Mapping Vulnerability to Climate Change: A Census-Based Approach to Typhoon Risk Assessment in the Philippines

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INTRODUCTION

As climate change intensifies typhoon frequency and severity, disaster risk management demands precise identification of the most vulnerable populations to ensure effective interventions in resource-limited settings. Over the past five decades, tropical cyclones have been linked to 1,945 recorded disasters, resulting in 779,324 fatalities and approximately US$ 1.4 trillion in economic losses (World Meteorological Organization, 2024). In this context, identifying the most vulnerable populations through reliable and accessible indicators is crucial for improving disaster preparedness, risk communication, and targeted assistance.

Vulnerability is defined as “the degree to which a system or population is likely to experience harm due to exposure to perturbations or stress” (De Sherbinin et al, 2019, p.41). Key factors contributing to vulnerability are the population’s susceptibility and lack of resilience to the impacts of hazards (Leis & Keinberger, 2020; Dujardin et al., 2020).

Previous studies sought to measure vulnerability to climate hazards such as flooding (De Albuquerque et al., 2015; Dujardin et al., 2020; Leis & Keinberger, 2020), hurricanes (Schempp et al., 2019; Enenkel et al., 2018), and typhoons (Healey et al., 2021) in different parts of the globe. In the Philippines—ranked first globally in the World Risk Index (Bündnis Entwicklung Hilft & IFHV, 2024)—several initiatives have aimed to measure climate-related vulnerabilities. These include a barangay-level Social Vulnerability Index (SVI), using 18 census-based indicators to examine flood impacts from Topical Storm Washi (Ignacio et al., 2015), and the Risk and Vulnerability Assessments (RVA) of Regulano (2021), which incorporated hazard, exposure, sensitivity, and adaptive capacity using population dynamics.

A more recent approach, the Housing Vulnerability Index (HVI) for typhoon risks in the Philippines using the 2015 census, was developed by Healey et al. (2021). This used Principal

Component Analysis (PCA) to reduce 25 indicators to seven housing vulnerability dimensions, explaining 74% of the variance in a national-level model.

Despite these advances, vulnerability assessments remain constrained by inconsistent indicator selection and limited validation using actual loss and damage data. This study addresses that gap by developing a Typhoon Vulnerability Index (TVI) using a robust set of indicators that are conceptually grounded, empirically validated, and replicable across typhoon events and areas.

METHODS

This study develops a Typhoon Vulnerability Index (TVI) by reviewing 44 social vulnerability indicators. Multicollinearity tests and a stepwise regression were done using loss and damage data from Typhoon Rai/Odette (2021) and Typhoon Goni/Rolly (2020) as the dependent variable. This step identified statistically significant variables, followed by a manual selection process that balanced theoretical relevance and empirical robustness.

The final model includes 10 census-derived indicators from the 2020 Census of Population and Housing. Coefficients from the regression analyses of both typhoon models (Odette and Rolly) were compared to assess differences and similarities in how vulnerability factors explain levels of loss and damages across two events. To reduce the influence of differing variable scales, indicators were standardized (z-scored) using the mean and standard deviation of affected municipalities.

The Typhoon Vulnerability Index was computed using the most statistically robust model, providing a sound basis for assessing vulnerability in future typhoon events. This approach ensures a strong empirical foundation across two geographically distinct contexts while allowing for the selection of indicators for national-level vulnerability mapping. The resulting TVI scores were then calculated for each municipality and mapped using R and RStudio.

$$TVI_j = \sum_{i=1}^{10} (Indicator\ value_{ij} \text{ x } Indicator\ weight_i)$$

Where:

- TVI_j = Vulnerability score for municipality *j*
- Indicator value= The actual percentage value of indicator *i* in municipality *j* (e.g., Percentage of houses with poor walling materials)
- Indicator weight= normalized weights of indicator *i*, considering most statistically robust model
- $i \in \{1, 2, \ldots, 10\}$ = Selected indicators

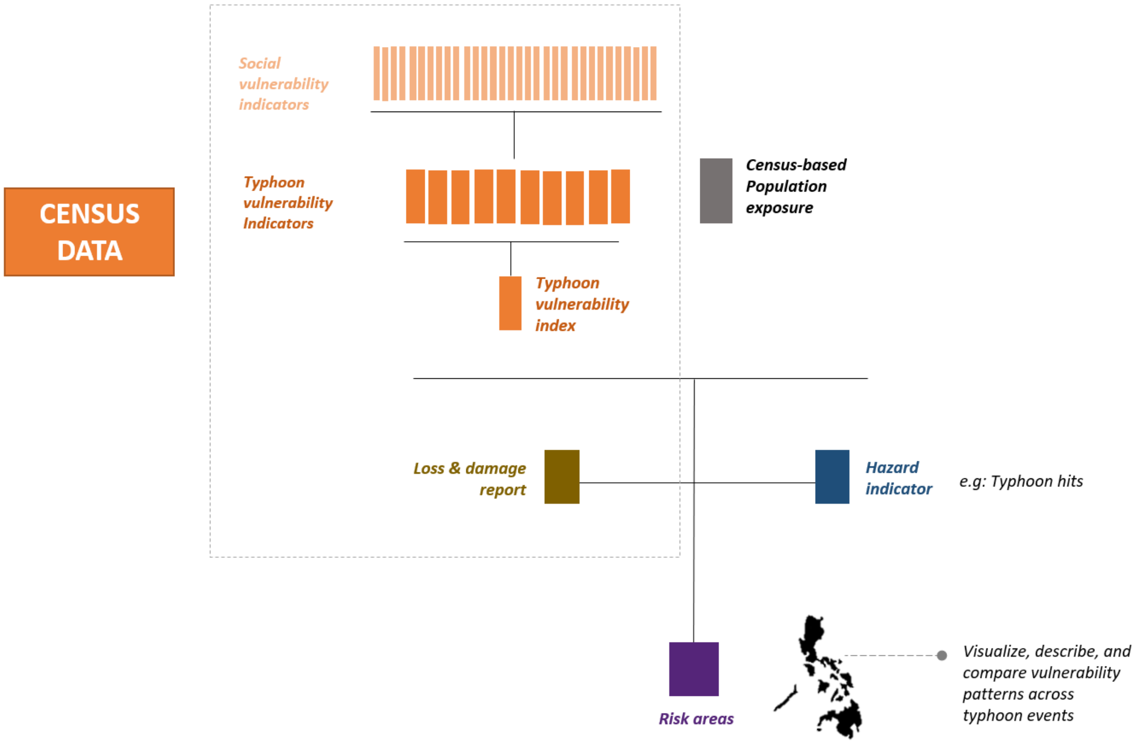

Figure 1. Typhoon Vulnerability Index computation (adapted from Leis & Kienberger, 2020)

RESULTS

A. Typhoon vulnerability indicators

The final regression model showed that Typhoon Odette explained 28.45% of the variance in affected population (Adj. R^2= 0.2845) with 8 out of 10 indicators statistically significant (p <0.05). Typhoon Rolly's model had a slightly higher adjusted R^2 of 0.3639 but only 2 statistically significant indicators. Most indicators had VIF < 5, suggesting minimal multicollinearity.

Six out of ten indicators showed a positive association with vulnerability. These include percentage of old houses, female adults without secondary education, percent rural, recent migration to lower-class municipalities, percent individuals with ages under 20 years, and over 64 years.

Interestingly, four indicators showed statistically significant negative associations with vulnerability, such as percentage of houses with poor walling materials, households headed by women, overall percentage of women, and lack of connection to piped sewer systems.

Table 1. Linear regression and VIF results of social vulnerability indicators for Typhoon Rolly and Typhoon Odette

Indicator (Y)	Coefficient		Variance Inflation Factor (VIF)	
	Rolly	Odette	Rolly	Odette
(Intercept)	3.05824	3.93575*	-	-
Percentage of houses with poor walling materials	0.02112	-1.07031***	3.845377	2.316715
Percentage of old houses (30 years or more)	0.16605	1.60229***	3.312390	2.058173
Percentage of households with female head	-3.07619*	-2.08683	2.715072	1.909338
Percentage of individuals under 20 years old	-1.50992	1.03655	4.773293	5.112189
Percentage of individuals over 64 years old	2.88653	1.59452	7.878798	5.035114
Percentage of female adults with no secondary education	-0.42755	0.75999**	3.521164	2.884659
Percent female	-4.16486	-7.88856*	3.633083	2.164906
Percent rural	0.06927	0.29956***	3.327590	2.256447
Percentage of individuals migrated to lower-class municipality	3.90208	2.18202*	1.540416	1.279904
Percentage of houses not connected to a piped sewage	0.62094**	-0.15300*	1.539226	1.150526
Rolly	Residual standard error: 0.2363 on 40 DF Multiple R-squared: 0.4911; Adjusted R-squared: 0.3639 F-statistic: 3.861 on 10 and 40 DF; p-value: 0.001029			
Odette	Residual standard error: 0.3346 on 452 DF Multiple R-squared: 0.3; Adjusted R-squared: 0.2845 F-statistic: 19.37 on 10 and 452 DF; p-value: < 2.2e-16			

Note : Significance codes : 0= ‘***’ ; 0.001= ‘**’ ; 0.01= ‘*’ ; 0.05= ‘.’

These findings challenge common assumptions. For instance, the negative association between female-headed households and vulnerability may reflect the role of and responsibility given to women in the disaster preparedness of Filipino households. This dynamic is often attributed to females being tied at home and household activities (Reyes & Lu, 2016).

Likewise, homes with poor walling materials may reflect adaptive strategies in high-risk areas, where residents anticipate frequent rebuilding rather than investing in rigid housing infrastructure. Lastly, age-related indicators (under 20 and over 64 years old) were not significant in either model, suggesting that age alone may not be predictive of typhoon vulnerability at the municipal level.

B. Mapping typhoon vulnerabilities in the Philippines

The typhoon Odette-based model was selected for national mapping because it offered better statistical fit and captured vulnerability across a broader set of municipalities with consistent hazard intensity. The mapping of typhoon vulnerability scores per municipality offered a new lens through which disaster risk can be assessed at the local and national scale. Figure 2 shows high-vulnerability areas including Northen Luzon, Bicol region, Eastern Visayas, Bohol province, and the CARAGA region. These are characterized by higher rurality and persistent socio-economic disadvantages.

Focused geographic snapshots show that urbanized areas and city centers generally exhibited lower vulnerability, except for densely populated areas in the National Capital Region, which showed elevated levels of risk due to exposure concentration (figure 3).

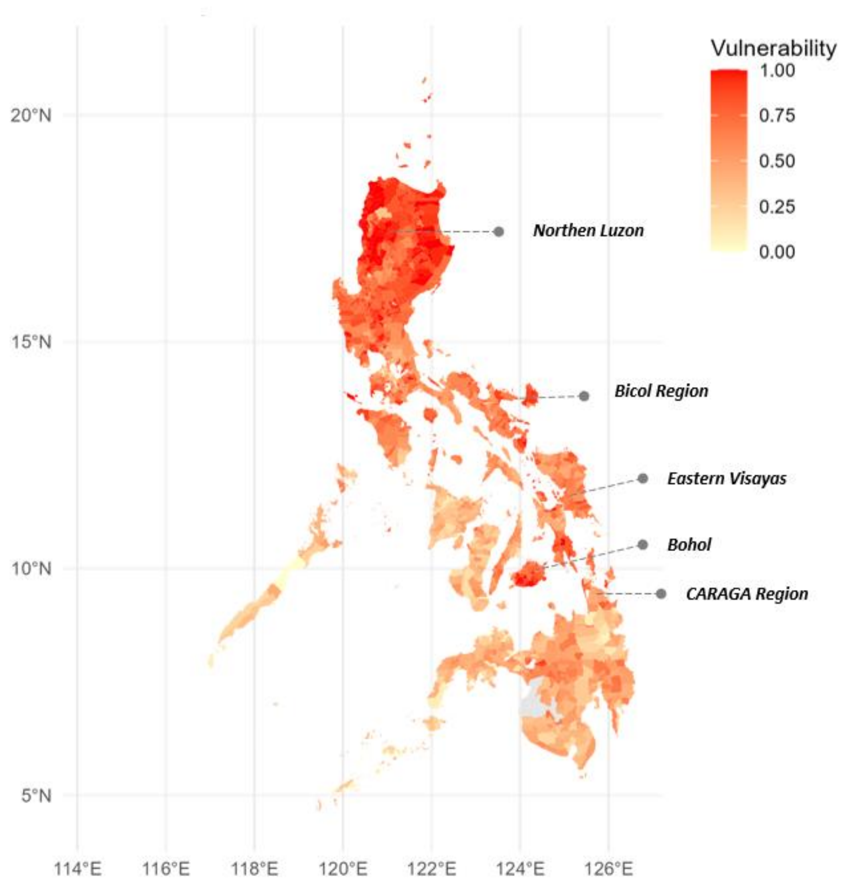

Figure 2. Typhoon vulnerability across the Philippines generated using loss and damage from Typhoon Rai (Odette) model.

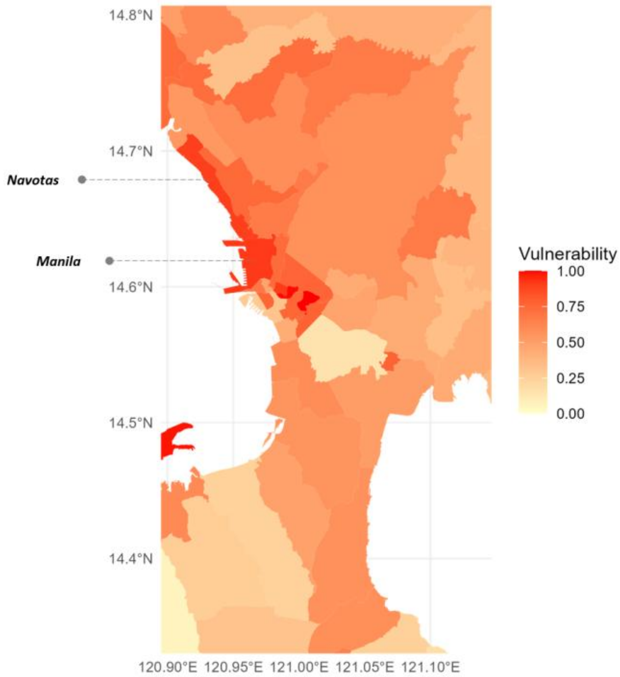

Figure 3. Typhoon vulnerability in the National Capital Region (NCR).

Tagbilaran, the capital city of Bohol exhibits lower vulnerability scores, likely due to better access to resources and services. Nearby rural municipalities show higher vulnerability (figure 4), consistent to other indicators that have positive association to typhoon loss and damage.

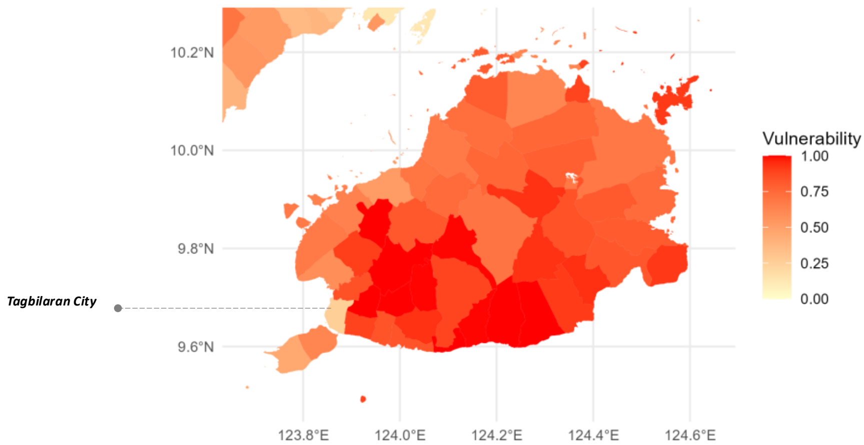

Figure 4. Typhoon vulnerability in Bohol province.

CONCLUSION

The findings underscore the importance of validating theoretically grounded social vulnerability indicators using both recent population data and actual disaster loss and damage records. While the maps in this study offer an overview of typhoon-related vulnerability across the Philippines, the static nature of census data may limit the model's ability to reflect recent changes in population exposure to rapidly evolving hazards like typhoons.

To address this limitation, future research can enhance the model's robustness by testing the TVI against other typhoon events and incorporating additional hazard characteristics such as track, windspeed, and rainfall intensity. Furthermore, integrating dynamic population estimates derived from social media user activity or mobile phone call details records, could enable near real time assessments of vulnerability.

Nevertheless, by integrating statistical modelling with spatial visualization, the Typhoon Vulnerability Index developed in this study offers a replicable and scalable tool for local governments and climate resilience actors in the Philippines. It also highlights the complex and sometime counterintuitive ways in which gender dynamics, housing conditions, and access to resources shape communities' vulnerability to typhoons.

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