Does Safer Housing Save Lives? An Analysis of Typhoon Mortality and Dwellings in the Philippines

Sarah Healey[1], Sophie Lloyd[1], Jasmine Gray[1], and Aaron Opdyke[1]

[1]School of Civil Engineering, The University of Sydney, Sydney, NSW Australia

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Abstract

Storms globally account for the highest loss of life among weather-related natural hazards. This study examines the relationship between components of housing vulnerability and typhoon related mortality in the Philippines at a municipal level between 2005 and 2015 using a Hurdle Negative Binomial (HNB) model. We find that in municipalities with greater prevalence of extreme substandard housing, unimproved household water sources, crowdedness, lower housing density, and less secure tenure, people are more likely to die from typhoons when controlling for typhoon proximity and wind speed as well as coastal proximity. We recommend targeted investments in safer housing in municipalities of Region VIII, Region XI and the Bangsamoro Autonomous Region of Muslim Mindanao (BARMM) where correlations between housing vulnerability and disaster mortality are the highest. This research provides new knowledge of the link between housing and mortality in disasters, offering one of the first national scale assessments to quantify the contributions of safer housing in reducing loss of life in disasters.

1 Introduction

Over the last 20 years, 157 typhoons have made landfall in the Philippines, killing an estimated 20,000 people, leaving over 600,000 homeless, and affecting an estimated 126 million people (CRED, 2021). The typhoon death toll from typhoons in the Philippines is five times that of neighbouring Taiwan and twelve times that of Japan, despite similar typhoon exposure (CRED, 2021; Fudeyasu et al., 2014). Housing has an important role in shaping disaster vulnerability, with inadequate housing exacerbating disaster related losses (Kunii et al., 1995; Rodríguez et al., 2018; Fothergill and Peek, 2004). Housing characteristics such as construction material, tenure, and crowdedness have been used to quantify housing vulnerability and point to potentially heightened mortality (Morenikeji et al., 2017; Tusting et al., 2019; Ren et al., 2019; Yust et al., 1997; Englhardt et al., 2019). Despite the relevance of housing vulnerability in explaining disaster losses, studies assessing the relationship between housing and mortality from natural hazards at a sub-provincial level in the Philippines and across multiple typhoon events are limited (Chang and Chang, 2019; Yonson et al., 2018). Understanding where and why relationships between housing and mortality exist is necessary to provide benchmark standards for prioritisation of disaster risk reduction.

Target A of the Sendai Framework for Disaster Risk Reduction focuses on the human losses sustained during disasters, targeting the "[substantial reduction in] global disaster mortality by 2030, aiming to lower the average per 100,000 global mortality rate in the decade 2020–2030 compared to the period 2005–2015" (UNISDR, 2015, p. 12). The ability to achieve this goal hinges on improving our understanding of the distribution and determinants of vulnerability so that governments and policy makers can better focus disaster risk reduction (DRR) efforts to communities most in need. This research thus aimed to answer the following question: **What is the relationship between housing vulnerability and typhoon related mortality in the Philippines?** The research objectives were: (1) to assess the link between housing vulnerability and typhoon associated mortality in the Philippines between 2005 and 2015; and (2) to identify regions in the Philippines where disaster risk reduction should be focused to reduce mortality.

We begin by reviewing existing disaster literature on current understanding of housing vulnerability and its relationship to mortality, both globally and within the Philippines. We then draw on dimensions of housing vulnerability existing at a municipal level across the Philippines to construct a Hurdle Negative Binomial (HNB) model of typhoon-related mortality between 2005 and 2015. Finally, we discuss where to focus disaster risk reduction efforts and reduce typhoon-related mortality in the Philippines.

2 Background

Vulnerability considers the physical, social and political environment of a population (Rodríguez et al., 2018; Adger, 2006), and is manifested through factors such as socioeconomic status, gender, age, level of wealth, access to resources and provision of safe housing (Yonson et al., 2018; Eadie et al., 2020). The most vulnerable often reside in hazard exposed areas, creating a perpetuation of disaster risk due to repeated destruction and loss following disasters (Cardona et al., 2012; Bourque et al., 2007). It is no coincidence that almost 90% of disaster related deaths occur in low income countries (Bourque et al., 2007). Vulnerability has been widely used in disaster scholarship with foci on varying dimensions to explain these inequalities (Blaikie et al., 1994; Comfort et al., 1999; Bankoff, 2003; Cutter et al., 2003; Bankoff, 2019).

2.1 Housing Vulnerability

Housing vulnerability manifests through unsafe conditions such as poor housing materials and construction, limited access to amenities, and household socioeconomic conditions such as crowdedness (Morenikeji et al., 2017; Tusting et al., 2019; Ren et al., 2019; Yust et al., 1997; Englhardt et al., 2019). Up to 87% of earthquake related fatalities occur within homes due to substandard building material and poor housing construction (Kunii et al., 1995; Glass et al., 1977). Typhoon associated mortality across Southeast Asia has also been linked to substandard building materials and construction practices. For example, inadequately anchored roofs can lift-off in high winds, leaving occupants exposed and damaging walls (Mas et al., 2015; Goyal et al., 2012). Housing is also often included in prominent vulnerability frameworks (Cutter et al., 2003). Under this umbrella, housing vulnerability can be conceptualised as consisting of structural characteristics, housing-type characteristics, provision of amenities, and socioeconomic factors (Healey et al., 2022; Morenikeji et al., 2017; Tusting et al., 2019; Ren et al., 2019; Yust et al., 1997; Englhardt et al., 2019; Glass et al., 1977; Goyal et al., 2012).

2.2 Counting Disaster Mortality

Fundamental challenges remain in quantifying global disaster mortality patterns (Rodríguez et al., 2018; Chang and Chang, 2019; Arnold, 2019). Data from the International Disaster Database (EM-DAT) (CRED, 2021) estimates total disaster mortality between 1996 and 2015 to be 1.35 million, however this is likely a significant underestimation (Green et al., 2019). The "lack of agreement [among researchers] on what constitutes a disaster related death" (Rodríguez et al., 2018, p. 360), contributes to reporting inconsistencies that give an inaccurate picture of deaths following disasters. To help address this issue, deaths can be separated into impact and post-impact stages (Shultz et al., 2005). Examples of impact stage deaths can include drowning during a tsunami, flood or typhoon event, asphyxiation via burial under a landslide or trauma from being hit by moving objects (NDRRMC, 2013). Post-impact deaths are largely a result of illness or lack of services to disaster stricken communities and can be difficult to quantify or attribute to a particular cause as the death can occur a substantial time after the hazard has passed (Rodríguez et al., 2018).

Accurately counting and reporting the deceased therefore remains a significant challenge, particularly in low- and middle-income countries where health systems are underfunded (Mikkelsen, 2015; Chang and Chang, 2019; Yonson et al., 2018; Rodríguez et al., 2018; Arnold, 2019). Medical examiner reports or the official death registry provide the most robust disaster mortality statistics (Shultz et al., 2005; Rampatige et al., 2014), however the services and infrastructure required for official reporting require continued improvement as "approximately 60% of deaths go unaccounted for in registration systems globally" (Mikkelsen, 2015; Clarke et al., 2018; Green et al., 2019, p 454). Moreover, damage to critical infrastructure during disasters means obtaining accurate mortality data via an official registry is difficult (Arnold, 2019). Mortality data is therefore often collected informally. For example, following Hurricane Maria which hit Puerto Rico in 2017, mortality data was collected from household surveys and by physically counting the deceased, noting any obvious cause of death (Arnold, 2019).

While studies that assess and map the spatial distribution of disaster mortality and vulnerability are common (Rabby et al., 2019; Nguyen et al., 2019; Lawal and Arokoyu, 2015; Chen et al., 2013; Mavhura et al., 2017), few studies have been conducted at national levels with granular detail, instead focusing on singular disaster cases (Klinenberg, 2000), or on a single region or state (Kim et al., 2019; Zahran et al., 2008). These approaches are useful in uncovering localised variations in vulnerability and mortality, however there is a need to investigate wider trends.

2.3 Housing Vulnerability and Typhoon Related Mortality in the Philippines

The Philippines is exposed to an average of 20 typhoons per year (Bankoff and Christensen, 2016; Cinco et al., 2016). Typhoons are characterised by wind speeds greater than 118 km/h, with storm diameters ranging from 65 km to over 1600 km and associated storm surges of around 6 m in height (Bankoff and Christensen, 2016). Epiphenomena typically associated with typhoons, including flooding, storm surges and landslides are often responsible for a large proportion of fatalities when compared to the primary phenomena of heavy rain and high winds (Cinco et al., 2016; Gray et al., 2022). Causes of death such as drowning, electrocution or trauma from being hit by objects mainly arise from flooding and storm surges, whereas asphyxiation or crushing can be the result of landslides (Chang and Chang, 2019). Considering the combination of high exposure and variable degrees of population vulnerability, much of the Philippines is considered at substantial risk to typhoons (Yonson et al., 2018). Between 1980 and 2013, typhoons caused over 30,000 deaths in the Philippines and affected roughly 5 million people each year (Yonson et al., 2018). The average damage per typhoon is estimated to amount to around US $41 million, placing additional stress on its economy (Boyce, 1993).

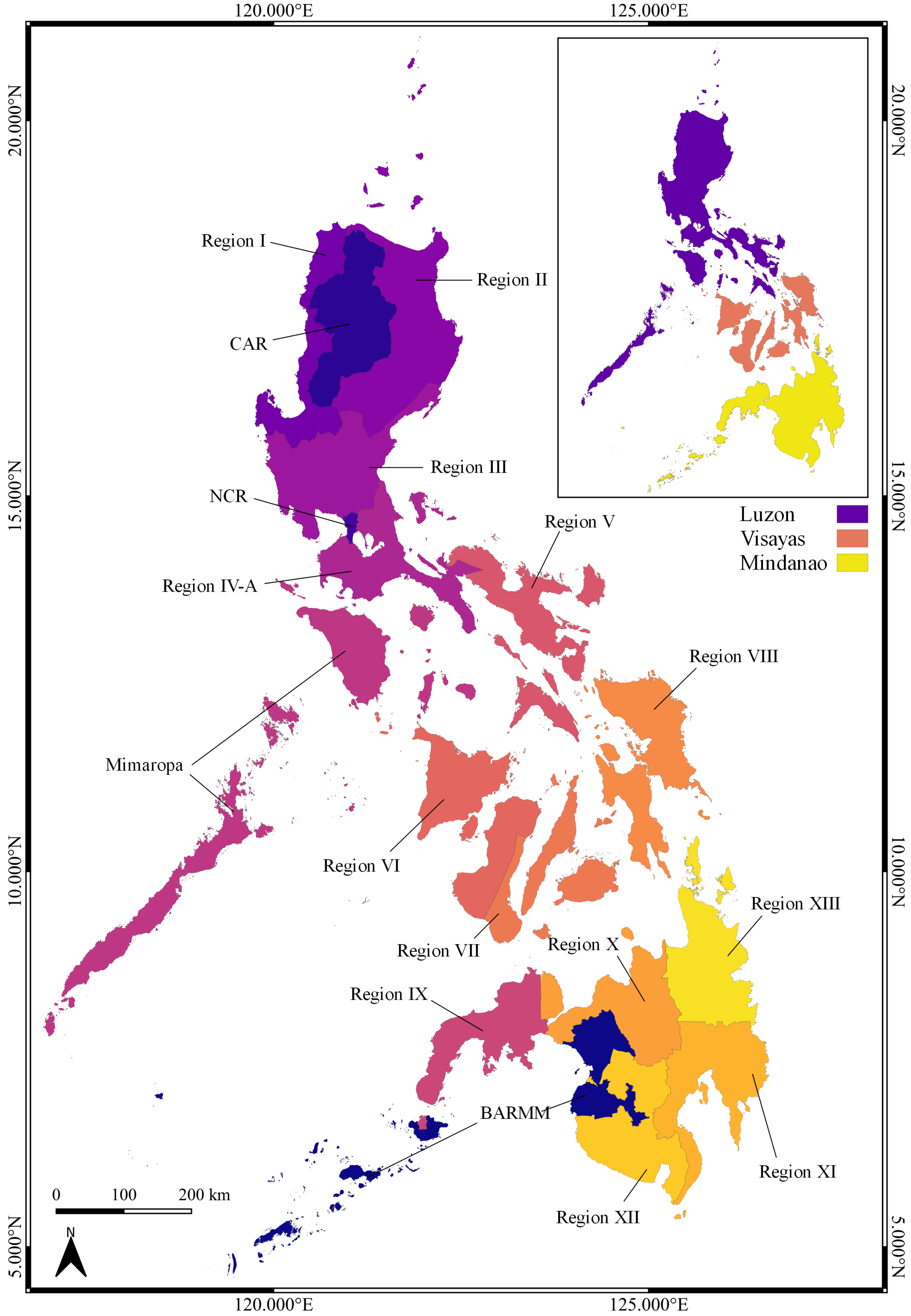

Figure 1: Administrative regions of the Philippines and main island groups

The Philippines comprises three main island groups running North to South; Luzon, Visayas and Mindanao (shown in Figure 1). The northern island of Luzon is exposed to the bulk of typhoon tracks when compared to the central islands of the Visayas and Mindanao in the south (Bankoff and Christensen, 2016; Bankoff, 2003). In the context of typhoons, housing vulnerability is a significant contributor to systemic inequality and enhanced mortality (Rygel et al., 2006; Ching et al., 2015;

Nguyen et al., 2019; Rabby et al., 2019). However, existing research that maps housing vulnerability in the Philippines is generally limited to a small selection of regions, leaving national gaps (Toda et al., 2016; Prasetyo et al., 2020; Naelga et al., 2021).

3 Methods

To investigate the relationship between housing vulnerability and typhoon mortality in the Philippines, we tested a suite of regression models including Poisson, Negative Binomial (NB), Zero-Inflated Poisson (ZIP), Zero-Inflated Negative Binomial (ZINB), and Hurdle Negative Binomial (HNB).

3.1 Data Collection

The data used for this study included: (1) housing vulnerability principal components developed in Healey et al. (2022); (2) typhoon mortality and housing damage data; (3) exposure characteristic data. To provide a consistent geographic signature to the housing and mortality data, municipal level data was linked to known administrative boundary codes. Municipal boundaries were sourced from the United Nations Office for Coordination of Humanitarian Affairs (UNOCHA) and derived from the Philippines Statistics Authority (PSA) and Philippines National Mapping and Resource Information Authority (NAMRIA). The municipal boundary codes were linked to known boundaries as of April 2016, the most recent data available. The exposure characteristic data included coordinates of data points measured at 6-hour intervals along each typhoon track. The coordinates provided the spatial signature for this data type and allowed for mapping alongside the municipal boundaries. Ethics approval for the collection and use of mortality data was granted by University of Sydney Ethics Committee under protocol number 2021/341.

3.1.1 Housing Vulnerability Data

Seven components of housing vulnerability previously derived in Healey et al. (2022) were used in this study. These dimensions were based off 25 housing indicators that encompassed both the physical and social dimensions of housing drawn from the 2015 Philippines census on population and housing collected by the Philippines Statistics Authority (PSA). We used 2015 data as it was the most recent available dataset at the time of publication. The selected housing vulnerability components are summarised in Table 1 below. Full details of how each housing vulnerability component was determined can be found in Healey et al. (2022).

3.1.2 Mortality and Housing Damage Data

Typhoon mortality data was sourced from Situational Reports (SitReps) published by the National Disaster Risk Reduction and Management Council (NDRRMC) following hazard events. The NDRRMC was established by the Philippine Government in 2010 and is responsible for all aspects of disaster management in the Philippines. SitReps summarise the impacts of a disaster, outlining characteristics of the hazard, economic costs, infrastructure damage, affected populations, casualties, and missing persons. SitReps pertaining to typhoons that caused death in the Philippines between 2005 and 2015 were downloaded from the NDRRMC database, or from ReliefWeb where reports were not published by the NDRRMC. Casualty information including age, gender, cause, place of residence, and place of death was then extracted from each SitRep and coded using the known administrative boundaries to provide a consistent geographic signature across events. For use in the regression models, typhoon mortality was considered as the numerical count of deaths in each municipality following each typhoon that made landfall between 2005 and 2015.

Housing damage data was also sourced from the SitRep published following Typhoon Yolanda (Haiyan) in 2013, one of the deadliest typhoons to make landfall in the Philippines (Cinco et al., 2016). The damage data included the percentage of homes in each municipality totally destroyed by Haiyan, and the percentage of homes partially destroyed. Percentages were calculated with respect to the total number of occupied homes per municipality. Housing damage data was used to provide an example of the spatial overlap between housing damage and mortality sustained during Typhoon Yolanda (Haiyan), aiding to the discussion surrounding the importance of safe housing and building practices particularly when many individuals fail to evacuate and shelter at home during typhoons (Ching et al., 2015).

3.1.3 Exposure Characteristic Data

Exposure characteristic data was sourced from the United States National Oceanic and Atmospheric Administration (NOAA) which provides satellite data of all typhoons between the years 1956 and 2018. Sequential storm track data measured at 6-hour intervals during each typhoon included the date, time, sustained wind speed (reported in knots) and coordinate location. Data covering the period between 2005 and 2015 was then extracted from the larger database with our reference time period. The distance between each typhoon track and the centroid of Philippine municipalities was measured using the 'Distance Matrix' feature in QGIS. The sustained wind speed measured at the closest identified measurement point along each track was then extracted and converted to kilometres per hour. It is acknowledged that the wind speed experienced in each municipality is not necessarily congruent to the measured sustained wind speed at the closest data point, particularly when the distance between a municipality and typhoon track is large, however for the scope of this research it was considered a reasonable assumption. Additional scope exists to use meteorological wind speed models, as was done by Fang et al. (2021), to more accurately determine the wind speed experienced in each municipality. Proximity to the coastline was also identified as an important characteristic that influences housing damage and typhoon mortality (Mas et al., 2015). Coastal municipalities were identified as those that touched a surrounding ocean. Coastal municipalities were assigned binary code '1', and inland municipalities were assigned '0'.

3.2 Regression Modelling

Regression was used to assess the relationship between housing vulnerability and typhoon-related mortality in the Philippines. Individual housing vulnerability components sourced from Healey et al. (2022) were the independent variables while typhoon mortality count was the dependent variable. Typhoon mortality was measured as the number of deaths in each municipality during each typhoon that made landfall in the Philippines between 2005 and 2015. An offset term was used to account for municipal population size since municipalities with larger populations were expected to see higher death counts, not necessarily because of increased housing vulnerability or exposure, but purely because there were more residents. Offset terms such as population are commonly used in regression studies to standardise mortality counts (Feng, 2020). Exposure characteristics including the minimum distance between municipalities and each typhoon track, as well as the sustained wind speed measured at the closest data point on each typhoon track were included as control variables. Whether the municipality was located on the coastline or not was also included as a control variable. The controls were applied to determine whether the observed trends in mortality were indeed explained well by housing vulnerability components, or whether hazard characteristics were perhaps more significant in determining typhoon mortality. Table 1 outlines the variables used in the regression analysis.

Before use in the proposed regression models, independent and control variables were first screened for collinearity. Zero-order correlations and Variance Inflation Factors (VIF) were analysed in Or-

Table 1: Variables and data sources

Variable	Source	Variable	Description	Measure
Housing	PSA Census (2015)	Independent	PC1 (Housing Density)	Continuous
			PC2 (Housing Quality)	
			PC3 (Crowdedness)	
			PC4 (Tenure Security)	
			PC5 (Extreme Substandard Housing)	
			PC6 (Drinking Water Source)	
			PC7 (Structural Integrity)	
Mortality	NDRRMC SitReps	Dependent	Municipal mortality count per typhoon	Count
Exposure	NOAA	Control	Distance (km)	Continuous
			Wind Speed (km/h)	Continuous
			Coastal	Binary
Population	PSA Census (2015)	Offset	Logarithm of municipal population	Continuous

dinary Least Squares (OLS) regression, a method adapted from Zahran et al. (2008). Collinearity between variables was not identified as all variables showed correlation of less than 0.3 and greater than -0.3 (a common cutoff value in vulnerability studies). VIF scores ranged from 1.002 to 1.227 (average 1.071), and were therefore all within the acceptable range.

The dependent variable was also inspected for outliers prior to model scrutiny. The highest three mortality counts of 2,678, 1,375, and 902 deaths were determined to be outliers and were removed to improve model performance as we expect different underlying processes may explain these high mortality counts. The next highest mortality count was 402, significantly less than the smallest of the identified outliers. We found that after removing these outliers, the variance in errors (RMSE) across all models was drastically reduced from an average of 8.198 to an average of 2.309.

3.2.1 Model Selection

To select the most robust model for the number of typhoon deaths across the Philippines, we considered five regression models. Poisson, Negative Binomial (NB), the Zero-Inflated Poisson (ZIP), the Zero-Inflated Negative Binomial (ZINB), and the Hurdle Negative Binomial (HNB) were investigated as they are suitable for count-type dependent variables and have been widely adapted and scrutinized across numerous studies containing large zero counts (Prasetijo and Musa, 2016; O'Rourke and Vazquez, 2019; Pew et al., 2020; Musal and Aktekin, 2013; Esnard et al., 2018), including disaster mortality studies (Kim et al., 2019; Zahran et al., 2008).

The dispersion of the data was initially screened to check if Poisson assumptions were met. Equidispersion is assessed by determining the ratio between the mean and variance. A variance ratio of 1 indicates equidispersion. If the variance ratio is greater than 1, the data is said to be overdispersed. The variance ratio for this study was 1085.79, substantially larger than 1 suggesting that the data was overdispersed. This overdispersion is illustrated in Figure 2, as the data is highly left-skewed toward the low counts. We hypothesised that the Poisson model was not suitable, and other models which can handle overdispersion were investigated. Model selection was largely dictated by the large number (99.7%) of zero counts. The high frequency of zeros and low mortality counts in general (ie. less than 5) resulted in a very small mean, which caused the overdispersion. A high frequency of zero values is not unusual in disaster mortality studies, especially when looking at mortality on a national scale (Kim et al., 2019). In the context of this study, it makes sense that the number of zero counts is so high since the number of deaths in every municipality for each typhoon event has been recorded, regardless of whether the municipality was affected or not.

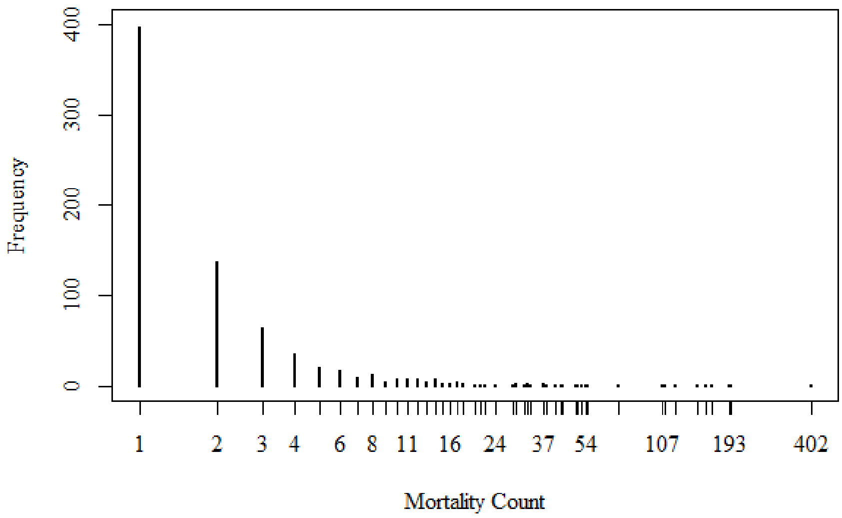

Figure 2: Municipal mortality count per typhoon between 2005 and 2015 for municipalities with one or more deaths

NB, ZIP, ZINB, and HNB models handle overdispersion, and have been used in mortality studies since low death counts and low means of the dependent variable are common (Kim et al., 2019; Musal and Aktekin, 2013; Zahran et al., 2008; Weng et al., 2016). NB models are particularly useful when the sample variance is much larger than the sample mean, but are not suited to zero-inflated datasets. Zero-inflation occurs when there is an excessive count of observed zeros, and was checked by examination of the dependent variable. Since 99.7% of mortality count values are zero, and upon inspection of Figure 2, the data was classified as zero-inflated. The zero-inflated and hurdle models (ZIP, ZINB, HNB) are the superior choice when there is an excessive proportion of observed zero values, as they produce two separate models for the zeros and count data. ZIP and ZINB rely on the assumption that both structural and sampling zeros exist in the dataset. In the context of modelling typhoon-related mortality, we hypothesised structural zeros to be instances of no deaths in regions not affected by a particular typhoon, and sampling zeros to be instances of no deaths in affected regions. Since the source of zeros is not known it was important to also consider a hurdle model (HNB).

Like ZIP and ZINB, hurdle models create two separate regression models for the zeros and count data. In contrast, hurdle models do not separate the structural and sampling zeros but rather group all the zeros together in one model, and all the positive counts in another model. Hurdle models therefore assume that all the zeros in the dataset are derived from the same source. The positive count model can be described by a truncated Poisson, negative binomial or geometric distribution, while the zero distribution is commonly binomial. Since the dataset did not follow a Poisson distribution, a hurdle negative binomial (HNB) model was proposed. HNB used a truncated negative binomial model with logit link for the positive count data, and a binomial model with log link for the zeros. Since the zero-inflated and hurdle models (ZIP, ZINB, HNB) produce separate analyses for the zeros and count data, both can be studied independently. A more in depth analysis can therefore be achieved as the researcher can understand why no deaths are occurring, in addition to why deaths may or may not be occurring in affected regions.

R statistical software was used to run the Poisson, NB, ZIP, ZINB, and HNB models. To inform model selection, Akaike Information Criteria (AIC) and Root Mean Square Error (RMSE) were used (Akaike, 1998; Cavanaugh and Neath, 2011). AIC is commonly used to compare the fit of generalised linear models, zero-inflated and hurdle models, and has been widely used in similar model selection processes (Feng, 2020; Kim et al., 2019). Since AIC is based on the log likelihood and the number of parameters in the model, it will be larger for models with more variables. Therefore, the AIC value is compared across proposed models with an equivalent number of parameters, with a comparatively lower AIC indicating a better fit. The RMSE between the observed and predicted values of each model was also screened to inform model selection. The RMSE is a measure of the standard deviation of the residuals, with a smaller value indicating a better model fit as the deviation of errors is minimised. The final HNB model selected to investigate the relationship between housing vulnerability and typhoon mortality was given by:

$$P(Y=y)=\begin{cases}\pi; & y=0,\\ (1-\pi)P(Y|Y>0); & y=1,2,\ldots\end{cases} \tag{1}$$

where π: probability of observing zeros

$$P(Y|Y>0)=\frac{\Gamma(y+\alpha)}{\Gamma(y+1)\Gamma(\alpha)}\left(\frac{\mu}{\mu+\alpha}\right)^{y}\left(\frac{\alpha}{\mu+\alpha}\right)^{\alpha}\left[1-(\frac{\alpha}{\mu+\alpha})^{\alpha}\right]^{-1}; \quad y=1,2,\ldots \tag{2}$$

where μ is the mean and α is the dispersion parameter and μ & $\alpha>0$.

4 Results

We first present a descriptive summary of the compiled typhoon mortality data, discuss the considered models, and then present our final Hurdle Negative Binomial (HNB) results which identify relationships between components of housing vulnerability and typhoon mortality.

4.1 Descriptive Statistics

Between 2005 and 2015 there was a total of 11,902 typhoon related deaths in the Philippines. Over the 10 year study period there were 126 typhoons that made landfall, causing 11,705 deaths. There were 11 typhoons that occurred offshore and hence were not included in this study. These 11 typhoons caused 197 deaths, accounting for 1.66% of the 11,902 total deaths between 2005 and 2015. Since only accounting for a small percentage of total deaths, these offshore typhoons were deemed suitable to exclude from the analysis. Of the included 11,705 deaths, 96 (0.82%) were missing province location and 487 (4.16%) were missing municipality location information. The NDRRMC SitReps report the location for each case as ‘place of death’ and the ‘residential address’ of the individual. Of the deaths with a reported municipality location, 9,877 (88%) had no recorded place of death whilst only 552 (4.92%) were missing the residential address locator. Where both place of death and residential address were provided, the former was used as the municipal location associated with a case. If the place of death was not recorded, the residential address was used to define the municipal location where the death occurred. Due to the high percentage of cases not assigned a place of death, and the fact that many of people die within their homes or close-by (ie. within the same municipality), the residential address was assumed to be a suitable proxy where place of death was not given (Ching et al., 2015; NDRRMC, 2013).

There were a total of 1,647 municipalities in the Philippines. Mortality counts recorded in each municipality following individual typhoon events ranged from 0 to 2,678 deaths. 2,678 was the highest mortality count recorded, and occurred in Tacloban City following Typhoon Yolanda (Haiyan) in 2013. The next two highest mortality counts were 1,375 deaths and 902 deaths which occurred in neighbouring Tanuan and Palo, also following Haiyan. These three death counts were considered outliers as they were 500 or more counts higher than the next recorded count of 402 deaths which occurred in New Bataan following Typhoon Pablo (Bopha) in 2012. 99.98% of municipal mortality counts were less than or equal to 20, with 99.94% less than or equal to five deaths. 99.7% of municipalities recorded zero deaths following individual typhoon events that made landfall between 2005 and 2015. We record deaths irrespective of whether a municipality was affected by an individual typhoon or not, explaining the high frequency of zero scores and generally low counts of deaths in each municipality. A zero value exists likely because the typhoon occurred a large distance away. Fang et al. (2021) use a radius of 500 km from the eye of the typhoon to define the envelope of wind hazard, suggesting that at distances greater than 500 km, the wind speed is unlikely to be destructive and cause losses.

Figure 3 illustrates the spatial distribution of mortality counts at a municipal level across the Philippines (also see Figure 1 for geographic reference of provinces and regions). For the purpose of mapping, mortality counts were represented as the total death count in municipalities for the 126 typhoons that made landfall in the Philippines between 2005 and 2015 (rather than on an individual event basis). Mortality rate, measured per 100,000 people, is also shown in Figure 3. The observed differences when population size was considered further justify the need to use municipal population as an offset term. Municipalities in Region VI and VIII in the Visayas show the greatest difference when mortality count is adjusted for population size.

902 of the 1647 municipalities in the Philippines (55%) were located on the coast. The mean death count (excluding zeros) from typhoons that made landfall between 2005 and 2015 was 5.53 deaths for coastal municipalities and 2.82 deaths for inland municipalities. In total, there were 428 coastal municipalities which recorded one or more death from an individual event during the study period, and 338 inland municipalities which recorded one or more death. There were 18 coastal municipalities which recorded 20 more deaths during an individual typhoon, while only 2 inland municipalities recorded more than 20 deaths from a single event. The maximum number of deaths recorded in a coastal municipality during a single typhoon was 193, whereas the maximum for an inland municipality was 402. Table 2 summarises the descriptive statistics for each studied variable.

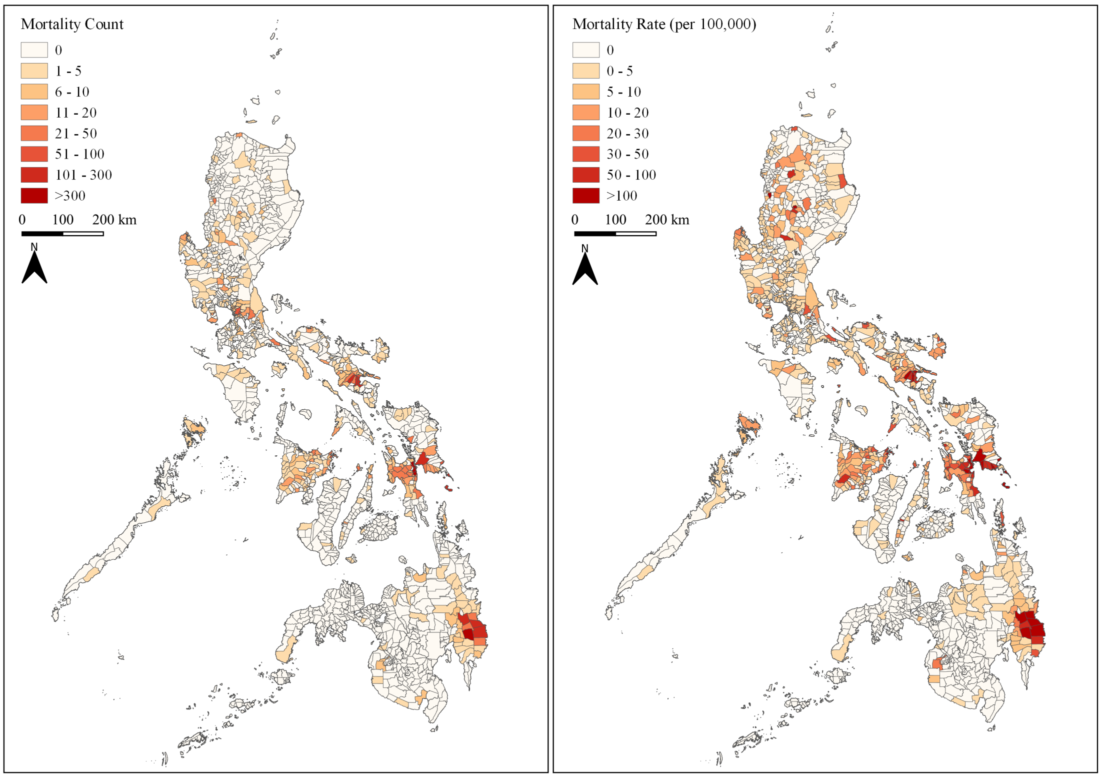

Figure 3: Mortality count (left) and mortality rate per 100,000 people (right) by Philippine municipality for typhoons between 2005 and 2015

Table 2: Summary of descriptive statistics

Variable Type	Name	Mean	SD	Min	Max
Independent	PC1 (Housing Density)	0.00	1.000	-1.470	6.130
	PC2 (Housing Quality)	0.000	1.000	-4.470	1.883
	PC3 (Crowdedness)	0.000	1.000	-2.288	5.814
	PC4 (Tenure Security)	0.000	1.000	-2.583	4.771
	PC5 (Extreme Substandard Housing)	0.000	1.000	-0.890	11.861
	PC6 (Drinking Water Source)	0.000	1.000	-3.285	3.714
	PC7 (Structural Integrity)	0.000	1.000	-3.447	5.012
Dependent	Mortality	0.046	7.037	0	2678 (402)[1]
Control	Distance	635	402	1	2187
	Wind Speed	110	66	37	315
	Coastal	902[2]	-	0	1
Offset	Population	61,311	123,377	184	2,936,116

[1]Maximum value for all records (including outliers) is reported, with maximum value used in regression (no outliers) parenthesised.
[2]Frequency of coastal municipalities is reported.

4.2 Model Selection

Table 3 outlines the relative fit measures of Akaike Information Criteria (AIC) and Root Mean Square Error (RMSE) which were used to compare the goodness of fit of the five proposed models. Coefficient exponents (Exp(B)), standard errors (SE), and significance levels for each model are also presented. Even though the RMSE was found to be the smallest for the Poisson and ZIP models, these were unsuitable based on AIC comparison. The ZINB and HNB models were the two best performers based on comparatively low AIC and RMSE values (10875/1.389 and 10487/1.447 respectively). We then used Vuong's hypothesis test to compare the significance and goodness of fit of the ZINB and HNB models (Vuong, 1989; Feng, 2021), finding that HNB provided a significant improvement ($p < 0.05$) over ZINB. HNB was therefore selected as the preferred model.

The suitability of HNB was confirmed by an assessment of Random Quantile Residuals (RQRs). Dunn and Smyth (1996) developed RQRs as a way of calculating continuous residuals when the dependent variable is discrete. RQRs have been subsequently validated as a means of determining the adequacy of zero-inflated models, such as the HNB (Feng, 2020, 2021). Normalisation of residuals evident in the RQR scatter plot, histogram and Q-Q plot further proved the appropriateness of the HNB model.

4.3 Hurdle Negative Binomial (HNB) Regression Model

Table 4 reports HNB regression results for typhoon mortality counts. Results from both the count model and zero model are reported. In the count model, significant variables which suggest the greatest increase in mortality count are extreme substandard housing, drinking water source and household crowdedness. For every 1 SD increase in extreme substandard housing, that is homes that are constructed from trapal (tarpaulin) or makeshift materials, mortality the odds of mortality increase by 55.4% (SE 0.084). Likewise, results show that for every 1 SD increase in household crowdedness, there is an observed 40.9% increase in the odds of a mortality (SE 0.186). For every 1 SD change in drinking water source, or unimproved water sources, mortality odds are increased by 47.5% (SE 0.096). Additional significant variables show that living in a coastal municipality is correlated with a reduced odds of mortality by 44.4%, an unexpected result (SE 0.179). A 1 SD change in tenure security (indicating less secure tenure), represented by reduced ownership tenure and increased land rental tenure, increases the odds of mortality by 21.3% (SE 0.095). For every 1 km/h increase in sustained wind speed, measured at the closest data point on each typhoon track, the odds of a mortality increase by 0.8% (SE 0.001). The only significant term which resulted in reduced mortality was housing density, resulting in a 25.9% decrease in the odds of mortality for each 1 SD increase (SE 0.069).

Housing quality, structural integrity, and distance to the typhoon track were found to be not statistically significant predictors of mortality. Housing quality had a negative relationship (factor of 0.889, SE 0.102), whereas distance to the typhoon track shows minimal association with mortality (factor of 0.999, SE 0.000). Structural integrity, measured as the partial adoption of more robust roofing (concrete/masonry and galvanised iron) and wall materials (concrete/brick/stone), had a positive relationship to mortality (factor of 1.111, SE 0.112).

A majority of the variables (8 out of 10) in the zero model contradict the findings from the count model and those supported by theory. Meaningful outcomes of the zero model are limited however by the amount of missing values in baseline mortality data, which exist due to reporting challenges and the limited resources in the Philippines to capture typhoon death counts more accurately (Chang and Chang, 2019; Arnold, 2019). Our zero model should therefore be considered with caution, and is not as useful as the count model in representing the relationships between housing vulnerability and typhoon mortality. For the purpose of this research, the zero model was important to remove the

Table 3: Comparison of model results

Parameter	Poisson	NB	ZIP	ZINB	HNB
	Exp(B)	Exp(B)	Exp(B)	Exp(B)	Exp(B)
		Count Model			
Intercept	0.000*** (0.054)	0.000*** (0.068)	0.000*** (0.062)	0.000*** (0.268)	0.000 (16.35)
PC1 (Housing Density)	0.732*** (0.013)	0.771*** (0.016)	0.644*** (0.016)	0.709*** (0.070)	0.741*** (0.069)
PC2 (Housing Quality)	0.879*** (0.021)	0.828*** (0.027)	0.937*** (0.026)	0.831** (0.099)	0.889 (0.103)
PC3 (Crowdedness)	1.510*** (0.025)	1.119*** (0.039)	2.061*** (0.033)	1.151 (0.181)	1.409** (0.186)
PC4 (Tenure Security)	1.155*** (0.016)	1.297*** (0.023)	0.850*** (0.018)	1.208*** (0.083)	1.213*** (0.095)
PC5 (Extreme Substandard Housing)	1.395*** (0.006)	1.448*** (0.013)	1.320*** (0.008)	1.621*** (0.083)	1.554*** (0.084)
PC6 (Drinking Water Source)	1.447*** (0.019)	1.505*** (0.026)	1.095*** (0.022)	1.433*** (0.091)	1.475*** (0.096)
PC7 (Structural Integrity)	0.879*** (0.018)	0.995 (0.024)	1.019 (0.021)	1.141 (0.121)	1.111 (0.112)
Distance	0.986*** (0.000)	0.989*** (2.000e-04)	0.997*** (0.000)	0.999 (0.000)	0.999 (0.001)
Wind Speed	1.017*** (0.000)	1.015*** (0,000)	1.007*** (0.000)	1.009 (0.001)***	1.008*** (0.001)
Coastal	0.914*** (0.033)	0.696*** (0.046)	0.782*** (0.034)	0.602*** (0.155)	0.556*** (0.179)
		Zero Model			
Intercept			0.002*** (0.117)	0.000*** (0.298)	0.000*** (0.112)
PC1 (Housing Density)			0.524*** (0.029)	0.485*** (0.079)	0.674*** (0.031)
PC2 (Housing Quality)			0.996 (0.048)	0.913 (0.105)	0.880*** (0.031)
PC3 (Crowdedness)			2.017*** (0.073)	1.504*** (0.170)	1.042 (0.069)
PC4 (Tenure Security)			0.634*** (0.041)	0.771*** (0.084)	1.117*** (0.043)
PC5 (Extreme Substandard Housing)			0.920*** (0.027)	1.125*** (0.055)	1.211*** (0.028)
PC6 (Drinking Water Source)			0.929** (0.044)	1.025 (0.100)	1.376*** (0.047)
PC7 (Structural Integrity)			0.969 (0.041)	1.076 (0.126)	0.904*** (0.042)
Distance			1.007*** (0.000)	1.010*** (0.000)	0.991*** (0.000)
Wind Speed			0.992*** (0.001)	0.992*** (0.001)	1.011*** (0.000)
Coastal			0.905 (0.087)	0.704*** (0.159)	1.037 (0.086)
		Model Fit			
AIC	32538	18105	19249	10875	10487
RMSE	1.377	5.958	1.376	1.389	1.447

Significance codes: 0.01 ’*’; 0.05 ’**’; 0.1 ’***’
Robust standard errors are in parentheses.

Table 4: Hurdle negative binomial model results

Parameter	Coefficients	Exp(B)	Std. error	z value	Pr (> |z|)
	Count Model (Truncated neg bin with log link)				
Intercept	-20.380	0.000	16.350	-1.246	0.213
PC1 (Housing Density)	-0.210	0.741	0.069	-4.353	0.000***
PC2 (Housing Quality)	-0.118	0.889	0.102	-1.155	0.248
PC3 (Crowdedness)	0.343	1.409	0.186	1.844	0.065**
PC4 (Tenure Security)	0.193	1.213	0.095	2.033	0.042**
PC5 (Extreme Substandard Housing)	0.441	1.554	0.084	5.233	0.000***
PC6 (Drinking Water Source)	0.389	1.475	0.096	4.044	0.000***
PC7 (Structural Integrity)	0.106	1.111	0.112	0.942	0.346
Distance	0.000	0.999	0.000	-0.646	0.518
Wind Speed	0.008	1.008	0.001	7.358	0.000***
Coastal	-0.586	0.556	0.179	-3.274	0.001***
	Zero Model (Binomial with logit link)				
Intercept	-15.190	0.000	0.112	-136.250	0.000***
PC1 (Housing Density)	-0.394	0.674	0.031	-12.885	0.000***
PC2 (Housing Quality)	-0.128	0.880	0.045	-2.846	0.004***
PC3 (Crowdedness)	0.041	1.042	0.069	0.595	0.552
PC4 (Tenure Security)	0.111	1.117	0.043	2.575	0.010**
PC5 (Extreme Substandard Housing)	0.192	1.211	0.028	6.829	0.000***
PC6 (Drinking Water Source)	0.319	1.376	0.047	6.779	0.000***
PC7 (Structural Integrity)	-0.101	0.904	0.042	-2.400	0.016**
Distance	-0.009	0.991	0.000	-29.370	0.000***
Wind Speed	0.011	1.011	0.000	23.264	0.000***
Coastal	0.036	1.037	0.086	0.418	0.676

Significance codes: 0.01 ’*’; 0.05 ’**’; 0.1 ’***’ implications of missing data from the separate count model. The count model is more robust with missing values removed, allowing the results from the count model to be given greater bearing.

5 Discussion

The relationship between housing vulnerability and disaster mortality is complex. In the context of typhoon hazards, studies have shown that while robust construction and strong housing materials provide a crucial defence against losses, only considering the physical form of homes only provides surface level understanding of the observed patterns of vulnerability. The interaction and nuance of factors, such as access to secure land and tenure, offers further explanation of the variability in housing vulnerability across the Philippines, providing potentially deeper understanding as to why some municipalities experience higher mortality following typhoons. Vulnerability literature echoes that these factors are often consequences of systemic socioeconomic and political structures that have continually favoured some households over others (Herbert, 2019; Usamah et al., 2014). Solutions to reducing housing vulnerability and typhoon associated deaths in the Philippines are therefore not simple, and require long-term commitment from policy makers and government agencies.

We discuss our findings by first looking at the influence of historical typhoon exposure on typhoon resistant housing construction. Our results suggest that exposure is perhaps not as important in driving disaster losses as espoused in literature. Access to secure land and housing tenure is then examined more deeply by contextualising the unequal availability of land as a consequence of systemic poverty. Our examination of secure tenure leads to discussion of current urban housing in the Philippines, and how cities represent an interesting intersection between extreme high and low housing vulnerability and losses. The observed spatial overlap between extreme substandard housing, tenure security, and mortality is then discussed by looking at the nature of informal housing in the Philippines. We conclude with a summary of the practical implications and significance of the research, and highlight limitations that can be addressed through future work.

5.1 Exposure and Local Knowledge of Disaster Risk

Our results show a general trend of increasing housing vulnerability from north to south. Municipalities in Luzon show a larger proportion of houses with “low” or “very low” vulnerability when compared to southern islands. Interestingly, the north of the Philippines is exposed to the brunt of typhoon tracks, experiencing many more typhoons than the south of the country. Despite this higher exposure, relative to population, fewer people die in these northern regions with safer housing as a possible explanation. Further, results show typhoon mortality in coastal municipalities is lower by 44% (SE 0.179) as compared to inland municipalities when controlling for other variables. This seemingly counter-intuitive result, which contrasts where the majority of typhoon-related deaths occur, could be explained by the recognition that exposure can create local knowledge and result in the formation of capacities in coastal municipalities. The findings of this study therefore challenge the influence of exposure as the main driver of disaster losses. Results from the north of the Philippines suggest that high exposure in these regions could actually counter vulnerability as residents are encouraged to construct more robust homes (Blaikie et al., 1994; Rodríguez et al., 2018) - a possible link that merits continued study to better understand casual mechanisms.

Recent literature acknowledges ’the power of vulnerability’, suggesting that exposed people have unique lived-in perspectives to disasters that enables them to reduce their inherent vulnerability to hazards (Lizarralde et al., 2021). For example, the Batanes province, located in the northern most area of the Philippines, shows ‘very low’ relative housing vulnerability yet is exposed to approximately 8 of the 20 destructive typhoons that affect the Philippines each year. As a result of consistent exposure to strong winds and destructive typhoons, the Indigenous Ivatan people use building techniques tailored to the extreme conditions (Uy and Shaw, 2008). Traditional homes are commonly constructed using thick stone walls and layered cogon (grass) roofing. Other techniques such as the small and narrow size of doors and windows, as well as the use of thick wooden shutters and bars protect homes from destructive winds. Such examples of local, placed-based knowledge show that the highly exposed can reduce their vulnerability (Hadlos et al., 2022).

5.2 Access to Secure Land and Housing Tenure

Insecure tenure emerges from an array of root causes of vulnerability that are often associated with dynamic pressures such as poverty. Results show that in the BARMM, household crowdedness is pervasive across municipalities in the region. In Mindanao, GDP per capita is five times less than that of the national capital Manila, and over 50% of the population in the BARMM live below the poverty threshold (Herbert, 2019). Poverty in Mindanao and the BARMM is exacerbated by the uneven distribution of secure tenure within the region and decades of conflict between groups. Conflict has been entrenched by discriminatory land administration policies, creating deep-rooted inequality in land ownership (Drbohlav and Hejkrlik, 2017) which perpetuates high vulnerability and increased disaster risk (Herbert, 2019; Sarangani, 2021).

In other regions, insecure tenure has similarly been found to increase housing vulnerability and losses through the association with less robust forms of construction. Less secure tenure and the consequent threat of eviction act as a major disincentive for households to invest in quality materials and construction, particularly in low-income areas (Morin et al., 2016). For example, a study conducted in Cagayan de Oro City in Northern Mindanao (Region X) found that rental tenure was high due to a majority student migrant population (Naelga et al., 2021). Students were drawn to 'cheap' houses, typically comprising lightweight wooden ceilings and galvanised iron roofs. Low-income, greater migration flux and lack of secure tenure perpetuate high relative housing vulnerability. Moreover, insecure tenure and associated unsafe housing is cyclical in the context of typhoon hazards as poorly constructed homes are continually destroyed, increasing the demand on fragile livelihoods and income following a storm and restricting the ability to re-build more robust homes. In another example, affected individuals in Tacloban City, located in Region VIII in the Visayas, that were surveyed following Typhoon Yolanda (Haiyan) in 2013 indicated that recovery simply meant building back to pre-disaster conditions (Su and Le Dé, 2020). Within weeks of Typhoon Yolanda (Haiyan) researchers observed that many of the destroyed homes had been reconstructed using the same unsafe methods and materials as before the disaster (Mas et al., 2015). Policy makers must address the systemic inequality in regions which see great disparities in land and housing tenure security.

5.3 Urban Housing

This study found that urban housing was correlated with lower mortality, for example, the National Capital Region (NCR) experienced relatively few typhoon related deaths over the 10 year study period. The influence of housing density on reduced housing vulnerability and typhoon associated mortality is likely due to more robust forms of construction. Significantly however, there are also uneven pockets of disadvantage that have not been captured by this study. For example, the informal settlements which are growing in Manila appear within a district of relative "low" housing vulnerability. While this study offers insights into the spatial distribution of housing vulnerability and associated mortality at lower administrative levels than previously assessed, these complexities of vulnerability should be further captured in future work to understand more localised patterns.

Levels of household disadvantage are especially wide in urban areas, where the most vulnerable are unable to access affordable land, quality housing and services (Rahman and Amanullah, 2011; Morin et al., 2016). The limited availability of land and housing for the lowest income households means that many often live in informal settings, where construction of basic services such as improved water sources may not be possible. In contrast, lower income households in rural areas may be less reliant on governments for safe water supply, as is the case in Camalig Municipality in Albay Province (Region V) (Usamah et al., 2014), explaining the greater access to improved sources seen in rural regions in both the north and south of the country. Therefore, even though urban centres appear to have low relative housing vulnerability, it is important to contextualise that this study may not have captured localised informal housing. In urban areas, the overall housing vulnerability and manifestation of particular housing dimensions such as extreme substandard housing could therefore be drastically underestimated, also contributing to a significant underestimation in the disaster risk and potential for losses in these areas.

5.4 Extreme Substandard and Informal Housing

Results indicated that extreme substandard housing, or houses constructed from makeshift or limited materials, is the strongest predictor of typhoon related mortality. Maps show that extreme substandard housing was concentrated to municipalities in Region VIII in the Visayas and Region XI in Mindanao. There is also a smaller pocket of municipalities in Region III measuring $>$1.5 SD. This type of housing is common to informal settlements that are also characterised by lack of tenure, lack of services and can be overcrowded (Rahman and Amanullah, 2011). Less secure tenure had a similarly strong relationship with typhoon associated mortality. The failure or inability to enforce building codes reinforces vulnerability (Naelga et al., 2021) Naturally, the places where this occurs are frequently most at risk to typhoon hazards and associated epiphenomena such as flooding and storm surges. For example, Carrasco et al. (2016) found that informal populations housed along riverbanks were disproportionately affected following Typhoon Sendong (Washi) in 2011.

Typhoon Yolanda (Haiyan) which devastated the Visayas in 2013 resulted in high mortality rates and significant housing damage that was particularly observable in Region VIII (Figure 4). Both the high mortality and housing damage experienced in Region VIII could be attributed to the mostly 'very high' observed housing vulnerability of the region, possibly generated through the prevalence of extreme substandard housing and less secure tenure. Figure 4 shows spatial patterns between mortality rates and housing damage in Region VIII following Haiyan. This echoes the importance of safe and robust housing construction in reducing the likelihood of damage and consequent loss of life. Results show that in Leyte, 28% of municipalities reported a death rate higher than 50 per 100,000 people following Haiyan. Results also show that 79% of municipalities in Leyte had >0.5 SD extreme substandard housing, while 67% measured less secure tenure (tenure security component >0.5 SD). Tacloban City had the third highest mortality rate of 1,106 deaths per 100,000 people and reported 25% of homes as completely destroyed following Haiyan (Figure 4). A study by Rahman and Amanullah (2011) found that as of 1997, 38% of the population of Tacloban City were informal settlers, suggesting that the the prevalence of extreme substandard housing is not just a phenomena to arise in the post-Haiyan data used in this study. To address the targets of the Sendai Framework and reduce mortality, policy makers must address the issue of growing informal settlements and unsafe housing construction by improving the availability and access to safer materials and formalised services.

5.5 Government Response to Post-Disaster Housing Recovery

In the Philippines, the wealthy "Filipino power elite" have benefited from increased land ownership and consequent economic and political power that extends the divide between rich and poor (Arroyo and Åstrand, 2019, p. 163). For instance, historical dispossession of Indigenous land across Mindanao

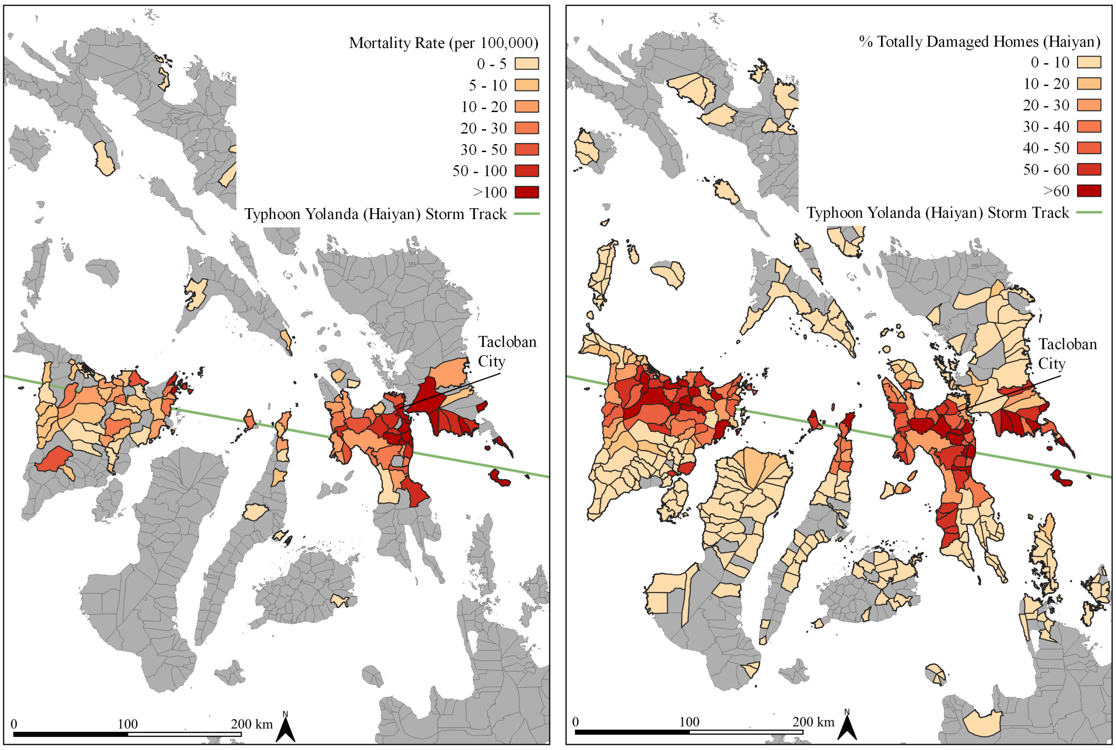

Figure 4: Mortality rate (per 100,000 people) and housing damage in the Visayas Region following Typhoon Yolanda (Haiyan)

and among the minority Muslim population in the BARMM, has caused decades of conflict which has further impoverished Indigenous and minority groups (Herbert, 2019; Drbohlav and Hejkrlik, 2017). Government response is often influenced by the wealthy, enhancing this national divide between those with land and the landless. For example, agrarian reform programs established in the 1970s and 1980s that aimed to even the distribution of land and housing between lower income rural households and wealthier households faced significant push back from wealthy landowners that were also members of the government and civil society (Emtage and Suh, 2005). In the context of disasters, the response of governments has similarly been found to favour wealthy stakeholders over the affected, and often highly vulnerable, population.

As an example, the housing recovery response of the National Housing Authority (NHA) was found inadequate following Typhoon Yolanda (Haiyan), largely due to the delayed reconstruction of permanent housing units. Delays to housing reconstruction were somewhat attributed to the inability to find suitable land, however the decision as to whether land was suitable for reconstruction was left to private contractors. Valuable agricultural land represented most of available land in Haiyan affected regions, and this land was deemed unsuitable for social housing (Arroyo and Åstrand, 2019). It took three years for only 14% of the target number of permanent housing units to be rebuilt (Opdyke, 2017). In the worst hit municipalities of Tanauan and Tacloban City, which sustained mortality rates of 2,499 people per 100,000 and 1,106 people per 100,000 respectively, only 929 houses of the target 15,619 units were built in the two years following the disaster (Arroyo and Åstrand, 2019). This lack of recognition by policy makers in the Philippines for the need of decentralised housing initiatives has furthered the disparity between rich and poor. Similarly, the government centric 'top-down' approach of housing reconstruction following Typhoon Pablo (Bopha) in 2012 was also found to reproduce pre-disaster vulnerabilities. Carrasco et al. (2016) suggest that the lack of community-based reconstruction approaches meant that the needs of residents were not met, resulting in widespread construction of extensions that compromised the safety of houses to future typhoon events.

5.6 Limitations and Future Work

Several limitations are acknowledged in this research. While social aspects of housing including poverty incidence and crowdedness were captured by the housing vulnerability index, additional socioeconomic variables were not considered within the regression model. To improve understanding of the relationship between housing vulnerability and losses, these variables such as household income, gender, age, educational attainment, and participation in the labour force could be used as additional control variables. Moreover, other factors have been shown to effect the ability to receive and understand typhoon warnings, and in some cases can also act as a barrier for evacuation (Ching et al., 2015). Since the ability to understand and respond to warnings by evacuating to safe areas is paramount to save lives, future modelling should consider these dimensions as candidate variables. For example, the elderly have been found to be less likely to understand warnings and have reduced mobility, therefore limiting their capacity to evacuate (Ching et al., 2015), yet the influence of age on mortality has not been considered in this work. Future work could also use interpolation along typhoon tracks to better estimate wind speed at more regular intervals. For example, other studies have used modelling to construct a more accurate gradients of wind speed (Fudeyasu et al., 2014).

6 Conclusion

Our study assessed the relationship between dimensions of housing vulnerability and typhoon related mortality in the Philippines between 2005 and 2015 using a Hurdle Negative Binomial (HNB) regression model. Greater prevalence of extreme substandard housing, unimproved household water sources, crowdedness, lower housing density, and less secure tenure were identified as the housing components with the largest associations with municipal typhoon mortality. While results of the count HNB model were sound, results of the zero model contradicted these findings, potentially due to missing mortality data. Our findings suggest that housing risk reduction interventions would be best focused in municipalities in Region VIII in the Visayas, and Region XI and the BARMM in Mindanao where mortality rates are the highest. Results further highlight that there are lessons to be learned from areas in the north of the Philippines, which are highly exposed yet experience few deaths. While housing vulnerability and typhoon mortality have been previously investigated at subnational levels in the Philippines (Usamah et al., 2014; Yonson et al., 2018), studies often use a case study approach to interrogate mortality from singular typhoon events (Kure et al., 2015; Ching et al., 2015; Mas et al., 2015). To our knowledge, this is the first study to quantitatively link housing vulnerability and loss of life from typhoons at a national scale in the Philippines.

The practical implications of this research offer understanding about the physical and social dimensions of housing associated with typhoon mortality, and identify vulnerable areas of the Philippines that would most benefit from DRR interventions. This research provides evidence showing where DRR efforts need to be better focused to reduce overall typhoon mortality in the Philippines. We make recommendations for both short and long term solutions, such as structural improvements to informal and unsafe houses and land tenure policy reform. The findings of our research provide policy makers in the Philippines with deeper insight into the links between housing vulnerability and typhoon mortality, positioning a pathway for the government to achieve the goals set out in the Sendai Framework. Esteban et al. (2013) simulate a 17% to 58% increase in the direct damage to housing as a result of typhoons in the Philippines by the year 2085, assuming adaptive capacity and housing vulnerability remain constant. DRR interventions must therefore be focused to highly vulnerable regions, irrespective of historical exposure and losses if the Sendai Framework targets are to be met.

The benchmark standards of housing vulnerability and associated losses provided in this study can also be used as a point of comparison to assess the effectiveness of the Sendai Framework. There is scope for this study to be repeated using data from a 2020-2030 study period to identify whether the uneven distribution of housing vulnerability and consequent scale of mortality in the Philippines has been reduced, ultimately proving whether DRR has been successful in the country. Other nations could also adopt a similar research design for typhoons or other hazards, further exploring the the role of safer housing in different contexts in reducing disaster risk.

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