0.06	53.66	80.09
Cao Bang	-1.15	2.21	1.57	1.93	0.17	0.95	85.71	79.19

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538 **Table 5.** Standardized adaptive capacity indicators of low-risk vulnerable provinces (N = 10 provinces)

Province	HDI (z-score)	Hospital Beds (z-score)	Doctors (z-score)	Clean Water Access (z-score)	Internet Access (z-score)	Social Media Usage (z-score)	Adaptive Capacity Index	Adaptive Capacity Score (0-100)	Vulnerability Score (0-100)
Bac Ninh	1.63	-0.01	-0.02	0.59	1.45	0.46	0.68	61.89	33.51
Ba Ria – Vung Tau	2.04	-1.37	-1.18	0.59	0.9	0.98	0.33	52.93	31.54
Vinh Phuc	1.21	0.2	0.97	0.59	1.27	0.11	0.72	62.97	30.64
Quang Ninh	1.63	2.02	-1.12	0.43	0.17	-0.42	0.45	56.14	29.49
Dong Nai	1.21	0.3	-0.59	0.56	1.27	1.16	0.65	61.1	28.65
Thai Nguyen	1	2.27	0.29	0.32	1.08	0.98	0.99	69.78	27.82
Hai Phong	1.83	2.06	0.55	0.57	1.08	0.63	1.12	73.08	11.53
Binh Duong	1	-0.53	-1.3	0.59	1.99	2.73	0.75	63.57	8.43
Ho Chi Minh city	2.04	0.71	1.38	0.59	1.99	2.2	1.49	82.28	6.35
Da Nang	1.83	3.79	3.06	0.59	2.18	1.68	2.19	100	0

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540 **Table 6.** Provincial exposure, sensitivity, adaptive capacity, and flood vulnerability metrics for Vietnam

Province	Exposure Rate	Exposure Score (0-100)	Sensitivity Index	Sensitivity Score (0-100)	Adaptive Capacity Index	Adaptive Capacity Score (0-100)	Vulnerability Index	Vulnerability Score (0-100)
Ha Noi	0.22	23.29	-0.28	41.43	0.34	53.2	11.51	43.77
Vinh Phuc	0.05	3.66	-0.1	48.02	0.72	62.97	-11.3	30.64
Bac Ninh	0.31	32.28	-0.78	23.29	0.68	61.89	-6.31	33.51
Quang Ninh	0.07	6.67	-0.42	36.16	0.45	56.14	-13.3	29.49
Hai Duong	0.35	37.22	-0.51	33.15	0.26	51.21	19.15	48.16
Hai Phong	0.07	5.8	-0.79	22.77	1.12	73.08	-44.51	11.53
Hung Yen	0.92	100	-0.07	49.05	0.05	45.98	103.08	96.46
Thai Binh	0.73	79.38	-0.33	39.44	0.41	55.03	63.79	73.85
Ha Nam	0.7	75.21	-0.44	35.53	0.11	47.35	63.38	73.62
Nam Dinh	0.47	50.88	-0.25	42.43	-0.24	38.66	54.65	68.59
Ninh Binh	0.35	36.71	0.1	54.94	0.49	57.14	34.52	57.01
Ha Giang	0.14	14.18	1.2	95.04	-1.77	0	109.23	100
Cao Bang	0.09	8.1	0.95	85.71	-0.95	20.74	73.07	79.19
Bac Kan	0.04	2.65	0.38	65.19	-0.11	41.85	26	52.1
Tuyen Quang	0.26	26.73	0.47	68.51	-0.6	29.4	65.85	75.04
Lao Cai	0.13	12.59	0.57	72.29	-0.13	41.31	43.57	62.22
Yen Bai	0.08	7.7	0.47	68.44	-0.36	35.52	40.62	60.52
Thai Nguyen	0.1	9.21	-0.2	44.37	0.99	69.78	-16.2	27.82
Lang Son	0.05	3.87	0.26	61.04	-0.19	39.95	24.96	51.51
Bac Giang	0.15	14.62	0.32	63.18	0.58	59.45	18.35	47.7
Phu Tho	0.25	25.76	0.19	58.35	0.68	61.96	22.16	49.89
Dien Bien	0.14	14.22	1.34	100	-0.72	26.41	87.81	87.67
Lai Chau	0.08	7.77	1.06	89.89	-0.93	21.08	76.59	81.22
Son La	0.03	2.04	1.08	90.43	-1.27	12.47	80	83.18
Hoa Binh	0.06	5.56	-0.06	49.43	-0.45	33.36	21.63	49.59
Thanh Hoa	0.23	23.72	-0.23	43.12	0.19	49.54	17.3	47.1

Nghe An	0.2	20.84	0.17	57.58	0	44.66	33.76	56.57
Ha Tinh	0.25	25.64	-0.25	42.31	-0.09	42.43	25.52	51.83
Quang Binh	0.12	11.34	-0.14	46.59	-0.37	35.45	22.48	50.08
Quang Tri	0.73	79.31	0	51.53	-0.46	32.98	97.86	93.46
Thua Thien Hue	0.31	32.55	-0.77	23.8	-0.28	37.63	18.72	47.91
Da Nang	0.34	35.46	-1.42	0	2.19	100	-64.54	0
Quang Nam	0.26	27.48	-0.13	46.69	0.04	45.74	28.43	53.5
Quang Ngai	0.16	16.04	-0.06	49.17	0.01	44.96	20.25	48.79
Binh Dinh	0.26	26.89	-0.82	21.95	-0.08	42.64	6.21	40.71
Phu Yen	0.12	11.17	0	51.51	-0.15	40.86	21.81	49.69
Khanh Hoa	0.31	32.9	-0.74	24.82	0.24	50.73	6.99	41.16
Ninh Thuan	0.25	25.7	-0.34	39.05	-0.42	34.16	30.59	54.74
Binh Thuan	0.09	8.1	-0.27	41.63	-0.13	41.42	8.31	41.92
Kon Tum	0.07	6.68	0.67	75.61	-0.46	32.98	49.31	65.52
Gia Lai	0.04	3.27	0.71	77.19	-1.14	15.74	64.72	74.39
Dak Lak	0.03	2.29	0.1	55.24	-0.15	40.84	16.69	46.75
Dak Nong	0.04	2.72	0.78	79.67	-0.36	35.5	46.89	64.13
Lam Dong	0.05	3.48	-0.13	46.85	0.24	50.79	-0.47	36.87
Binh Phuoc	0.03	2.08	0.01	51.84	-0.24	38.55	15.37	45.99
Tay Ninh	0.07	6.66	-0.15	45.9	0.31	52.45	0.11	37.2
Binh Duong	0.05	3.93	-1.15	9.75	0.75	63.57	-49.89	8.43
Dong Nai	0.12	11.76	-0.47	34.58	0.65	61.1	-14.76	28.65
Ba Ria Vung Tau	0.01	0	-0.23	43.19	0.33	52.93	-9.74	31.54
Ho Chi Minh city	0.08	7.79	-0.84	20.98	1.49	82.28	-53.51	6.35
Long An	0.54	57.62	0.15	57.02	-0.19	39.89	74.74	80.16
Tien Giang	0.12	11.23	0.16	57.3	-0.33	36.41	32.12	55.62
Ben Tre	0.11	10.82	-0.01	50.99	-0.06	43.29	18.52	47.8
Tra Vinh	0.03	2.2	0.43	66.96	-0.44	33.54	35.62	57.64
Vinh Long	0.29	30.61	0.3	62.4	0.04	45.75	47.27	64.34
Dong Thap	0.17	17.63	0.07	54.04	-0.33	36.44	35.23	57.42
An Giang	0.49	52.62	0.06	53.66	-0.52	31.65	74.62	80.09
Kien Giang	0.31	32.23	0.01	51.69	0.09	47	36.92	58.39
Can Tho	0.32	33.3	-0.29	40.9	1.07	71.76	2.43	38.54
Hau Giang	0.56	60.58	0.61	73.41	-0.27	37.92	96.07	92.43
Soc Trang	0.34	36.49	0.21	59.09	-0.36	35.7	59.88	71.6
Bac Lieu	0.53	57.43	-0.36	38.64	-0.24	38.51	57.56	70.27
Ca Mau	0.49	52.63	0.22	59.6	0.28	51.86	60.36	71.88

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