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Spatial Analysis of the Relationship Between Climate-Environmental Risks and the Vulnerable Population in Thailand for Policy Interventions

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Abstract: This study examined climate-related risks to public health, settlements and human security in Thailand, with a particular focus on vulnerable groups such as children and the elderly. Distinguishing itself from traditional assessments, this research innovatively integrated future climate projections from 2016–2035 under a high-emission scenario of RCP8.5 with data about current structural vulnerability, based on the Multidimensional Poverty Index (MPI) in 2024. This approach proactively identified "at-risk" areas where future environmental hazards might exacerbate existing social inequalities. The analysis on 76 provinces except Bangkok, utilized Bivariate Polygon Render to visualize risk-poverty intersections and Local Spatial Autocorrelation (Local Moran's I) to rigorously detect statistically significant spatial clusters. Results indicated that the Northeastern and Western regions consistently faced elevated risks. Quantitative analysis confirmed critical "High-High" hotspots in the Northeast, specifically in Khon Kaen (LMI = 1.103, $p = 0.004$) and Buriram (LMI = 1.724, $p = 0.008$), where high climate exposure significantly overlapped with child multidimensional poverty. Conversely, Mae Hong Son emerged as a significantly "Low-High" spatial outlier (LMI = -0.634, $p = 0.008$), highlighting a region with concentrated elderly vulnerability despite lower relative climate risks. These findings underscored the utility of MPI over simple population counts for policy targeting. Ultimately, the study supports climate justice principles by providing spatially explicit evidence to guide interventions that address both local needs and structural inequalities.

Keywords: Climate justice; Climate Risk Index; Multidimensional Poverty Index; Spatial analysis; Vulnerability

1. Introduction

Climate change is no longer a distant concern; it is an existing reality that affects people's lives in many ways. In Thailand, the impacts are increasingly visible through rising temperatures, floods, droughts, and air pollution (IPCC, 2007; Limjirakan & Limsakul, 2012). These environmental changes do not affect everyone equally. Vulnerable groups face greater risks due to limited resources and lower adaptive capacity (Leichenko & Silva, 2014). Understanding these unequal impacts leads us to the concept of climate justice, which connects environmental change with social fairness. It asks whether climate burdens are shared fairly and whether affected communities have a voice in decisions that shape their future (Apraku et al., 2025; UNDP, 2009). Recent research has shown that public perception matters even when people are unfamiliar with the term "climate justice". They often agree that poorer communities suffer disproportionately and that environmental problems are tied to economic structures (Ogunbode et al., 2024).

Despite the growing body of literature on climate change in Thailand, a critical knowledge gap remains. Most existing studies analyzed climate risks (meteorological data) and social vulnerability (socio-economic data) in isolation. Furthermore, traditional vulnerability assessments in Thailand often rely heavily on income-based poverty measures. This study argued that monetary metrics were insufficient for climate risk analysis because they failed to capture the structural deprivations such as lack of education, poor health, or inadequate living standards that directly limited the adaptive capacity of a household. To address this, we utilized the Multidimensional Poverty Index (MPI) which was developed by Alkire & Foster (2011) to offer a more granular view of deprivation. In the Thai context, the government, through the Office of the National Economic and Social Development Council (NESDC) and Thai People Map and Analytics Platform (TPMAP), has localized this index to identify specific needs at the sub-national level (NSTDA, 2021; OPHI, 2019; TPMAP, 2018). By using the MPI, we could identify populations who may have income above the poverty line but lack the essential infrastructure and health resilience to withstand climate shocks.

This research specifically targeted two demographic groups including children and the elderly. These groups were selected not merely due to their statistical size, but due to their distinct physiological and social vulnerabilities. Children are uniquely susceptible to environmental hazards due to their developing physiology and dependency on caregivers, thus rendering them disproportionately affected by waterborne diseases and malnutrition during climate disasters (Pacheco, 2020). Conversely, the elderly face heightened risks owing to pre-existing health conditions, reduced mobility, and social isolation, which severely hinder their ability to evacuate or access services during extreme events (UNEP, 2025).

Spatial analysis tools such as Geographic Information System (GIS), bivariate mapping, and Local Moran's I provide the methodological framework to visualize the intersection between climate risks and social vulnerability. These tools help identify "hotspots" and outliers, making inequality visible and guiding policy more effectively (Chang et al., 2021; Xu et al., 2021). Recent studies in India and Algeria have demonstrated how combining climate data with poverty indicators could reveal areas requiring urgent attention (Dib & Sardou, 2025; Singh et al., 2025). Building on these global precedents, this study filled the identified gap in the Thai context by integrating projected climate risks under the RCP8.5 high-emissions scenario (2016–2035) with current data on structural vulnerability, measured using the MPI in 2024. The research aims to move beyond general observations to provide spatially explicit evidence that supports fair and inclusive policy responses rooted in climate justice.

2. Methodology

This study employed an integrated spatial analysis approach to assess the intersection of future climate risks and current social vulnerabilities among children and the elderly in Thailand. The methodology was designed to operationalize the concept of climate justice by overlaying projections of physical hazard with socio-economic deprivation data.

To ensure methodological robustness and address the temporal disparity between datasets, this study adopted a "Scenario-based Stress Test" approach. Specifically, we utilized the Climate Risk Index (CRI) derived from projected trends for the near-future period (2016–2035) and overlaid it with the most recent vulnerable population data in 2024 from TPMAP.

It is important to clarify that this analysis does not aim to forecast future demographic shifts, which are subject to high uncertainties regarding migration and birth rates. Instead, it poses a critical policy question: "If the current vulnerable populations were to face the projected climate hazards of the next decade, which geographic areas would lack the structural capacity to cope?" This condition isolates the climate variable and allows policymakers to identify "lock-in" risk areas where future hazards will exacerbate existing structural inequalities.

2.1 Materials and Sources of Data

This study utilized secondary data from official national databases, to ensure consistency with the National Adaptation Plan framework in Thailand (Department of Climate Change & Environment, 2023). The data sources are summarized in Table 1, which includes the spatial data for the Provincial boundaries of Thailand (Figure 1).

Table 1. Sources of data

No.	Data Used in the Study	Type of Data	Year of Data	Source of Data
1	Vulnerable child population	Statistical data	2024	Thai People Map and Analytics Platform (TPMAP)
2	Vulnerable elderly population	Statistical data	2024	TPMAP
3	Vulnerable children under the criteria of the Ministry of Education (MPI)	Statistical data	2024	TPMAP
4	Vulnerable elderly population (MPI)	Statistical data	2024	TPMAP
5	Climate Risk Index (CRI)	Statistical data	2024	Office of Natural Resources and Environmental Policy and Planning
6	Provincial boundaries of Thailand	Spatial data	2020	Open Development Thailand

Figure 1. Provincial boundaries of Thailand
Source: Open development Thailand (2020).

2.1.1 Climate Risk Index

Data on the CRI were sourced from the Climate Change Risk Maps Database System (CCRMDS), a collaborative development by the Office of Natural Resources and Environmental Policy and Planning (ONEP) and Ramkhamhaeng University (RU-CORE). This composite index was constructed based on downscaled projections from three Global Climate Models: EC-Earth, HadGEM2-ES, and MPI-ESM-MR. To provide a conservative basis for the planning of disaster risk reduction, the analysis specifically utilized the RCP8.5 scenario, representing a high emission “worst-case” trajectory. The CRI aggregated three primary hazard dimensions, i.e., Heat, Flood, and Drought, and were calculated using 24 extreme climate indices that captured variations in intensity, duration, and frequency (e.g., maximum daily temperature, consecutive dry days, and heavy precipitation days). To ensure a balanced assessment in which no single hazard disproportionately influenced the composite score, the hazard indices were aggregated using equal weighting following a normalization process (ONEP & RU-CORE, 2021).

2.1.2 Vulnerable population and Multidimensional Poverty Index

Data regarding vulnerable populations were obtained from the TPMAP in 2024. Diverging from traditional income-centric poverty metrics, TPMAP employed the MPI, which was adapted from the methodology of Alkire & Foster (2011). In the Thai context, the MPI encompasses five core dimensions: health, education, income, living standards, and access to public services. The index is further tailored to capture specific demographic vulnerabilities; for children, assessment extends beyond general household poverty to include child-specific deprivation indicators such as nutrition and school attendance, while elderly vulnerability incorporates factors including dependency ratios, healthcare accessibility, and household isolation. To ensure a comprehensive evaluation, this study applied both raw population counts to assess the magnitude of vulnerable groups and MPI intensity scores to determine the severity of deprivation.

2.2 Steps of Analysis

Data analysis proceeded with the following steps:

2.2.1 Data preparation and normalization

Data from the CCRMDS and TPMAP were integrated using provincial codes as the common key. Since the datasets utilized different measurement scales (e.g., population counts vs. climate probability scores), normalization was essential. We applied Min-Max Normalization to rescale all variables to a range of [0, 1]. Unlike Z-score standardization, which assumes a normal distribution and centers data around zero, Min-Max normalization preserves the original distribution shape and strictly bounds the data between 0 and 1. This is critical for this study because the CRI is already an index on a 0–1 scale. Using consistent scaling ensures valid comparability when overlaying risk and vulnerability layers in the Bivariate Mapping process. Min-Max Normalization is as follows:

$$X_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

2.2.2 Spatial cluster analysis

To detect statistically significant patterns, we employed two complementary spatial statistical techniques:

(1) Bivariate Polygon Render

This technique visualized the spatial relationship between two distinct variables (Climate Risk vs. Vulnerability) on a single choropleth map. A 2 × 2 matrix legend (4 quadrants) was employed to classify provinces into two tiers (Low and High) for each variable. This classification yielded four distinct intersection categories: High Risk–High Vulnerability, High Risk–Low Vulnerability, Low Risk–High Vulnerability, and Low Risk–Low Vulnerability, hence facilitating a clear identification of priority areas for policy intervention.

(2) Local Spatial Autocorrelation (Local Moran's I)

While visual mapping provides an overview, it does not confirm statistical significance. We applied Local Moran's I (LISA) to identify "Hotspots" (clusters of high values) and "Spatial Outliers". We utilized a Queen Contiguity weight matrix (first order), which defined neighbors as any spatial units sharing a common boundary or vertex. This matrix was appropriate for provincial geography of Thailand, where administrative boundaries were irregular polygons. A *p*-value of < 0.05 was selected as the threshold for statistical significance. While False Discovery Rate (FDR) corrections were sometimes used in large datasets, for a national analysis of 76 provinces, the standard 95% confidence interval ($p < 0.05$) provided a robust balance between Type I and Type II errors, to ensure that emerging policy-relevant clusters were not overly suppressed.

The Local Moran's I analysis yielded four primary classifications or Quadrants (LMQ), which defined the nature of spatial clustering:

Quadrant 1 (LMQ = 1): High-High (HH) represents a hotspot where a province has a high value (High Vulnerability/Poverty) and is surrounded by provinces with similarly high values.

Quadrant 2 (LMQ = 2): Low-High (LH) represents a spatial outlier where a province has a low value (Low Vulnerability/Poverty) but is surrounded by neighboring provinces with high values. This indicates a potential buffer zone or area requiring perimeter prevention measures.

Quadrant 3: Low-Low (LL) represents a coldspot where a province has a low value and is surrounded by provinces with similarly low values.

Quadrant 4: High-Low (HL) represents a spatial outlier where a province has a high value but is surrounded by neighboring provinces with low values.

This method not only identified "hotspot" of high vulnerability but also revealed areas of local instability that might not align with broader spatial trends. Its dual function as a tool for cluster detection and for diagnosing influential observations rendered it particularly valuable for spatially targeted policy interventions (Anselin, 1995).

2.3 Limitations of the Study

To ensure rigorous interpretation of the results, this study recognized three key limitations. Firstly, the analysis was limited to the provincial level. This was the smallest unit of accessible data. Analysis at this level might obscure the nuances or concentrations of actual problems at sub-area levels, such as sub-districts or communities.

Secondly, the research combined future risk data (forecasts from 2016–2035) with current population data in 2024. The results therefore indicated the future risks faced by current vulnerable populations but not a projection of the future population. Lastly, the risk index used in the analysis was a relative index, scaled from 0 to 1, to compare risk levels between provinces only. It was not an absolute value that could truly indicate the magnitude of risk.

Based on the research methodology described above, the next chapter presents the results of the study, which will reveal the landscape of risk and vulnerability in Thailand.

3. Results

3.1 Overview of the Risks of Climate Change in Thailand

Climate change has multidimensional impacts, particularly on public health. This risk assessment was based on three components: the Hazard Index, the Non-Climatic Index, and the Risk Index, which is the average of the first two indices. All of these underwent a standardization process for comparative ranking.

For the period 2016–2035 under the high greenhouse gas emissions scenario (RCP 8.5), the results of analysis showed that the Northeast region had relatively high public health risk indices on average for both the Hazard and Non-Climatic Indices. The Eastern and Lower Central regions consistently had moderate to high overall risk, due to their moderate hazard levels and high non-climatic indices. The Northern and Southern regions, on the other hand, had low to moderate overall risk.

In addition to public health, human settlements and security were important dimensions. From 2016–2035, the Northeast region remained a region with high overall risk, particularly in the central and lower regions, where non-climate hazards and indices were high. The North and the South were at low to moderate overall risk, as illustrated in Figure 2a and 2b.

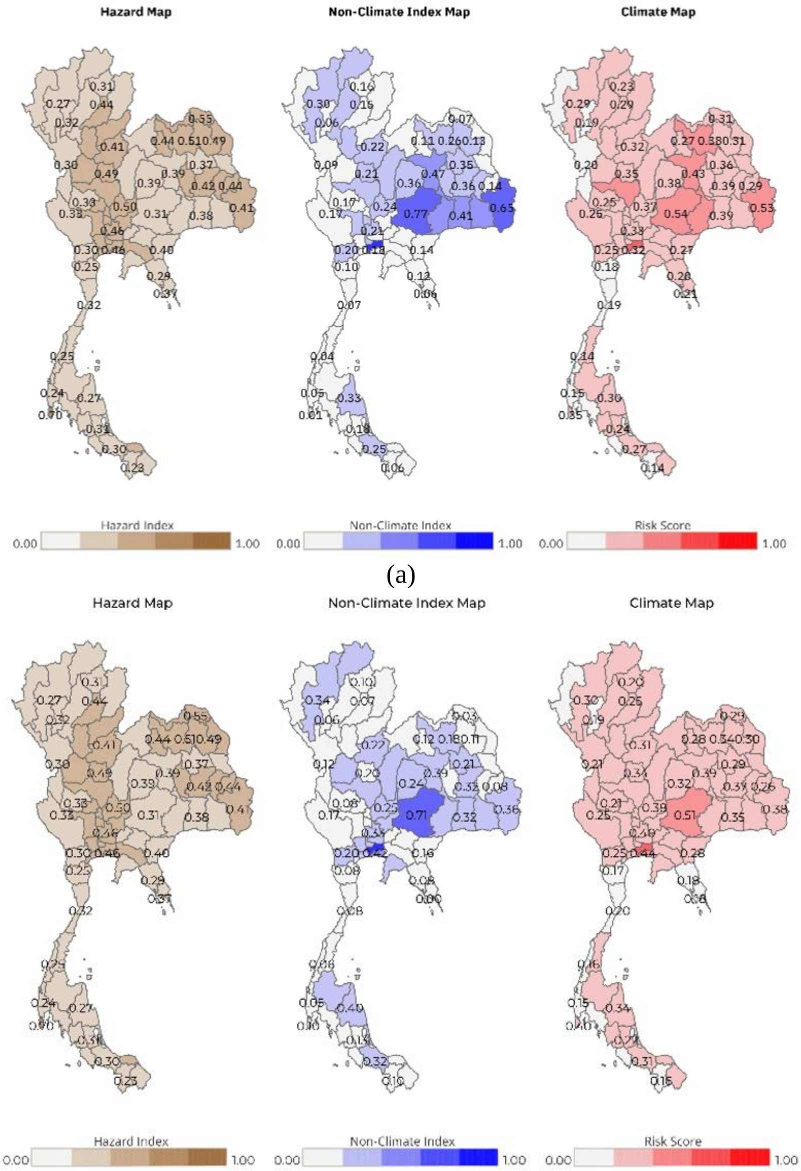


Figure 2. Climate risk maps: (a) Public health dimension, 2016–2035; (b) Human settlements and security dimension, 2016–2035
Source: Department of Climate Change & Environment (2025).

3.2 Situation of Vulnerable Children and Elderly People in Thailand

The distribution of vulnerable children in Thailand showed that the Northeastern region had the highest number of vulnerable children, while those in the Eastern region were concentrated in a few provinces. However, the Northern and Western regions had low numbers of vulnerable children. When analyzed with the MPI, the results differed. The MPI map focused not on total numbers but on structural vulnerability. While the Northeastern region had a large number of vulnerable children, this did not necessarily mean that all areas were experiencing multidimensional poverty. Therefore, using both data sources was important for a comprehensive understanding of the problem (Figure 3a).

Regarding the vulnerable elderly, the Northern and Northeastern regions had the highest numbers of vulnerable elderly, reflecting the widespread structural burden of the aging population. In contrast, the Central and Southern regions had a mixed population, with areas in moderate to high levels, but not as prominent as the first two regions. When the MPI data was analyzed together, the picture clearly differed from the total population. The MPI map indicated that while some regions had a high number of vulnerable elderly, not all areas fell below the MPI threshold. Comparing the two data sources revealed both the magnitude of the problem (the number of elderly people requiring assistance) and the qualitative severity (structural problems), which helped policymaking be more accurate and align with spatial reality (Figure 3b).

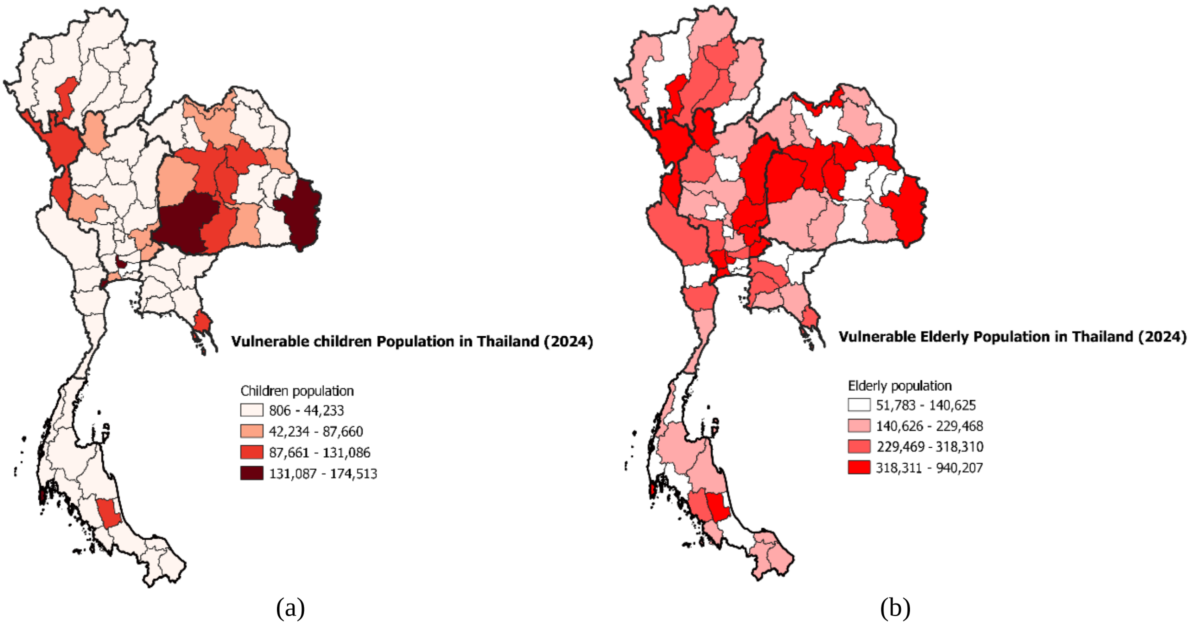


Figure 3. Maps of vulnerable (a) children and (b) elderly people in Thailand (2024)
Source: TPMAP (2018).

3.3 Analysis of Vulnerable Child and Elderly Populations below MPI in Relation to Composite Climate Risk

To facilitate the interpretation of spatial relationships in Figures 4 and 5, a bivariate color scheme was employed to classify provinces into four distinct categories based on the intersection of Climate Risk (X-axis) and Vulnerable Population (Y-axis):

(1) High-High (Black/Dark Red): Provinces exhibiting both high climate risk and high vulnerability, representing the most critical areas requiring urgent intervention.

(2) Low-High (Dark Blue): Provinces with low climate risk but high vulnerability, indicating areas where social fragility is the primary concern despite lower environmental exposure.

(3) High-Low (Pink/Light Red): Provinces with high climate risk but low vulnerability, suggesting areas with better adaptive capacity despite high exposure.

(4) Low-Low (White/Pale): Provinces with relatively low levels of both risk and vulnerability.

3.3.1 Public health

Vulnerable Child Population

Based on the analysis of the relationship between the combined risk index and vulnerable children in the public health dimension for the near future (2016–2035) under the RCP8.5 scenario, the bivariate mapping revealed distinct spatial clustering. The northeastern region was dominated by "High-High" clusters (Black/Dark Red areas). This pattern indicated a spatial convergence where the highest quartiles of projected climate hazards (specifically heat and drought indices) overlapped directly with the highest concentrations of child multidimensional poverty. Conversely, the Western region exhibited "Low-High" patterns (Dark Blue), indicating that while climate risk scores in these provinces were relatively low compared to the Northeast, the structural vulnerability of the child population remained critically high (Figure 4a).

Vulnerable Elderly Population

For the elderly, "High-High" clusters were observed in the Central region and specific Northeastern provinces. This reflected areas where high elderly dependency ratios coincided with intensifying climate hazards, particularly urban heat islands and flood risks. Notably, the Northern region displayed significant "Low-High" areas (Dark Blue), suggesting a concentration of vulnerable elderly populations in areas where the composite climate risk score appeared moderate relative to other regions (Figure 4b).

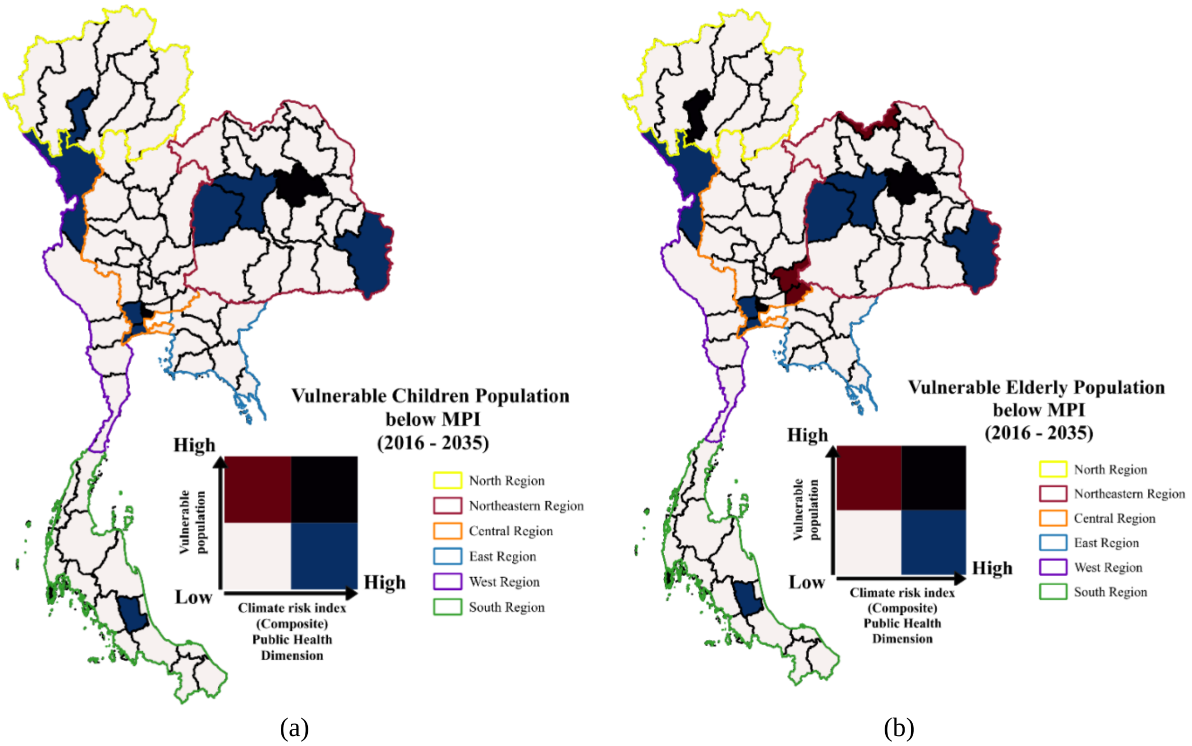


Figure 4. Maps of vulnerable (a) child and (b) elderly population below Multidimensional Poverty Index (MPI) in the public health dimension

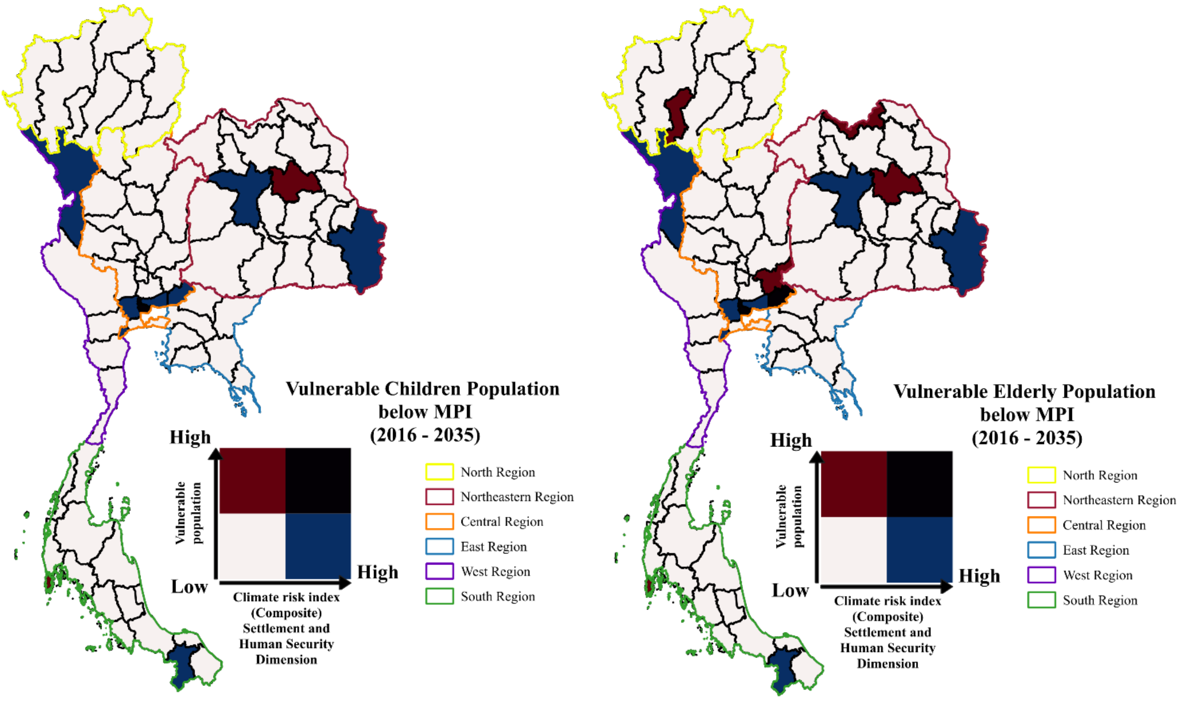
3.3.2 Settlements and human security

Vulnerable Child Population

When analyzing settlements and human security risks, the Northeastern region again emerged as a critical zone, exhibiting a mix of "High-High" (Black) and "High-Low" (Dark Red) patterns. This spatial overlap suggested that settlement stability for children in these agrarian provinces was severely threatened by climate extremes, particularly floods and droughts that disrupted essential services. The Central region displayed "High-High" clusters in the metropolitan area, reflecting the exposure of dense and low-income urban settlements to flood risks. Additionally, the "Low-High" (Dark Blue) pattern along the border in the Western region suggested pockets of high child vulnerability and probably lower resilience of settlement infrastructure, despite a lower calculated composite climate risk score (Figure 5a).

Vulnerable Elderly Population

The distribution of vulnerable elderly populations revealed distinctly regional challenges. The North was characterized by "High-Low" (Dark Red) areas, indicating that while the absolute vulnerability count might be lower relative to the Northeast, the physical risk to settlements (e.g., from flash floods or landslides in mountainous terrain) remained critically high. The Northeast displayed "High-High" (Black) and "Low-High" (Dark Blue) clusters, reinforcing the status in the region as a hotspot where structurally vulnerable elderly populations were exposed to settlement insecurity. In the Central region, "High-High" areas highlighted the vulnerability of the urban elderly to metropolitan climate hazards, where high population density exacerbated evacuation challenges. The Southern region, while mostly "Low-Low" (White), indicated "Low-High" (Dark Blue) pockets, thus signaling coastal areas where elderly vulnerability remained high (Figure 5b).



(a) (b)

Figure 5. Maps of vulnerable (a) child and (b) elderly population below Multidimensional Poverty Index (MPI) in settlements and human security dimension

3.4 Spatial Autocorrelation

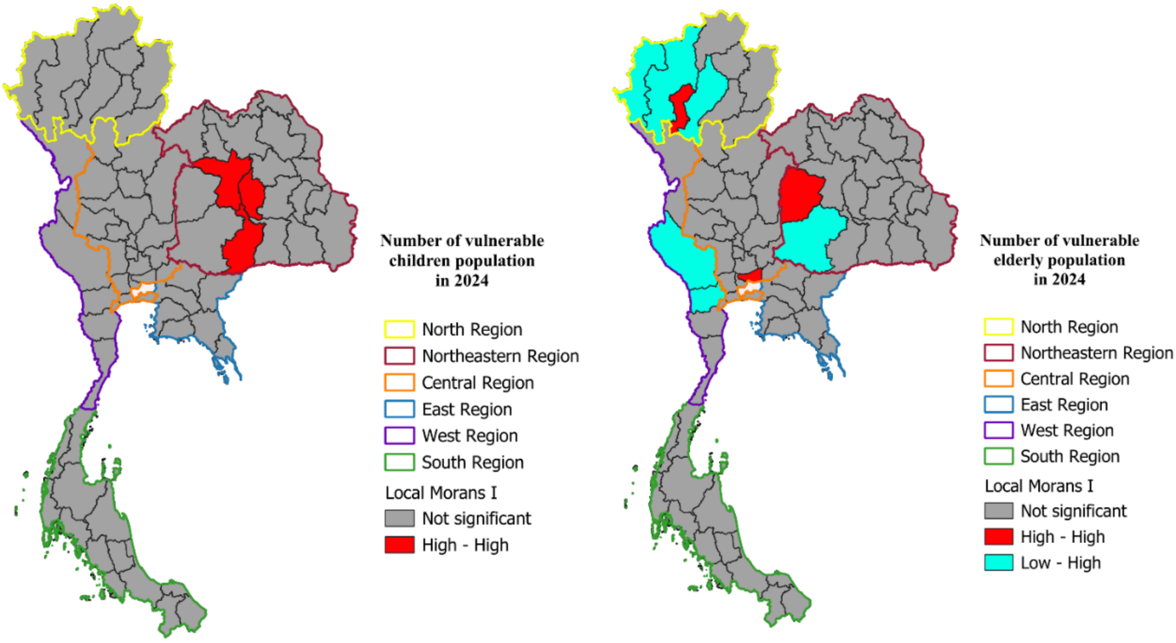
To validate the spatial patterns observed in the Bivariate Polygon Render, Local Moran's I was employed as a complementary statistical tool. This allowed the identification of statistically significant clusters and spatial outliers, thereby confirming the robustness of the visual groupings.

The spatial clustering analysis of the vulnerable child population in 2024 revealed distinct regional patterns. The Local Moran's I analysis confirmed statistically significant clusters ($p < 0.05$). Specifically, High-High Hotspots were detected in the Central Northeastern region. Khon Kaen and Buriram were identified as significant hotspots. This statistical significance confirmed that these provinces not only had high individual vulnerability and risk scores but were surrounded by neighbors with similarly high values, to create a regional cluster of compounded risk. This quantitative evidence reinforced the finding that the Northeast was a critical zone of concentrated multidimensional poverty affecting children (Table 2 and Figure 6a).

Table 2. Local Moran's I statistical testing

Name of the Province	LMI	LMP	LMQ
Vulnerable Child Population			
Khon Kaen	1.103	0.004	1
Burirum	1.724	0.008	1
Mahasarakham	1.552	0.028	1
Vulnerable Elderly Population			
Mae Hong Son	-0.634	0.008	2
Chiang Mai	-0.843	0.015	2
Lampang	-0.009	0.015	2
Ratchaburi	-0.909	0.015	2
Lamphun	1.593	0.018	1
Pathum Thani	0.112	0.031	1
Kanchanaburi	-0.093	0.043	2
Chaiyaphum	0.930	0.047	1
Nakhon Ratchasima	-0.080	0.050	2

Note: LMI (Local Moran's I), LMP (Local Moran's *p*-value), LMQ (Local Moran's Quadrant), Local Moran's *p*-value < 0.05 is significant at CI 95%. Source: The data was prepared by the authors using the local Moran's I.



(a) (b)

Figure 6. Maps of hotspot analysis of vulnerable (a) child and (b) elderly population in 2024
Note: The data was prepared by the authors using Hotspot Analysis technique.

For the vulnerable elderly population in 2024, the statistics revealed spatial inequalities in underlying structural vulnerability. While most provinces were classified as "not significantly different", reflecting heterogeneity across regions. Statistically significant "High-High" clusters were observed in the central metropolitan area, indicating centers of high elderly vulnerability surrounded by similarly vulnerable areas. Furthermore, uniquely spatial relationships were identified in the form of outliers. Mae Hong Son emerged as a significantly "Low-High" spatial outlier. This indicated a localized pocket of high elderly vulnerability situated within a broader region of lower relative climate risk, highlighting a specific demographic challenge distinct from the climatic trend. Such outliers provided crucial information for designing perimeter prevention measures and monitoring hidden vulnerabilities that might be overlooked in broader regional scans (Table 2 and Figure 6b).

4. Discussion and Recommendations

This study examined the spatial distribution of climate-related public health risks among vulnerable populations in Thailand, with a focus on children and the elderly. By integrating MPI with spatial clustering techniques, the findings revealed significant geographic disparities in vulnerability and exposure. The discussion below synthesized these findings with existing literature and organized around four key themes: (1) climate risk and spatial inequality, (2) demographic vulnerability and multidimensional poverty, (3) spatial analysis for policy targeting, and (4) implications for climate justice and human security.

4.1 Climate Risk and Spatial Inequality

The results confirmed that climate-related risks were not evenly distributed across Thailand. Provinces in the Northeast and along the Western border consistently showed higher concentrations of vulnerable populations exposed to elevated climate risks. This pattern reflected the broader scientific consensus that climate change exacerbated existing inequalities through spatially differentiated exposure and sensitivity (IPCC, 2007). Observed trends in temperature extremes and changing precipitation patterns in Thailand further supported the notion that certain regions were disproportionately affected by climate hazards (Limjirakan & Limsakul, 2012; Vesteri, 2017).

These findings align with global research on climate justice, which emphasizes the need to address structural disparities in exposure and adaptive capacity (Apraku et al., 2025). Vulnerability is not merely a function of environmental hazards but emerges from the intersection of physical threats and social conditions such as poverty, age, and access to services (IOM, 2024; Leichenko & Silva, 2014). In this context, spatial inequality becomes a critical lens for understanding who is most prone to risk and where interventions should be prioritized.

Specifically, the identification of "High-High" clusters in the Northeast, such as Khon Kaen and Buriram as shown in Figure 6a, could be attributed to the region's socio-economic structure. The Northeast is the agricultural heartland in Thailand, yet it suffers from chronic water scarcity and lower household incomes, which directly erodes the adaptive capacity of families with children. When overlaid with RCP8.5 projections, this existing fragility is exacerbated by intensifying heat and trends of drought.

In contrast, the "Low-High" outlier pattern observed in the Northern region, particularly in Mae Hong Son as shown in Figure 6b, highlighted a different driver of vulnerability. Here, the risk was driven less by the aggregate climate score and more by the sheer concentration of elderly populations in remote and mountainous terrain. This geographic isolation limits access to essential healthcare services, thus creating a structural deficit that makes the aging population acutely sensitive even to moderate climate variations.

Beyond the regional differences revealed by maps and statistics, the socio-economic structure overlapping with climate risks should be considered. Northeastern Thailand has an economy heavily reliant on agriculture, particularly rain-fed field crops. Facing prolonged droughts, household resilience is lower than in other regions. Furthermore, low average household income and limited water management infrastructure exacerbate the vulnerability in the region (Leichenko & Silva, 2014; Limjirakan & Limsakul, 2012).

4.2 Demographic Vulnerability and Multidimensional Poverty

Moreover, children and the elderly are particularly susceptible to climate-related health impacts due to physiological sensitivity and limited adaptive capacity (Pacheco, 2020; Ripple et al., 2022; UNEP, 2025). The integration of demographic data with the MPI in this study revealed that provinces with high poverty scores often coincided with high climate risk zones. This supports the argument that vulnerability is multidimensional and must be understood through both socioeconomic and environmental indicators (Alkire & Foster, 2011; Sen, 1999).

The MPI framework used in this study builds on the work of Alkire & Foster (2011) and reflects the national efforts of Thailand to localize poverty measurement through TPMAP (2018). By incorporating indicators such as education, health, and living standards, the MPI offers a comprehensive view of deprivation than income alone. This approach is consistent with Sen's capability framework, which emphasizes the importance of expanding individuals' freedoms and opportunities (Sen, 1999).

International studies have similarly demonstrated the value of aggregated vulnerability indicators in identifying priority areas for climate adaptation. For example, Chang et al. (2021) applied composite indices to flood risk assessments, while Singh et al. (2025) examined the spatial overlap between climatic exposure and multidimensional poverty in India. These studies reinforce the importance of integrating demographic and poverty data into climate risk analysis.

In the North, although the number of children below the MPI threshold is not as high as in the Northeast, the North has the highest proportion of elderly in the country. The large elderly population in mountainous areas limits access to health services due to distance, transportation, and the distribution of medical personnel. While not a "hotspot" in terms of numbers, structurally it reflects a more severe level of vulnerability (Pacheco, 2020; UNEP, 2025). Integrating the MPI with geographic data helps illustrate that vulnerability is not simply reflected in population, but also through infrastructure constraints and access to essential services for quality of life.

4.3 Spatial Analysis for Policy Targeting

Besides, the use of spatial analysis tools, specifically Bivariate Polygon Render and Local Moran's I, enabled the identification of statistically significant clusters and spatial outliers. These methods validated the visual patterns observed in the data and revealed hidden structures that might not be apparent through descriptive statistics alone. Local Moran's I was especially effective in detecting areas of high–high clustering and low–high outliers, thus providing a robust basis for spatial targeting of interventions (UNDP, 2022).

Similar methodologies have been applied in other contexts to inform policy. Wang et al. (2024) and Xu et al. (2021) used spatial techniques to assess PM2.5 exposure in relation to land use in China, while Dib & Sardou (2025) conducted territorial analysis of drought-prone agricultural zones in Algeria. These examples highlight the versatility of spatial tools in translating complex data into actionable insights.

In Thailand, the concentration of vulnerable elderly populations in peri-urban provinces and the clustering of child vulnerability in the Northeast suggest that climate adaptation strategies should be tailored to demographic and geographic realities. Specifically, utilizing MPI-adjusted spatial data allows a more precise allocation of resources than raw population counts. For instance, while raw data might direct funds solely to populous cities, MPI-adjusted hotspots like Buriram reveal critical needs in rural areas where structural poverty impedes climate resilience. Spatial indicators allow policymakers to move beyond national averages and address localized needs, particularly in regions where vulnerability is often underrepresented.

4.4 Implications for Climate Justice and Human Security

The observed spatial patterns support the principles of climate justice, which call for equitable distribution of climate burdens and benefits. As Ogunbode et al. (2024) argued, public support for climate action was strengthened when policies were perceived as fair and responsive to local needs. In Thailand, this means prioritizing regions with overlapping environmental and social vulnerabilities and ensuring that adaptation efforts are inclusive and participatory. The study also contributes to the discourse on human security, which recognizes climate change as a threat multiplier that exacerbates existing social tensions and resource constraints (Vesteri, 2017).

Migration patterns, aging populations, and urban expansion further complicate the landscape of vulnerability. Addressing these challenges requires integrated planning that combines spatial analysis with community engagement and institutional coordination. Global initiatives such as the climate justice framework of the United Nations Development Programme (UNDP) and warnings from the United Nations Environment Programme (UNEP) on heatwave risks for older people underscore the urgency of protecting vulnerable groups. In this context, spatially explicit data could enhance the effectiveness of social protection and resilience planning, in order to ensure that no one is left behind (IOM, 2024; UNDP, 2009; UNDP, 2022; UNEP, 2025).

Meanwhile, this study highlighted the structural inequities associated with climate adaptation in Thailand. Under a distributive justice framework, disaster response and adaptation budgets were often disproportionately concentrated in large urban centers and key economic regions such as Bangkok and its vicinity. In contrast, the spatial analysis revealed that provinces with high poverty levels and high climate risk, particularly in the Northeast and Northern (statistically significant hotspots like Khon Kaen, Buriram, and Lamphun), tended to receive fewer investments and less structural support. This imbalance produced a spatial gap between "resource-rich" and "resource-poor" regions, thereby reinforcing pre-existing social and economic inequalities. Recognizing these spatially differentiated outcomes, which align with international findings, reinforces the argument of distributive justice and underscores the need for targeted interventions that are both place-specific and socially inclusive (Apraku et al., 2025; Leichenko & Silva, 2014; Singh et al., 2025).

Under a procedural justice framework, limitations in participatory governance remain apparent. Vulnerable groups, especially children and the elderly, are often overlooked in climate-related decision-making processes, which undermines the inclusiveness and responsiveness of adaptation policies. Strengthening the role of local mechanisms, such as Subdistrict Administrative Organizations (SAOs) and municipalities, would allow more systematic inclusion of vulnerable populations in policy design and implementation. This would ensure that climate adaptation is not merely a technical exercise but also a social process that addresses the lived realities of at-risk communities (Ogunbode et al., 2024; UNDP, 2009).

Furthermore, the threat multiplier effect of climate change specifically affects the human security of vulnerable groups in different ways:

(1) As vulnerable children in the Northeastern region rely heavily on agriculture and expose to prolonged droughts, rural poverty is exacerbated. This climate-induced stress directly threatens children's human security by impacting food security with reduced crop yields and household income as well as limiting access to education due to economic hardship and potential forced migration of families.

(2) Vulnerable elderly in the Northern region, particularly in mountainous and remote areas as exemplified by the outlier province Mae Hong Son, and in the peri-urban metropolitan hotspots: the large elderly population is acutely susceptible to health impacts. Climate-related hazards when combined with geographical constraints limit their access to health services due to distance, difficulties of transportation, and the uneven distribution of medical personnel, hence structurally reflecting a severe level of vulnerability. Similarly, the outlier province, Ratchaburi, highlights hidden vulnerabilities in areas that might otherwise be overlooked.

Addressing these inequities requires moving beyond national averages and using spatial indicators to meet localized needs, so adaptation strategies are tailored to the demographic and geographic realities of each province.

Table 3. Policy recommendations

Dimension	Region/Examples of Provinces	Policy Recommendations
Health	Northern Region – Chiang Mai, Mae Hong Son	Establish Mobile Health Units for elderly populations in mountainous and remote rural areas, alongside investments in subdistrict-level health infrastructure.
Human Security	Northeastern Region – Khon Kaen, Buriram, Maha Sarakham	Develop drought-resilient water and agricultural systems, coupled with scholarship programs for children in impoverished households to reduce forced migration.
Urban Environment	Greater Bangkok Metropolitan Area – Pathum Thani, Nonthaburi	Design urban planning strategies for elderly hotspots, including safe public spaces, accessible public transport, and expanded green areas to mitigate PM2.5.
Disaster Risk Management	Southern Region – Nakhon Si Thammarat, Songkhla	Invest in Early Warning Systems and flood–storm protection infrastructure, including dedicated shelters for children and elderly populations.

4.5 Policy Recommendations

Building on the findings, region-specific strategies are essential for translating spatial evidence into actionable climate adaptation. These recommendations integrate health, human security, urban environment, and disaster risk dimensions, and are tailored to the socio-demographic and geographic realities identified in the study. Table 3 summarizes proposed interventions, emphasizing both immediate protective measures for vulnerable populations and long-term structural investments that can enhance resilience and equity across regions.

5. Conclusions

This study investigated the spatial dimensions of climate-related public health risks in Thailand, specifically focusing on vulnerable children and the elderly under the RCP8.5 high-emission scenario for the near future (2016–2035). By adopting a "Scenario-based Stress Test" approach, this research uniquely integrated future climate risk projections with current data on structural vulnerability via the MPI. The objective is to identify geographic "lock-in" areas where future environmental hazards are likely to exacerbate existing social inequalities, so as to provide spatially explicit evidence to support equitable climate adaptation planning.

The findings revealed pronounced regional disparities that challenge "one-size-fits-all" policies. The Northeastern region consistently emerged as a critical "High-High" cluster, particularly in provinces such as Khon Kaen and Buriram, where high concentrations of child multidimensional poverty intersected with intensifying composite climate risks. While the index was composite, regional context suggested these were primarily driven by the susceptibility to drought and heat stress in the area. Conversely, the Northern region exhibited distinct "Low-High" outliers, such as Mae Hong Son, where vulnerability was driven by the density of elderly populations in remote and mountainous terrain with limited healthcare access, rather than aggregate climate exposure alone. These results validated the utility of the MPI over simple population counts, thus offering a more granular lens for targeting structural deprivation.

As regards the implications for policy and regional applicability, these findings had direct implications for the National Adaptation Plan and spatial planning legislation in Thailand. Policymakers should prioritize the identified hotspots for targeted interventions such as implementing climate-resilient social safety nets for children in the Northeast to address water and heat security as well as establishing mobile healthcare units for the elderly in the remote North. Furthermore, the methodological framework employed here, i.e., overlaying Global Climate Models with multidimensional poverty data holds significant potential for replicability across the Association of Southeast Asian Nations. Neighboring countries with similar socio-economic structures and availability of data, such as Vietnam and Lao People's Democratic Republic, could adopt this approach to identify hidden vulnerabilities and advance regional climate justice.

While this study provided a robust national overview, future research should aim to refine the spatial resolution to the sub-district (Tambon) level to capture localized heterogeneities that provincial data may obscure. Additionally, future works should incorporate dynamic demographic modeling to account for migration patterns and aging trends, rather than relying on static population data. Integrating these dynamic variables will further enhance the precision of climate adaptation strategies, so as to ensure that resources are allocated not just to where the hazards are, but to where the people are least able to tackle.

Author Contributions

Conceptualization, P.T. and C.P.; methodology, C.P.; software, C.P.; validation, P.T. and C.P.; formal analysis, P.T. and C.P.; investigation, P.T. and C.P.; resources, C.P.; data curation, C.P.; writing—original draft preparation, C.P.; writing—review and editing, P.T.; visualization, C.P.; supervision, P.T.; project administration, P.T.; funding acquisition, P.T. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

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Conflicts of Interest

The authors declare no conflicts of interest.

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