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The measurement of disaster risk: An example from tropical cyclones in the Philippines

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The Measurement of Disaster Risk: An Example from Tropical Cyclones In the Philippines

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Abstract

What shapes people's disaster risk exposure? Using a sub-national (provincial) panel econometric and deductive approach we answer this question by focussing on tropical cyclones, and using the Philippines as a case study for our measurement approach. We construct a new provincial level panel dataset, and use panel estimation methods to assess the influence of socioeconomic (vulnerability), geographic, demographic, topographic (exposure), and meteorological (hazard) characteristics on the resulting fatalities and affected persons from recent tropical cyclones. We find strong evidence that socioeconomic development reduces people's vulnerability and loss of human lives. Further, good local governance is associated with fewer fatalities. Rapid and unplanned urbanization generates vulnerabilities and increases harm. Exposure, including topography, and hazard strength are likewise important determinants. However, disaster impacts on people appear to be influenced much more by vulnerability and exposure, than by the hazard itself. We quantify this difference in order to contribute to policy planning at national and sub-national scales.

1. Introduction

We develop a measurement tool and measure the vulnerability and risk of Philippine provinces to tropical cyclones by measuring the vulnerability of the provinces' exposed people using an evidence-based approach. The Philippines, the most exposed country to tropical cyclone hazards globally, provides a good test-case of our measurement procedure. Our methodology enables prioritization of disaster risk reduction policies at the national and sub-national levels based on the differing vulnerabilities and risk we measure. Existing indices of vulnerability are all inter-country (e.g. Dilley et al., 2005; Peduzzi et al., 2009; Cardona and Carreño, 2013; Welle et al., 2013; Kreft et al., 2015) or very local (e.g. Cutter et al., 2000, 2003; Rygel et al., 2006; Joerin et al., 2014; Creach et al. 2015), but as inputs for evidence-based decision-making, subnational measures of vulnerability have a bigger practical significance.[1]

We use a deductive approach, using an econometric algorithm, to determine the factors that made people vulnerable to disasters based on past experience with tropical cyclones. As Pelling (2013) points out, a deductive approach based on large datasets "adds realism to the analysis" compared to inductive approachs, which are "not empirically verifiable against specific disaster-related outcomes". The importance of measuring precisely and deductively disaster risk lies in the production of "outputs that are meaningful for development action", particularly if the research outputs "are to contribute to development planning" (Pelling 2013, p. 167). A subnational assessment is of practical usefulness for area-specific disaster risk reduction planning (Peduzzi et al., 2009), given that risk and vulnerability are place-specific, and most effective planning is thus also area-specific.

It is widely accepted that the level of socioeconomic development, the characteristics of urbanization, and quality of local governance shape human vulnerability and the risk from disasters,

[1] An example is of an inter-country index is the Disaster Risk Index (DRI), constructed by the United Nations Development Programme (UNDP) to systematically analyse the linkage of vulnerability to development. The DRI is a global index whose purpose is to establish the relative human vulnerability across countries (Peduzzi, Dao, Herold, & Mouton, 2009).

and we operationalize these insights into our measurements. A flurry of subnational studies have examined human vulnerability, using either qualitative or non-econometric quantitative methods. These studies either focus on a specific disaster or undertake comparative analyses of few disasters events (e.g. Hewitt, 1997; Lewis, 1999; Bankoff et ., 2004; Wisner et al., 2004 for some summaries). We adopt a more general approach by looking at experiences across provinces for all tropical cyclones that occurred during recent times. We construct a new provincial-level panel dataset, and use panel data estimation methods with geographical information systems to assess the influence of socioeconomic, topographic, geographic, and hazard characteristics on the resulting fatalities and affected persons in the aftermath of these tropical cyclones.

We note that the theoretical literature offers numerous definitions of vulnerability in the context of natural hazards, but despite a myriad of frameworks, a consensus has yet to be reached. For the purpose of this study, we refer to factors influencing peoples' vulnerability as those economic, social, political, physical, and environmental factors that increase or reduce their ability to withstand the adverse direct impacts of natural hazards. This is a simplified adaptation of the selected existing definitions of vulnerability (Blaikie, Cannon, Davis, & Wisner, 1994; Bohle, 2001; Cardona et al., 2012; Davidson & Shah, 1997; UNDP-DHA, 1994; UNISDR, 2005; Wisner, Blaikie, Cannon, & Davis, 2004).[2]

We use the Philippines as case study for a number of reasons. The country is one of the most at risk countries across the globe (UNU-EHS, 2014). Tropical cyclones, which are the second most frequently occurring hazards in the world, are the most frequent as well as the most lethal and destructive hazards in the Philippines (Jose, 2012). In addition, the Philippines' decentralized system of local governance makes it suitable for a subnational level of inquiry. The provincial local government units (PLGUs) in the country have extensive autonomy; they have the authority to generate local revenues and to decide in allocating development funds across programs and

[2] A more thorough discussion of the conceptual differences and the ways in which vulnerability and resilience have been meausred is available in Yonson and Noy (2016).

projects, including those related to disaster risk reduction and management (DRRM). Furthermore, the country is undergoing urbanization, rapid development, and democratization that are all typical processes for middle-income countries and are all hypothesized to have an impact on disaster risk.

This research aims to contribute to efforts to refine disaster risk and vulnerability assessment tools aimed at mainstreaming the integrated concerns of disaster risk and climate change into the the entire development planning cycle.[3]

The Philippines passed landmark laws on climate change adaptation (CCA), and on DRRM in 2009 and 2010, respectively. Among others, these laws require the local government to integrate CCA and DRRM into local development decisions. Given the lag in the implementation of these laws and the 2005-2010 period covered in this study, our results can also be considered as establishing a point of reference in assessing the effectiveness of the implementation of these laws at the local level. Specifically, the results can serve as suitable benchmark against which to compare the future levels of vulnerability and disaster risk across provinces as well as the outcomes of most recent changes in policy and practice of DRRM.

As quick preview of our results, we find strong evidence that the level of socioeconomic development provides protection and builds human capacities, thereby reducing vulnerability and disasters impacts. Topography and hazard patterns are important determinants, but we find that disaster impacts on people are influenced more by vulnerability and exposure than by the hazard itself. Rapid and unplanned urbanization increases people's vulnerability and exposure to harm. Importantly from a policy lens, the quality of local governance can significantly alter the gravity of disaster impacts on people.[4]

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[3] In the Philippines, the provincial planning cycle comprise of the following processes: 1) provincial development and physical planning; 2) investment programming; 3) budgeting, project implementation; 4) and monitoring and evaluation. The country's Disaster Risk Assessment (DRA) methodology is contained in its Guidelines on Mainstreaming Disaster Risk Reduction in Subnational Development and Land Use/ Physical Planning in the Philippines (NEDA, 2008).

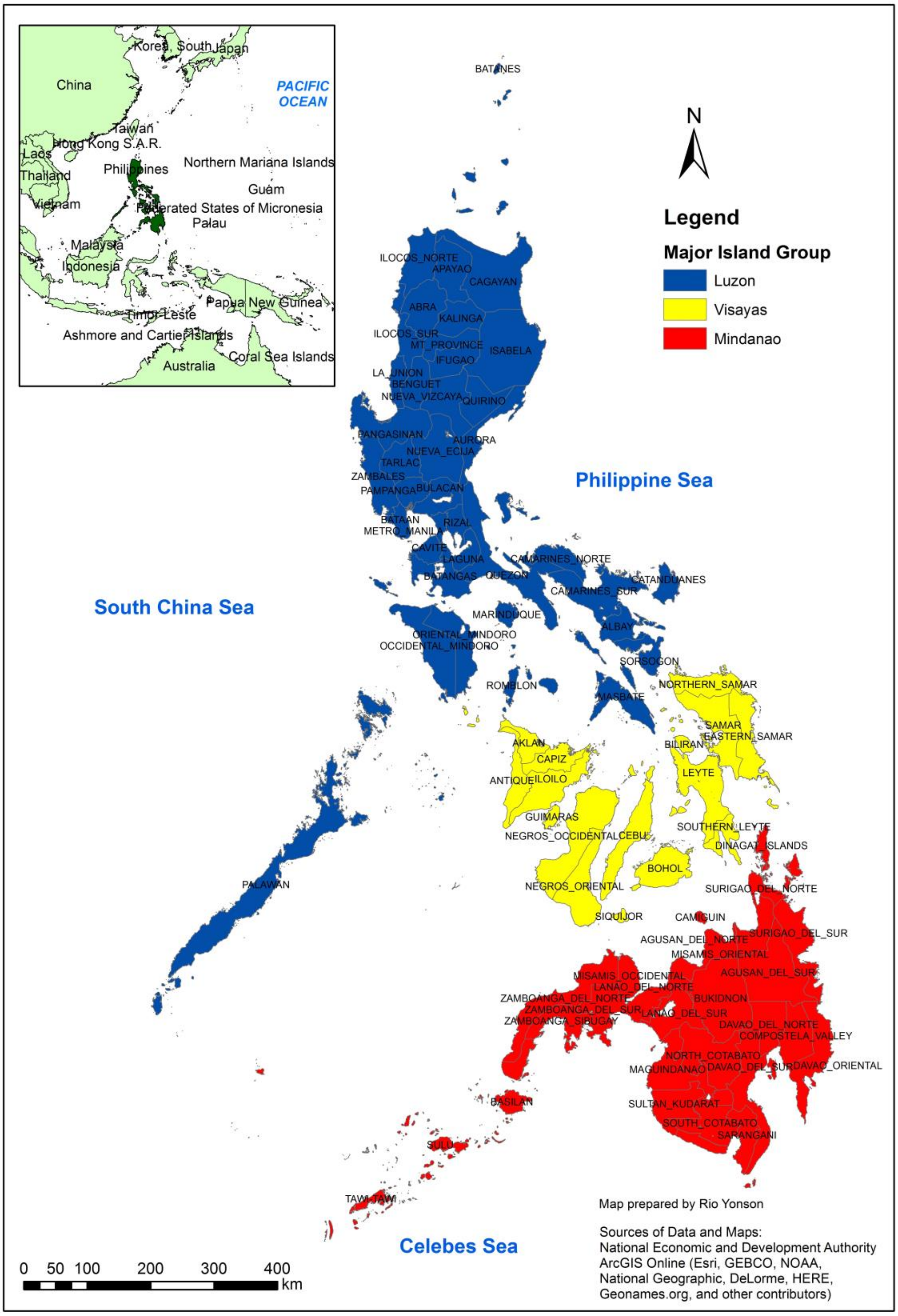
[4] These results are largely consistent with the existing inter-country empirical work adopting a similar quantitative approach (Anbarci, Escaleras, & Register, 2005; Kahn, 2005; Kellenberg & Mobarak, 2008; Noy, 2009; Peduzzi et al., 2009; Raschky, 2008; Toya & Skidmore, 2007). These results are likewise consistent with related in-depth studies on the Philippines using different methods (Antilla-Hughes & Hsiang, 2013; Gaillard et al., 2007; Israel & Briones, 2014).

The paper is organized as follows: Section 2 provides a background on tropical cyclone-related disasters and on development in the Philippines. Among others, we initially explore the aspects of development that influence vulnerability using descriptive statistics and existing accounts on experiences with tropical cyclone-induced disasters. Section 3 briefly presents selected related work across disciplines, and identifies the gap we aim to fill. Section 4 presents the risk model adopted and translated for use in our retrospective-deductive assessment, and estimation method, and determing the data we use. Section 5 presents our results and findings, while Section 6 provides general conclusions, policy implications and next steps.

2. Background on Tropical Cyclones and Development in the Philippines

The Philippines is an archipelago comprising of 7,107 islands that are grouped into three major groups: Luzon, Visayas and Mindanao (Figure 1). It is located within the Pacific Ring of Fire, as well as along the north Pacific typhoon belt. As of 2013, the country has 81 provinces, a population of over 92 million as of the 2010 Census, and population density of 308 per square kilometre (PSA, 2012; PSA-NSCB, 2015).

Figure 1. Administrative Map of the Philippines



The Philippines passed the Climate Change Act in 2009 and the Disaster Risk Reduction and Management Act in 2010.[5] Even before the corresponding institutional mechanisms were fully implemented, these laws were put to test as the country was hit by a series of lethal cyclones. In 2013, Typhoon Haiyan left a staggering trail of 6,092 deaths, while in 2012 and in 2011, Typhoon Bopha and Tropical Storm Washi claimed 1,248 and 1,258 lives, respectively (NDRRMC, 2014).[6] These three tropical storms were the most lethal globally during the years 2011-2013 (Guha-Sapir, Hoyois, & Below, 2012, 2013, 2014). Moreover, these tropical storms were the most costly disaster events in the Philippines in the said years (NDRRMC, 2014).

The Philippine Atmospheric, Geophysical, Astronomical Services Administration (PAGASA) reports that there have been no indications of decadal changes in tropical cyclone frequency during the period 1948 to 2010(PAGASA, 2014). However, there are observed increases in the intensities of recent tropical cyclone occurrences, which are often considered manifestations of the impacts of climate change (PAGASA, 2011; Yang, Wang, Huang, & Wang, 2015).

As can be seen from Table 1, a total of 652 tropical cyclones entered the Philippines for the period 1980-2013 (PAGASA, 2014). About half of these are reported as destructive having had adverse impacts on people (in terms of fatalities, injuries, and disruption in typical daily activities) and on assets. Column 3 of Table 1 shows the annual number of fatalities from tropical cyclones and associated hazards. The cumulative death toll from 1980 to 2013 reached over 30,000, while average annual fatalities is 885. For each destructive cyclone, an average of 102 persons die. Column 4 of Table 1 shows that about 5 million persons are affected annually, and over 570,000 are affected on average per destructive cyclone. Column 5 shows that costs of damage from tropical cyclones are likewise large. Annual average cost is USD355 million. Damage costs were highest in

[5] These laws are "often in advance of so many European countries" (Shepherd et al., 2013). The Special Representative of the UN Secretary-General on DRR has been quoted as saying that these laws are the "best in the world" and indicate a shift from a reactive to a proactive approach in addressing disasters (Ginnetti et al., 2013).

[6] In the Philippines, a typhoon is a tropical cyclone with a maximum wind speed of above 118 km per hour (kph), while a tropical storm (TS) has a maximum wind speed of 64-118 kph. A tropical depression (TD), has a maximum wind speed of 63 kph (PAGASA, undated).

2012 and 2013, mainly due to Typhoons Bopha and Haiyan, respectively. Average damage per destructive event is USD41 million.

Table 1. Number of Tropical Cyclones and Impacts on Population and Assets, 1980-2013

Year	Number of Tropical Cyclones that Passed the Philippine Area of Responsibility* (1)	Number of Destructive Tropical Cyclones** (2)	Number of Fatalities (3)	Number of Affected Persons (4)	Total Cost of Damages (In Million USD)*** (5)
1980	23	6	143	1,666,498	196
1981	23	7	696	1,750,142	161
1982	21	8	389	2,149,167	193
1983	23	4	126	747,155	49
1984	20	4	2,108	4,105,133	362
1985	17	4	211	1,643,142	136
1986	21	6	171	1,524,301	92
1987	16	6	1,020	3,691,555	199
1988	20	5	429	6,081,572	412
1989	19	7	382	2,582,822	207
1990	20	10	706	6,092,959	524
1991	19	6	5,414	1,815,989	292
1992	16	7	118	1,755,811	199
1993	32	14	827	7,363,591	739
1994	25	12	242	3,054,232	121
1995	16	11	1,356	7,683,526	590
1996	17	10	124	1,255,289	106
1997	14	6	95	2,399,435	35
1998	11	4	490	7,322,133	563
1999	16	9	103	1,793,742	66
2000	18	9	345	7,284,946	169
2001	17	10	440	3,769,262	135
2002	13	5	169	3,546,469	16
2003	25	10	139	3,362,991	77
2004	25	10	1,232	6,966,136	237
2005	17	5	54	1,019,646	46
2006	20	10	1,165	11,253,211	394
2007	13	8	124	2,998,885	60
2008	21	9	673	7,009,725	452
2009	22	16	1,140	12,250,050	923
2010	11	10	136	2,596,587	275
2011	19	19	1,557	9,884,577	628
2012	17	16	1,386	8,006,126	1064
2013	25	11	6,389	21,381,374	2354
Total	652	294	30,099	167,808,179	12,072
Average	19	9 (47% of annual average)	885	4,935,535	355
Average per Destructive Tropical Cyclone			102	570,776	41

Sources: Number of Tropical Cyclones that Passed the Philippine Area of Responsibility (PAGASA, 2014). Number of Destructive Tropical Cyclones, Impacts of Tropical cyclones (NDRRMC, 2014). Disaster impacts (i.e. number of fatalities and affected persons) include those resulting from tropical cyclone-induced flooding, landslide, and storm surge.

*The Philippine Area of Responsibility (PAR) is the area designated for PAGASA to monitor and issue bulletins on the formation and occurrence of tropical cyclone.

**Destructive tropical cyclones are those that had adverse impacts on people and assets.

*** Annual average exchange rates used to convert cost in PhP to USD taken from Bangko Sentral ng Pilipinas (Central Bank of the Philippines) website (BSP, 2014).

Several aspects of Philippine development may influence vulnerability and disaster impacts. Despite the sustained high economic growth rate in recent years, poverty reduction has been disappointing. In 2013, its 7.2% real GDP growth rate was higher than most of its neighbouring countries and almost at par with that of China. However, as of 2012, poverty incidence among population in the Philippines stood at 25.2%, only 1.4 percentage points lower than that in 2006 while the number of poor people increased by 1.1 million (WB, 2014). There is great variation across provinces, with poverty incidence in 2012 ranging from a low of only 3.4% to a high of 73.8%. A recent study estimates that among poor households, at least half are classified as chronicly poor (Bayudan-Dacuycuy & Lim, 2013).

In terms of urbanization, the rapid influx of people into the urban areas has resulted in high levels of urban poverty that translate to greater vulnerability, as well as greater hazard exposure as poor communities expanded further in hazard prone areas (ADB, 2009; Gaillard, 2008; Gaillard et al., 2007; Ginnetti et al., 2013; WB-EASPR, 2003). The encroachment of built-up areas to hazard prone locations has persistently been one of the prevalent land-use conflicts across provinces in the Philippines (Corpuz, 2013). Areas demarcated as hazard-prone are among those with densest human settlements. The consequences of unplanned urbanization, along with the poor enforcement of land-use plans, zoning ordinances and other pertinent policies and laws (such as water, forestry and building codes) combine together in building up exposure and exacerbating vulnerability to disasters (Liongson et al., 2000; Gaillard, 2011; Porio, 2011).

The country's experiences with disasters reveal that governance can largely alter the impacts. In 2011, Tropical Storm (TS) Washi entered the Philippine Area of Responsibility as a Category 1 tropical cyclone. It first hit one of the eastern coastal province in the Caraga Region, Surigao del Sur. There was only one death recorded in the entire region (NDRRMC, 2012). TS Washi then crossed the Northern Mindanao Region. Historically, tropical cyclones pass the region once in every twelve years and generally are not strong enough to cause much destruction (NEDA, 2005). While there were warnings on its arrival and expected strength, there was no adequate pre-emptive evacuation initiated by the local government units in areas expected to be exposed. Death toll in the region was 1,259 (NDRRMC, 2014). In Cagayan de Oro City, the regional centre of Northern Mindanao, the aftermath of the disaster revealed the failure of governance in the city (Ginnetti et al., 2013). The majority of the recorded provincial total of fatalities and affected persons of 698 and about 400,000, respectively, were from Cagayan de Oro City (NDRRMC, 2012, 2014).[7]

3. Disaster Risk and Vulnerability Frameworks

We very briefly review a number of frameworks that have been developed across disciplines on the nature of vulnerability in the context of natural hazards. This review enables us to identify suitable indicators for inclusion in our empirical model. In addition, we examine the empirical literature to determine the areas that have been studied, methodologies employed and, more importantly, to identify the gap in research that we aim to fill.

A. Frameworks on Vulnerability and Disaster Risk Assessment

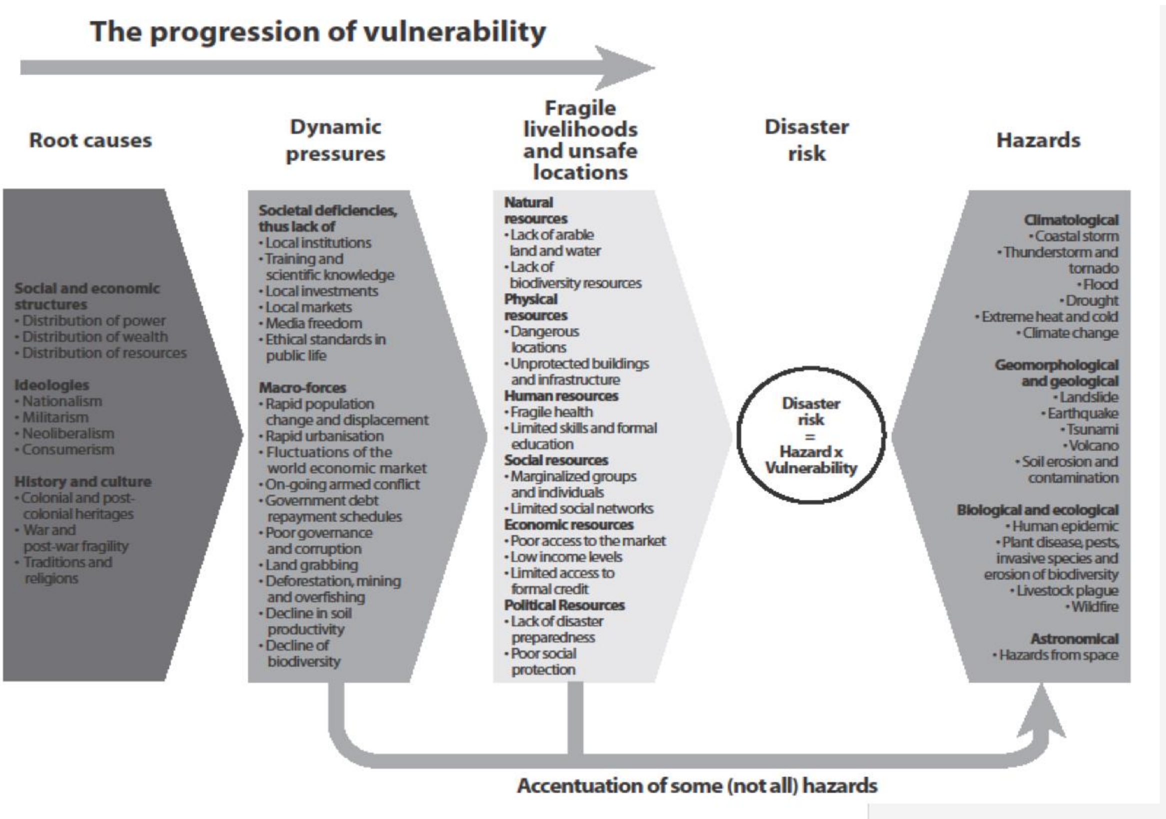
The Pressure and Release (PAR) framework provides a qualitative depiction of how disasters are generated when natural hazard affects the vulnerable individual or group of people (Blaikie et al., 1994; Wisner et al., 2004). This framework considers disaster risk as a product of hazard and vulnerability:

[7] In their study on internal displacement due to Tropical Storm Washi, Ginnetti et al. (2013) depicted the failure of governance, particularly the grave negligence of local officials that led to the high death toll in Cagayan de Oro City. As they reported, settlements along the riverbank and sandbars grew as a result of the mayor's housing program that offered a token price of just a Philippine peso (about USD 0.02) to poor families for them to have the right to build houses in said areas. With this outright infringement of existing land use policies, coupled with the provision of inappropriate incentives by the city leadership, the settlements reportedly continued to be densely populated. This is despite several recommendations from the concerned government agency to the city local government unit to relocate the residents due to the high risk from flooding. Despite the high death toll in the aftermath of TS Washi, the mayor did not implement the presidential order to prevent people from returning these areas (Ginnetti et al., 2013). An earlier in-depth study to investigate the causes of death in a series of tropical cyclones in the eastern part of Luzon in 2004 also provide a compelling evidence of the political construct that led to a disaster that took 1,400 lives in 2004 (Gaillard et al., 2007). The strength and the impact of the tropical cyclone were magnified by deforestation in the affected areas. Illegal logging has dramatically reduced the forest cover in the area. Yet, the cutting persisted because of "widespread corruption, shortcomings and failures within the government" (Gaillard et al., 2007).

$$Risk = Hazard\ x\ Vulnerability \quad (1)$$

It distinguishes among the three levels of progression of vulnerability (Figure 2). The first level of the progression is "root causes," which includes social and economic structures that determine the distribution of resources, wealth, and power; ideologies in governance; and, history and culture. An emphasis is made on the need to determine the historical origin of these structures and to explain the underlying ideologies that give ground for the legitimacy of these structures. This implies that root causes may be distant in space and time relative to location of present vulnerability (Wisner, Gaillard, & Kelman, 2012).

Figure 2. The Progression of Vulnerability Framework



Source: Wisner et al. (2012)

The second level of the progression comprises of "dynamic pressures" (Blaikie et al., 1994; Wisner et al., 2012). These are grouped into the deficiencies of society's social, economic and political processes, and macro-forces, such as rapid population growth and rapid urbanization, deforestation, decline in soil productivity, among others. Accordingly, the dynamic pressures serve as channels through which the root causes result in fragile livelihoods and unsafe locations (Blaikie et al., 1994; Wisner et al., 2012).

The UNDP-UNDRO adds "elements at risk", also often coined exposure, to the earlier risk equation (Equation 1), which effectively identifies who or what are at risk (UNDRO, 1992). Hence, disaster risk now comprises three components: hazard, elements at risk, and vulnerability that need to be quantified separately (UNDRO, 1992). This risk framework has been adopted in prospective or probabilistic disaster risk assessment methodologies in the following general form:

$$Risk = Hazard\ x\ Exposure\ \times\ Vulnerability \qquad (2)$$

where, *Risk* is either the annual expected number of fatalities or affected persons or expected cost of damage per year; *Hazard* is the probability of occurrence (expressed as reciprocal of the return period) of a hazard of a given severity; *Exposure* is the estimated number of people and value of assets exposed to such hazard; and *Vulnerability* is the degree of loss, expressed from 0 to 100 percent, of the elements at risk to a hazard of given severity (NEDA, 2008; Peduzzi et al., 2009; UNDP-DHA, 1994; UNISDR, 2013). This is the framework adopted in the Philippines' probabilistic disaster risk assessment (NEDA, 2008)

B. Determinants of Vulnerability: Identification and Quantification

A number of vulnerability indices have been developed and econometric empirical studies undertaken in the attempt to identify and examine what determines vulnerability and disaster risk. These can be divided into those using inductive 'index' methods, and those using deductive 'econometric' algorithms.

Index Methods

The two most well-known disaster vulnerability indices are the Prevalent Vulnerability Index (PVI) and the Social Vulnerability Index (SoVI). The PVI is part of the system of indicators developed for the Inter-American Development Bank (IADB) by the Instituto de Estudios Ambientales (IDEA).[8] The PVI allows a comparison of national vulnerability across years and across countries (Cardona, 2006). As indicated in Equation 3 below, the PVI depicts vulnerability as the confluence of exposure in hazard prone areas (indicated as $PVI_{Exposure}$), socioeconomic fragilities (indicated as $PVI_{Fragilities}$), and lack of resilience (indicated as $PVI_{Lack\ of\ Resilience}$). These sub-indices are aimed at measuring the direct impact of hazards events, as well as indirect impacts (Cardona, 2006).

$$PVI = (PVI_{Exposure} + PVI_{Fragility} + PVI_{Lack\ of\ Resilience})/3 \tag{3}$$

The exposure sub-index refers to physical susceptibility. The indicators used include population growth rate, urban population growth, population density, population in poverty, value of capital stock, share of net exports to GDP, share of gross domestic investment to GDP, and share of arable land and permanent crops to total land area. PVI explicitly takes exposure as necessary for the presence of disaster risk. The socioeconomic fragility composes a human poverty index, dependency ratio, Gini index, unemployment rate, food inflation, dependency of GDP growth on the agriculture sector, debt-GDP ratio, and human-induced soil degradation. The index for lack of resilience is represented by measures of human capital, human development, community and environmental protection, governance, economic redistribution and financial protection. The specific indicators include the Human Development Index, Gender-related Development Index (GDI), social expenditure to GDP ratio (health, education, pension), index of governance, and percentage of value of insured structures to GDP (Cardona, 2006).

As Pelling (2004, 2013) points out, PVI has a number of limitations. First, it measures solely intrinsic vulnerability; there is no consideration made to hazard type, scale of hazard impact and capacity for

[8] Apart from the PVI, the system of indicators developed includes Disaster Deficit Index (DDI), the Local Disaster Index (LDI) and Risk Management Index (RMI)(Cardona, 2006).

disaster response. Second, there is a degree of subjectivity in the selection of the indicator variables that are included in constructing the indices, as well as in the assignment of weights. Third, the PVI is inductive in nature, as the choice of variables included is based on case-study observations, and as such, its conclusions are not verifiable.[9]

The social vulnerability index (SoVI) considers social and place inequalities that affect the individual's susceptibility to harm and capacity to respond (Cutter, Boruff, & Shirley, 2003). Unlike the PVI that measures vulnerability at the national level, the Social Vulnerability Index (SoVI) is a measure of social vulnerability at the sub-national level (Cutter et al., 2003). The SoVI also adopts an inductive approach and shares the main limitations of the PVI. However, unlike the PVI, the assignment of weights in the SoVI is not ad-hoc, but is based on a statistical algorithm (the factor loadings of the principal component analysis).

With data for US counties, 42 socioeconomic and demographic indicators were included in the construction of the SoVI.[10] An initial test of the SoVI – examining the correlation between the number of US presidential declaration of disaster by county and the individual county SoVI – failed to verify this index.[11] This suggest that vulnerability to natural hazards cannot be measured independently of the type and magnitude of the hazard, as well as extent of exposure to it. There is no social vulnerability, say, to a storm surge if there is no exposure or no likelihood of the hazard occuring.[12]

Econometric Models

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[9] An inductive index like the PVI or the SoVI can be and verified using deductive methods and data from actual disaster events (Pelling, 2004). We pursue such a deductive path in this paper.

[10] Using principal component analysis, the 42 indicators were further reduced to 11 composite factors, as follows: personal wealth, age, density of built environment, single-sector economic dependence, housing stock and tenancy, race, ethnicity, occupation and infrastructure dependence.

[11] We note that presidential declarations are not a very good proxy for disaster risk; they are often motivated by political considerations and as ways to channel money from federal to local government units (for example, after hurricane Katarina, the federal government issued emergency declarations for all 50 states). So, this failure is not necessarily a condemnation of the SoVI.

[12] Examples of implementation of the SoVI's approach to measure social vulnerability in other countries include for Thailand (Siebeneck, Arlikatti, & Andrew, 2015) and for China (Zhou, Li, Wu, Wu, & Shi, 2014).

The econometric models of vulnerability assessment are mainly deductive using actual historical data. As Pelling (2013) points out, a deductive approach provides more realism than an inductive approach. Moreover, the use of historical data captures the dynamic nature of vulnerability (ISDR, 2004). In these models, the underlying causes of vulnerability are indirectly determined using different variants of the risk equation and frameworks presented earlier. For instance, the Disaster Risk Index or the DRI, which is designed to assess exposure and vulnerability to disasters (Peduzzi, 2006), adopts a definition of risk that is influenced by hazard, exposure and vulnerability, as in Equation 2. Specifically, the DRI equation is expressed, as follows:

$$R = H \times Pop \times Vul \tag{4}$$

where *R* is disaster risk, measured in terms of number of deaths, *H* is the hazard, measured in terms of its frequency and strength, *Pop* is the number of people living in the exposed area, and *Vul* is vulnerability - the variable of interest, which is influenced by socioeconomic and environmental context of the exposed population.

While the DRI adopts a cross-section approach, most of the works that followed adopted panel data analysis. These works likewise explore a general hypothesis that development plays a significant role in determining vulnerability. Despite the varied models and estimation methods in these works, the results give light on the more important factors or determinants of vulnerability. In a broad sense, they provide evidence that indeed the level of socioeconomic development, and certain aspects of development processes and institutions significantly determine the resulting number of deaths, affected persons, and costs of damage.

The cross-country empirical studies are unanimous in the findings that a country's level of economic development affects its vulnerability to disasters (Anbarci et al., 2005; Kahn, 2005; Raschky, 2008; Toya & Skidmore, 2007). However, there is difference in the findings as to the direction of relationship between the level of economic development and disaster, as well as the extent at which the development influences vulnerability between wealthy and less affluent countries and/or regions. Overall, less affluent countries are more vulnerable and face graver disaster impacts than more wealthy countries.

Using GDP per capita as proxy for economic development, Peduzzi et al. (2009) find that it is negatively correlated with deaths across all types of hazards considered, namely: tropical cyclone, drought, and flood. This finding is supported by Kahn (2005), who finds that more wealthy countries have fewer deaths from earthquakes than those of less affluent countries. Cavallo and Noy (2011) attribute this to the investments made by more wealthy countries on prevention and mitigation measures. These measures are lacking in less affluent countries given the limits of available resources and other social, polictical and economic constraints that hinder access to available resources (Anbarci et al., 2005; Cavallo & Noy, 2011).[13]

While not completely refuting these findings of a linear disaster-economic development relationship, Kellenberg and Mobarak (2008) argued that economic development may actually increase the risk people face by "changing micro behaviour in such a way so as to increase aggregate exposure to disasters" (Kellenberg & Mobarak, 2008). They suggest that disaster risk is also determined by processes such as urbanization. Wamsler (2006) substantiates this argument by asserting that this is largely because urban growth, planned or otherwise, happens without due consideration to reducing disaster risk.[14]

Kahn (2005) and (Raschky, 2008) examined the influence of the form and quality of institutions using several proxy measures including the country's level of democracy and good-governance indicators.

[13] In a similar light, Toya and Skidmore (2007) find that as economies develop, they experience fewer deaths. This is further confirmed by the lower damage cost-to-GDP ratios among developed countries than those in developing countries (Toya & Skidmore, 2007). It is interesting to note that while they find that income is also an important factor in determining the number of fatalities among developing countries, the magnitude of effect is lower than those in developed countries.

[14] Kellenberg and Mobarak (2008) argue that urbanization can, in different contexts, have varied effects on risk to disasters. That is, urbanization may reduce or increase vulnerability depending on the context within which it occurs. Specifically, they found that countries with comparable levels of income but with different degrees of urbanization have different risk levels. On one hand, in contexts with competent urban planning, where structures are appropriately designed and where there is adequate capacity to provide economic and social services, urbanization may not necessarily increase vulnerability to disasters. On the other hand, where the capacity of urban areas to deliver key services cannot cope with the rapid influx of population (as is the usual case in developing countries), urbanization may lead to increased exposure and vulnerability to disasters. They argue that better employment opportunities in dense urban areas attract low income families, even if such transfer means increased exposure to disasters. Hence, urbanization in this case increasingly entices people with existing vulnerability (because of relatively fewer resources and weaker capacities to adapt and cope in times of disaster) into harm's way.

Anbarci et al. (2005) examine income inequality, and argue that a polity that has low income and high inequality experiences difficulty in generating collective action to undertake preventive measures.[15]

We note that our review of the literature revealed no research at the subnational level that employed econometric methods to deduce the underlying causes of vulnerability. A subnational study has some advantages over a cross-country one, as many of the institutional and legal structures are identical across regions, and thus the biases introduced by missing variables are less severe and allow one to focus on cross-regional differences that may be obscured because of these biases. Moreover, as noted earlier, a subnational study is of practical usefulness in planning and policy-decisions pertaining to DRRM when almost all DRRM decisions to allocate scarce resources to regions are undertaken at the national level.

4. Model, Data, and Estimation Methodology

A. Risk Framework, Econometric Model and Estimation Method

We adopt a retrospective and deductive approach and translate the disaster risk framework expressed in Equation 2 into a disaster impact framework, expressed in Equation 5:

Disaster impact = Hazard x Exposure x Topography x Vulnerability (5)

As in Peduzzi et al. (2009), we take the logarithmic transformation of this multiplicative model. Hence, our econometric disaster impact model is as follows:

$$\ln Impact_{ijt} = \beta_0 + \beta_1\, lnHaz_{ijt} + \beta_2 lnExpo_{ijt} + \beta_3 lnTopog_i + \beta_4 \ln Vulner_{it} + \varepsilon_{ijt} \quad (6)$$

[15] Earlier work by Adger (1999), on Vietnam, finds that the increasing inequality and the breakdown of collective community action that results from its economic transition have contributed to greater vulnerability. He asserts that the restructuring towards a market system augers well in terms of reducing vulnerability because informal coping mechanisms have re-emerged.

where $Impact_{ijt}$ is the measure of actual direct impacts on people in province *i* of a past tropical cyclone *j*, in year *t*; Haz_{ijt} is a vector of physical characteristics that measure the strength of a particular past tropical cyclone *j* in year *t* that affected province *i*; $Expo_{ijt}$, is a measure of the extent of population exposure in *i* to *j* in year *t; $Topog_i$* is a vector of time-invariant topographic characteristics of each province *i*; and, $Vulner_{it}$ is the vector of control variables (it) we hypothesize as either positively or negatively affecting people's vulnerability to tropical cyclones. These are the level of socioeconomic development, characteristics of urbanization, and quality of local development governance. By controlling for hazard strength and the exposure to it, we can deduce the factors affecting people's vulnerability.

Since both our dependent and independent variables are log-transformed, each coefficient is therefore interpreted as elasticity of the dependent variable with respect to the particular regressor. We note that the logarithmic transformation of the dependent variable addresses its heavy skew and makes its distribution approximately normal.

We built a new provincial-level panel dataset of relevant indicators collected from different sources, and estimate Equation 6 using random effects method, as well as pooled OLS and fixed effects. We justify our use of random effects method both on technical grounds and practical considerations. We make use of a good set of explanatory variables, including measures of hazard strength and topograhic and geographic variables, to represent each component in the disaster framework. This allows us to plausibly make the assumption of exogeneity (Cov ($\mathbf{X}_{ijt}$, α_i) = 0). That is, the unobserved heterogeneity or the unobserved variation across provinces, α_i, is uncorrelated with all of the explanatory variables, the vector $\mathbf{X}_{ijt}$, in all time periods. Hence, ε_{ijt} is a composite error term comprising of the unobserved heterogeneity, α_i, and the idiosyncratic error, η_{ijt}. That is, $\varepsilon_{ijt} = \alpha_i + \eta_{ijt}$. The use of random effects estimation method allows us to control for time-invariant topographic variables. Given that one intent of this study is to inform physical and land use planning, topographic factors are key variables of interest, hence, the need for these to be purposely included in our model.

B. Variables and Sources of Data

To our knowledge, this study is the first subnational work using panel dataset and econometric method to answer the question we posed. Our choice of proxy indicators for each component of the risk framework are based on the existing related cross-country work, along with the consideration of the specific circumstances of the Philippines. Our dataset covers the period 2005-2010, as dictated by data availability.

a. Impacts

We consider two direct disaster impacts on people. Our first measure of disaster impact is the number of fatalities (% to provincial population) in province *i*, that is affected by tropical cyclone *j* in year *t* ($Fatalityp1_{ijt}$), while the second is the number of affected (% to provincial population) ($Affectedp1_{ijt}$)[16]. We note that none of the existing panel econometric inter-country studies attempted to identify the factors affecting the number of affected persons.[17] By scaling the number of fatalities and affected persons using total provincial population, we account for the varying sizes of the provinces. Doing so also has the added advantage of comparability of these measures across areas. The impact data from the National Disaster Risk Reduction and Management Council (NDRRMC) is available only for tropical cyclones.

b. Hazard

We use two measures of hazard strength considering that tropical cyclones can trigger other hazards: flood, landslide, coastal flooding, and storm surge. While the first three are induced more

[16] $ln(Impact_{ijt})$ in Equation 6 is $ln(1+fatalityp1_{ijt})$ in the first set of regression, and $ln(1+affectedp1_{ijt})$ in the second set of regression. By doing this, the observations with zero values for *fatalityp1* and *affectedp1* are not dropped from sample when the logarithmic transformation is done, but are instead given a value of zero.

[17] Padli, Habibullah, and Baharum (2010) is the only study we know that uses the number of affected persons as dependent variable but unlike our study, they use a cross-sectional country level dataset. There are good reasons not to use this measure in the inter-country context, as the definition of what constitutes an 'affected-person' is not consistent across countries.

by heavy downpour of rainwater than by strong winds, the opposite is generally true for storm surges where high wind speeds are a major contributing factor.

We use the amount of maximum 24-hour rainfall volume as our first measure of hazard strength. For a given tropical cyclone, the exposed provinces experienced different magnitude of the hazard, depending on whether they are directly under the tropical cyclone path or along the periphery. To account for this, the rainfall volume assigned to each province per tropical cyclone in a given year *($Rainfall_{ijt}$)* is based on the maximum 24-hour volume recorded in the nearest rain gauge station to each province. We use the daily rainfall volume recorded in 30 stations across the country.

We also make use of data on maximum wind speed per tropical cyclone *($Wind_{ijt}$)* as a second measure of hazard magnitude. We use data on the Tropical Cyclone Warning Logs of the PAGASA of the Philippines and the Joint Typhoon Warning Center (JTWC) of the United States Air Force/Navy.[18] These logs include details on the location and sustained maximum winds of the cyclone. Data is processed using GIS tools to determine the wind speed per province per tropical cyclone.[19]

c. Exposure

At the time that we conducted this study, the closest available proxy for exposed people for our first set of estimation (with $Fatalityp1_{ijt}$ as dependent variable) is the number of affected persons per million population, which we later use as another measure of risk to people.[20] We note that in a similar study by Raschky (2008), he likewise uses the number of affected persons as one of the explanatory variables “to control for the social magnitude of the disaster”. For the second set of estimation (with $Affectedp1_{ijt}$ as dependent variable), we use the provincial population as our proxy measure for exposed.

[18] Data is downloaded from www.typhoon2000.ph.

[19] A number of earlier related inter-country empirical work on tropical cyclones have used the number of occurrences within the country in a given year as the proxy for the hazard magnitude. We consider rainfall volume and wind speed as better measures of tropical cyclone strength, and of its capacity to destroy.

[20] While “exposed population” and “affected population” are used interchangeably in some related work (such as in NEDA (2008), we make the distinction between the two. Exposed population refers to those persons exposed to the hazard but who may not have been adversely affected. Affected population refers to those persons exposed to the hazard and who were adversely affected; that is, affected population is the exposed population who is vulnerable.

d. Topography and Geography

The geographic control variables commonly found in related empirical work are geo-location and land area (Adger, 1999; Anbarci et al., 2005; Kahn, 2005; Kellenberg & Mobarak, 2008; Noy, 2009; Peduzzi et al., 2009; Raschky, 2008; Toya & Skidmore, 2007). Given the distinct and complex topographic and geographic features of the Philippine archipelago, we use several additional control variables obtained with Geographic Information System (GIS) analysis tools. These variables are province-specific and do not change over time.

Instead of using total land area, we disaggregate the provincial land area by slope category. We use two broad slope categories.[21] $Slopeflat_i$ is the area of land within a given province with a slope range of 0 to 18%. $Slopesteep_i$ is the area of land with a slope above 18%.[22] Similarly, we also use two elevation variables. The variable $elev0300_i$ is the area within the province that is 0 to 300 meters above sea level (masl). Meanwhile, the variable $elev300a_i$ is the area within the province with elevation of more than 300 meters above sea level.[23] For location, we use dummy variables indicating the country's major island groups, and for provinces located along the eastern shoreline (19 provinces), as tropical cyclones always arrive from the east. We also use additional geographic controls: $River_i$ is the area of a river that traverses the province[24], while $landlocked_i$ is a dummy variable that has a value of 1 if a given province is landlocked (15 provinces).

e. Vulnerability

We disaggregate the components of the Human Development Index (HDI) to examine separately the influence of economic development and social development. We use real per capita income

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[21] There are six slope categories in the Philippines, as follows: (a) 0 to 3% – level to nearly level; (b) 3 to 8% – gently sloping; (c) 8 to 18% – undulating to rolling; (d) 18 to 30% – rolling to moderately steep; (e) 30 to 50% – steep; and, (f) above 50% – very steep. We only make two broad categories here to distinguish between the areas that are suitable for settlements use and those otherwise.

[22] To determine the overall direction of influence of the slope variable, we also run a separate preliminary regression using the average slope of each province ($slopemean_i$). From a land-use planning perspective and based on the Revised Forestry Code of the Philippines, areas with slope of above 18% are not suitable for settlements use, and hence must not be used for such purpose (GOP, 1975; NEDA, 2007).

[23] As we did for slope, we also run a separate preliminary regression using the average elevation of each province ($elevmean_i$) to determine the overall direction of influence of the elevation variable.

[24] We note that our data on the area for river is incomplete. Rivers traverse all provinces in the Philippines but our existing data do not have values for 13 provinces.

(percap$_{it}$), average educational attainment (in years) of the population *(schoolm$_{it}$)* and average life expectancy (*life$_{it}$*). We also proxy for the lack of resources using poverty incidence *(povinci$_{it}$)* as proxy. Due to the high correlation coefficient of -0.87 between per capita income and poverty incidence, we enter them into the model one at a time.

For our inquiry on the nature of the influence of urbanization on human vulnerability, we use both the overall population density in the province *(popden$_{it}$)*, and population density in built-up areas *(builtden$_{it}$)*. The former is computed as provincial population divided by the total provincial land area, and the latter, provincial population divided by the total built-up areas in the province.

We also derived an indicator for quality of local development governance. Given the provincial resolution of this study, we use public finance data of the local government units to construct a governance variable. We use the percentage of locally-generated tax revenues to the total income of local government units (LGU) *(taxinct$_{it}$)* within the provincial geographic boundary. These include the provincial, city, and municipal local government units.

The sources of basic data are the annual Statements of Income and Expenditures of LGUs prepared by the Philippine Bureau of Local Government Finance (BLGF, 2014). In the Philippines, the Total Current Operating Income of local government units comes from local and external sources.[25] Revenues from external sources comprise mainly funds provided by the central government, largely in the form of Internal Revenue Allotment or the IRA.[26] The annual provision of IRA seemingly provides disincentive for the LGUs to undertake local revenue generation. “LGUs have generally been unwilling to raise their own revenues, particularly through potentially rich sources such as property tax. The IRA has effectively substituted for own-source revenue generation” (Balisacan & Hall, 2006). Meanwhile, the collection of taxes, which is the main source of local revenues of LGUs,

[25] Tax revenues include real property tax, business tax, other taxes, while non-tax revenues include regulatory fees, service/user charges, receipts from economic enterprise, and other receipts (BLGF, 2014).

[26] Other external revenue sources are as follows: 1) Other share from national tax collections; 2) Inter-local transfer; and, 3) Extraordinary receipts/grants/donations/aids (BLGF, 2014)

is one of the more problematic areas of local governance, because of tax evasion and avoidance by the taxpayers, coupled with lack of transparency among the tax collection bodies (Balisacan & Hall, 2006). Given this specific circumstance of the Philippines, *taxinct* serves as a good indicator of institutional quality.[27] A high value of *taxinct* proxies, in this view, high level of integrity, commitment, accountability and effectiveness of the local government units in performing their mandated roles.

f. Specifications and Data

Given the above, the full specification of Equation 6 for our two sets for regressions are as follows[28]:

First set of regressions

$$\ln(Fatalityp1_{ijt}) = \beta_0 + \beta_1 \ln(Rainfall_{ijt}) + \beta_2 \ln(Wind_{ijt}) + \beta_3 \ln(Affectedp1_{ijt}) + \beta_4 \ln(Slopeflat_i) + \beta_5 \ln(Slopesteep_i) + \beta_6 \ln(Elev0300_i) + \beta_7 \ln(Elev300a_i) + \beta_8 dl_i + \beta_9 dv_i + \beta_{10} deast_i + \beta_{11} Landlocked_i + \beta_{12} \ln(Vulnerability_{it}) + \epsilon_{ijt} \quad (7)$$

Second set of regressions

$$\ln(Affectedp1_{ijt}) = \beta_0 + \beta_1 \ln(Rainfall_{ijt}) + \beta_2 \ln(Wind_{ijt}) + \beta_3 \ln(Pop_{it}) + \beta_4 \ln(Slopeflat_i) + \beta_5 \ln(Slopesteep_i) + \beta_6 \ln(Elev0300_i) + \beta_7 \ln(Elev300a_i) + \beta_8 dl_i + \beta_9 dv_i + \beta_{10} deast_i + \beta_{11} Landlocked_i + \beta_{12} River_i + \beta_{13} \ln(Vulnerability_{it}) + \epsilon_{ijt} \quad (8)$$

We undertake the Breusch-Pagan Lagrange Multiplier (LM) test to determine the appropriateness of using random effects over OLS to estimate the model. We conduct sensitivity tests to check the robustness of results. The first two robustness checks involve varying the set of control variables, particularly by dropping variables other than the vulnerability variables. The objective here is to examine the consistency of the sign and/or significance of the coefficients of the vulnerability

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[27] The Philippines has an indicator of the quality of governance called the Good Governance Index or the GGI (PSA-NSCB). We do not use the GGI as it is basically an average value of socioeconomic indicators, including those that we individually use as proxy for the different aspects of development that we examine in this study. We note, however, that the GGI includes local government finance indicator.

[28] We note, however, that for the first set of estimates (with *lfatalityp1* as the dependent variable), we do not control for *lriver.* Based on data gathered, of the 79 provinces included in our sample, only 67 provinces have data on the area of river. We ran regressions for the first set of estimates where we included *lriver* as control variable. We find that the coefficient of *lriver* is not statistically significant. Also, by including *lriver* as a control variable, there are only 636 observations, indicating that 96 observations are dropped. Hence, we dropped *lriver* in the first set of estimates to maintain the number maximum of observations. Further, we note that due to a high degree of correlation, we enter our vulnerability variables separately into the model to avoid the problem of multicollinearity.

variables given the change in the set of controls. If the sign and significance of the coefficient of the vulnerability indicator of interest do not change, then the said indicator can be considered robust (Leamer, 1983). The third and fourth tests involve using reduced datasets; the sub-sample for the third test excludes the outliers (observations with more than 100 fatalities), while the sub-sample for the fourth test excludes both the observations with more than 100 fatalities and observations with zero fatalities.

Within the period 2005-2010, a total of 104 tropical cyclones passed the Philippine Area of Responsibility (PAGASA, 2014) (see Figure 3). Of which, 57 were reported by the NDRRMC as destructive. Together, these destructive tropical cyclones claimed a total of 2,625 lives and affected 35,885,883 persons. These 57 destructive tropical cyclones make a total of 722 provincial 'hits' in the dataset, indicating that, on average, 13 provinces were affected by each tropical cyclone. During the six-year period, each province, on average, was affected by nine tropical cyclones. Figures 4-6 depict the distributions of the total number of events, number of fatalities and number of affected by province during the period covered. Visual inspection reveals that the number of events and impacts on people vary across provinces, regions and major island groups. Tropical cyclones typically pass the northern part of the country (the northern part of the Luzon major island group). Of the total number of observations, 550 are for the provinces in the Luzon island group, 118 in the Visayas island group, and the remaining 54, in the Mindanao island group.[29] The provinces of La Union, Pampanga and Zambales each have 21 observations; all three are located in the Luzon island group.

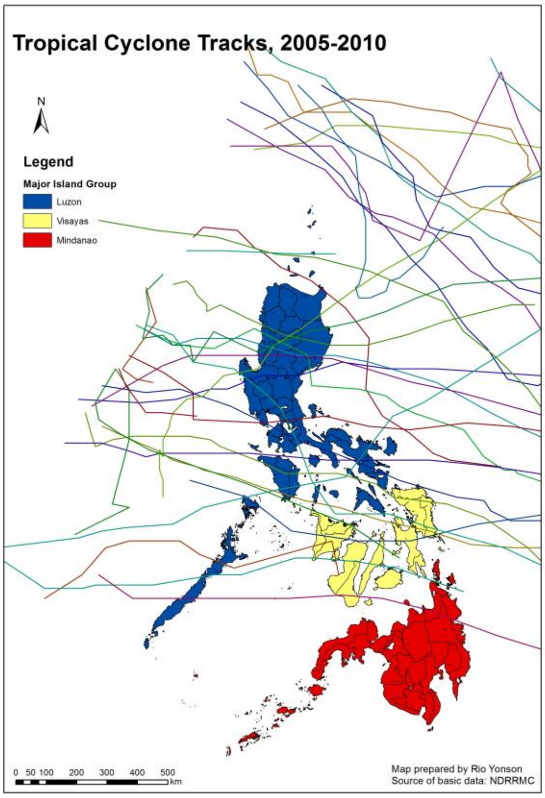
Table 2 below shows the descriptive statistics of the indicators used in the model, covering the period 2005-2010. The indicators are presented in their original form in the table but are entered into the model after a logarithmic transformation, except for the dummy variables. Relative to the affected province's population, the highest fatalities recorded is 508 per million population.

[29] To date there are 81 provinces in the country. The 81st province, Davao Occidental, was created only in 2013, while the 80th, the province of Dinagat Islands, was created in the last quarter of 2006. During the period 2005-2010, there are no separate records of disaster impacts, as well as socioeconomic data for Dinagat province. Hence, only 79 of the 81 provinces are included in the dataset for this paper.

Meanwhile, the average 24-hour rainfall volume was 101 mm, and average wind speed was 107 kilometers per hour.

Figure 3

Figure 4



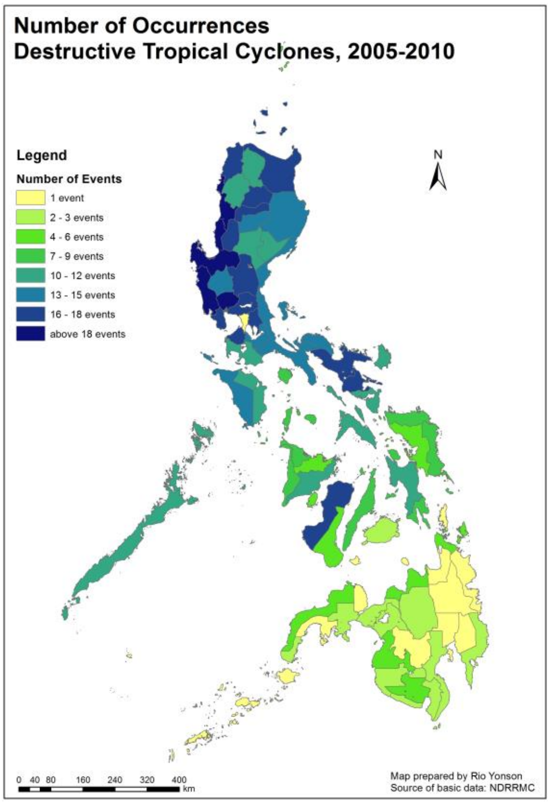
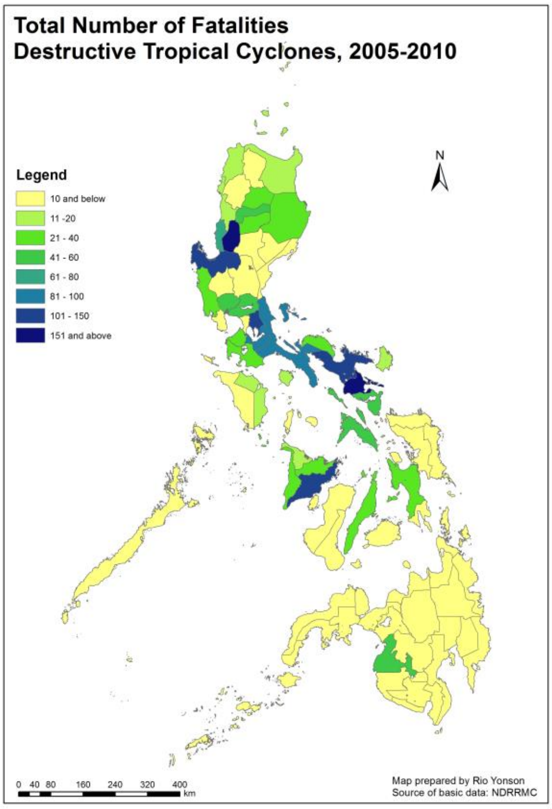


Figure 5

Figure 6



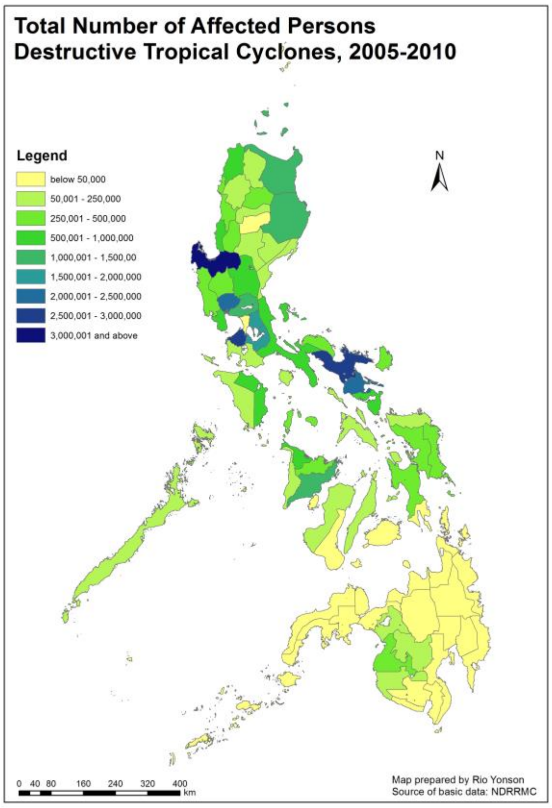


Table 2. Descriptive Statistics

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
fatalityp1p	Number of fatalities for every 1,000,000 population	722	7	28	0	508
affectedp1p	Number of affected persons for every 1,000,000 population	722	50745	121424	0	976959
rainfall	Maximum 24-hour rainfall volume per province per tropical cyclone (in mm)	722	101	97	0	685
wind	Maximum wind speed per tropical cyclone (in kilometres per hours)	722	107	44	45	215
pop	Population	722	1,148,584	901,142	18,800	4,132,500
slopeflat	Area in the province with slope 0-18% (in square kilometres)	722	1,178	950	12	3,638
slopesteep	Area in the province with slope above 18% (in square kilometres)	722	1,898	1,231	112	6,390
slope_mean	Average slope of the province	722	11	4	4	23
elev300	Area in the province with an elevation of at least 300 meters above sea level (in square kilometres)	722	911	683	24	3,588
elev300a	Area in the province with an elevation of above 300 meters above sea level (in square kilometres)	722	1,257	1,017	0	8,109
elevmean	Mean elevation of the province (in meters above sea level)	722	327	257	33	1,227
river	Area of river within the province	722	32	60	0	1005
landlocked	Dummy variable with a value of 1 if a given province is landlocked, value of zero (0) if province is coastal	722	0.25	0.43	0	1
dl	Dummy variable with a value of 1 if a given province is part of Luzon island group, value of zero (0) otherwise	722	0.76	0.43	0	1
dv	Dummy variable with a value of 1 if a given province is part of Visayas island group, value of zero (0) otherwise	722	0.16	0.37	0	1
deast	Dummy variable with a value of 1 if a given province is located in the east-most part of the country (along the eastern shoreline), value of zero (0) otherwise	722	0.25	0.43	0	1
percap	Real per capita income (in USD)	722	1430	465	578	2710
povinci	Poverty incidence	722	29.08	14.93	1.84	67.5
schoolm	Average years of schooling of the population (in number of years)	722	10.03	0.71	7.1	11.99

life	Average life expectancy (in number of years)	722	68.73	3.9	52.8	76.4
taxinct	Percentage of tax revenue to total LGU income	722	11.43	9.61	0.14	43.68
builtden	Population density in built-up areas (persons per square kilometre)	722	11,596	11,607	2,468	95,691
popden	Population density in the province (persons per square kilometre)	722	410	444	28	2,336

*The omitted island group is Mindanao

Average real income per capita range from a minimum of USD 578 (Tawi-Tawi) to a maximum of USD 2,710 (Benguet Province), and an average of USD 1,430 across provinces. Poverty incidence range from a 1.84% (Cavite) to a high of 67.5% (Zamboanga del Norte); the average incidence at the country level is 29.08%. The lowest average life expectancy is 52.8 years (Tawi-Tawi), while the highest is 76.4 years (La Union). The national life expectancy is 68.73 years. In terms of the average educational attainment (in years) of the population, provincial values range from 7.1 years (Sulu) to 11.99 years (Batanes). The country level average is 10 years.

Population density in built-up areas range from 2,468 persons per square kilometre (Tarlac) to a high of 95,691 persons per square kilometer (Lanao del Sur), which is over eight times higher than the average of 11,596 per square kilometer. Meanwhile, the ratio of provincial tax revenue to total LGU income range from a high of 43.68% (Laguna) and a low of less than 1% (Sulu), which practically indicates a full reliance on the revenue allotment from the central government. The average across provinces is only 11.43%.

Generally, the provinces with the worst socioeconomic and governance indicators (low per capita income, high poverty incidence, etc) are located in Mindanao, while the better off provinces are those located in Luzon. Conversely, the provinces in Mindanao, on average, experienced the least number of destructive tropical cyclones.

5. Results and Discussions[30]

A. Factors Influencing Vulnerability and Risk

Table 3 shows the estimation result under full model specification for our first set of regressions, where the dependent variable is the number of fatalities per million population, while Table 4 shows the result for the second set where the dependent variable is the number of affected persons per million population. Contained in Columns 1 to 5 of these tables are the estimates using pooled OLS method, while Columns 6 to 10 are those using random effects method.[31] The two methods yield very similar results, but the Breusch-Pagan Lagrange Multiplier test suggest the use of random effects over pooled OLS to estimate the model for our first set of regressions, except for our inquiry on urbanization. For the second set of regressions, the test results suggest the use of pooled OLS. Hence, in discussing the results of the first set of regressions, except on urbanization, we refer to the random effects estimates; we refer to the pooled OLS results for the second set.

Column 6 in Table 3 shows that the coefficient of per capita income is negative and highly significant, indicating that fatality is a decreasing function of income. This is even though more and stronger cyclones hit the higher income provinces of the north. Conversely, from the standpoint of inadequacy, the coefficient of poverty incidence (*lpovinci)* in Column 7 in Table 3 is positive, and significant. This quantitatively validates the earlier claims that in the Philippines, poverty is a critical factor in determining vulnerability to disasters (ADB, 2009; Shepherd et al., 2013).

Column 8 in Table 3 reveals that social development matters in ensuring safety from the adverse impacts of disasters. We find that high of level of education and good health are inversely correlated with fatalities. We next examine the influence of urbanization, which is closely linked with economic growth. In general, urban areas in the Philippines exhibit the benefits from the

[30] We note again that all variables are entered into the model in their respective logarithmic transformation. For brevity in the analysis, we simply refer to the name of the indicators and dispel with repeatedly indicating that they are in logarithmic form. The "l" attached to each variable name, except for the dummy variables, indicate that the variable is in logarithmic transformation.
[31] Appendix 4 shows the results of pooled OLS, random effects and fixed effects methods.

agglomeration of people and economic activities (Corpuz, 2013). However, our result reveals a positive and significant coefficient of the density in built-up areas (*lbuiltden*), as shown in Column 4 of Table 3. This points to the diminishing safety of people as the existing built-up areas become more population-dense. This may partly reflect the burgeoning of settlements in hazard prone areas and the lagging provision of adequate services for the additional population, particularly in areas exhibiting high population growth rate (WB-EASPR, 2003).[32]

It is interesting to note, however, that population density has a negative and significant coefficient; that is, an increase in overall population density in a province is negatively correlated with fatalities. These results together indicate that the risk is increasingly concentrated in the urban areas. In terms of local development governance, the coefficient for our proxy indicator is significant and inversely correlated with fatalities, as shown in Column 10 in Table 3. Our result denotes that good governance, even at the subnational level, is important in reducing vulnerability, and consequently, disaster impacts.

We note, however, that while all our vulnerability variables are important in explaining disaster fatalities, only poverty incidence is found important in explaining the number of affected persons per million population (Column 7 of Table 4). We reiterate that none of the related inter-country empirical studies used the number of affected persons as dependent variable. As noted, these studies used the number of affected persons as proxy indicator for the exposed persons, which we also adopted in our first set of regressions.

For the topographic control variables, the results in Columns 6 to 10 in Table 3 generally reveal that the ground slope categories are important in explaining the fatalities resulting from tropical cyclones. It is noted that while the coefficient for the areas with slope below 18% (*lslopeflat*) is

[32] The Philippine population grew at an average of 2.69% during the period 1950-2010, higher than the averages for South East Asia, the whole of Asia and the World (UN, 2014). Urban population grew much faster, driven mainly by migration of people from rural areas. During the period 1950 – 1990, urban population grew at an annual average of 4.47%, also higher than the averages for South East Asia, the whole of Asia and the World (UN, 2014). Thereafter, urban annual population growth rate slowed down, ranging from 1.12% to 2.21% from 1990 to 2010. The country's rate of urbanization has outpaced the provision of adequate services (WB-EASPR, 2003).

negative and significant, the coefficient for areas with slope above 18% (*lslopesteep*) is positive and also significant.[33] A plausible explanation for these is that areas with slope below 18%, which are legally deemed suited for settlements use, have stronger DRRM measures in place than those in areas with more than 18% slopes, which are areas officially not appropriate for settlements purposes. It has been noted that in the Philippines, communities in steep slopes are also becoming increasingly dense. Gaillard et al. (2007) find that when the traditional areas for settlement in the lowland are already reaching carrying capacity, many poor people resort to taking residence in marginal areas, such as those with steep slopes that are prone to rain-induced landslides.

The results for the second set of regressions shown in Table 4 reveal that the measurment of the area of the river per province (*lriver*) has a consistently positive and statistically significant coefficient, for each of the regressions presented. One plausible explanation for this is that in the Philippines, riverbanks, including the river buffer zones, are often densely populated especially by informal settlers. With heavy downpours, the occurrences of riverine flooding is common, particularly in urban areas where river drainages are blocked, including by human settlements (Liongson et al., 2000; Porio, 2011). Likewise, the coefficients of the *landlocked* indicator in Table 4 are consistently negative and significant across regressions. These results, apart from pointing to the low enforcement or compliance to the Philippine Water Code[34], likewise suggest the need for more effective weather forecasting, early warning systems, and information dissemination particularly to the most at-risk communities.

For the hazard variables, we find that the proportion of fatalities increases with increases in rainfall volume. However, there is no statistically significant result in terms of the link between fatalities

[33] The preliminary regressions that only control of topographic and geographic variables (Table 13 in Appendix 3) shows a positive and significant coefficient for the ln mean slope (*lslopemean*), and a negative and significant coefficient for ln mean elevation (*lelevmean*).
[34] The Philippine Water Code states that banks of streams and rivers, and shores of lakes and seas along urban areas are subject to a three-meter easement of public use (GOP, 1976). Similarly, the pertinent provisions of the code are supposed to be embodied in land use plans and zoning ordinances, to prohibit human settlements on these easement areas. Subsequently, the plans and ordinances have to be implemented and compliance to these has to be regularly monitored. However, this is not often the case. In addition to poor enforcement and monitoring of plans and policies, the continued increasing density in these areas is also a result of a complex set of socioeconomic factors and processes, as presented in Section II.

and wind speed.[35] In contrast, both rainfall volume and wind speed are important in explaining the proportion of affected persons (Table 4), most likely as the storm winds destroy people's vulnerable assets, such as agricultural crops and houses.

In terms of exposure, fatality is an increasing function of exposed people, as proxied for by the proportion of affected persons (Columns 6-10 in Table 3). However, there is an insignificant coefficient for population (Columns 6 to 10 in Table 4), which is our proxy for exposure for the second set of estimates (where the independent variable is affected persons).

As described earlier, we subject our specifications to several robustness checks. Tables 15 and 16 in the appendix show the estimation results where the variables for the two slope categories are dropped, while Tables 17 and 18 show the results where the variables for slope and elevation categories are both dropped. The results shown in these tables can be compared with those in the corresponding columns in Table 3 and 4, respectively. In the regressions for fatalities, all the vulnerability variables retained their respective sign and significance, except for the level of education. When subjected to the second robustness check, our proxy indicator for level of education changes sign and loses significance. Meanwhile, the quality of health, level of development (income), urbanization, and the quality of local development governance remain very qualitatively and quantitatively similar.

For the second set of regressions (with the affected population as dependent variable), poverty incidence losses significance when subjected to both the first and second robustness checks. Meanwhile, both proxies for hazard, as well as the area of the river and the dummy for landlocked retained their signs and level of significance.

Tables 19 to 22 in the Appendix show further results with additional sensitivity tests. In general, the result of the full model specification and all robustness checks reveal that the relationship between

[35] This is an interesting finding, as quite a few papers proxy for the strength of cyclone impact with wind speed measures. Our results suggest this may be an inappropriate proxy.

fatalities and the vulnerability indicators is robust, with the inclusion or exclusion of selected indicators, and with the reduced samples.

Table 3. Factors Affecting People's Vulnerability to Tropical Cyclones

Full model specification
Set 1: Dependent variable is lfatalityp1

	Pooled OLS					Random Effects				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Hazard										
lrainfall	0.0646*	0.0614*	0.0610*	0.0895***	0.0775**	0.0819**	0.0839**	0.0824**	0.0895***	0.0923***
	(2.37)	(2.26)	(2.34)	(3.84)	(2.96)	(2.99)	(3.08)	(3.03)	(3.54)	(3.51)
lwind	-0.0438	0.0112	-0.0254	-0.0243	-0.0309	-0.0455	0.00649	-0.0262	-0.0243	-0.0264
	(-0.53)	(0.14)	(-0.31)	(-0.32)	(-0.39)	(-0.53)	(0.08)	(-0.31)	(-0.29)	(-0.32)
Exposed										
laffectedp1	0.0809***	0.0804***	0.0822***	0.0779***	0.0784***	0.0818***	0.0804***	0.0821***	0.0779***	0.0799***
	(10.60)	(10.62)	(10.83)	(10.79)	(10.31)	(9.81)	(9.92)	(9.98)	(9.73)	(9.91)
Topography and Geography										
lslopeflat	-0.741***	-0.593***	-0.658***	-0.465***	-0.469***	-0.793***	-0.660***	-0.742***	-0.465***	-0.602***
	(-8.69)	(-6.59)	(-7.98)	(-6.10)	(-5.02)	(-5.24)	(-4.00)	(-5.49)	(-6.26)	(-3.77)
lslopesteep	0.366***	0.235**	0.504***	-0.118	0.400***	0.414***	0.289*	0.528***	-0.118	0.449***
	(4.86)	(2.82)	(7.41)	(-1.40)	(5.77)	(3.97)	(2.52)	(5.46)	(-1.71)	(4.53)
lelev0300	-0.125	-0.183*	-0.152	-0.0626	-0.163	-0.0840	-0.135	-0.0995	-0.0626	-0.0944
	(-1.41)	(-2.04)	(-1.76)	(-0.81)	(-1.88)	(-0.68)	(-1.06)	(-0.91)	(-1.42)	(-0.79)
lelev300a	-0.0662	-0.0610	-0.141***	-0.0536	-0.130***	-0.108*	-0.106*	-0.160***	-0.0536	-0.146***
	(-1.55)	(-1.40)	(-3.91)	(-1.52)	(-3.91)	(-1.96)	(-2.07)	(-3.52)	(-1.27)	(-3.46)
lriver										
landlocked	0.135	0.134	-0.0872	-0.0201	0.0249	0.168	0.180	-0.00976	-0.0201	0.0612
	(1.35)	(1.33)	(-0.85)	(-0.22)	(0.25)	(0.85)	(0.91)	(-0.05)	(-0.24)	(0.34)
dl	0.279*	0.305*	0.296*	0.133	0.0553	0.165	0.199	0.183	0.133	-0.0156
	(2.06)	(2.19)	(2.30)	(1.09)	(0.43)	(0.93)	(1.02)	(1.19)	(1.03)	(-0.10)
dv	-0.143	-0.0869	-0.155	0.00600	-0.181	-0.232	-0.188	-0.237	0.00600	-0.261
	(-0.99)	(-0.59)	(-1.10)	(0.04)	(-1.25)	(-1.12)	(-0.91)	(-1.28)	(0.03)	(-1.33)
deast	0.0970	0.0278	0.151	0.0132	0.0760	0.109	0.0427	0.143	0.0132	0.0903
	(1.07)	(0.31)	(1.73)	(0.16)	(0.86)	(0.76)	(0.29)	(1.15)	(0.17)	(0.72)
Vulnerability										
lpercap	-1.276***					-1.075***				
	(-7.78)					(-4.64)				
lpovinci		0.603***					0.549***			
		(7.95)					(4.06)			
llife			-5.309***					-4.390***		
			(-6.66)					(-4.36)		
lschoolm			-2.279***					-2.114*		
			(-3.31)					(-2.37)		
lbuiltden				0.140**					0.140*	
				(2.73)					(2.41)	
lpopden				-0.724***					-0.724***	
				(-13.80)					(-17.34)	
ltaxinct					-0.457***					-0.366***
					(-9.16)					(-5.09)
_cons	13.13***	2.067***	30.68***	7.681***	3.513***	11.72***	2.295**	26.58***	7.681***	3.482***
	(9.28)	(3.75)	(9.83)	(9.23)	(6.30)	(6.38)	(2.92)	(6.60)	(8.91)	(4.85)
N	722	722	722	722	722	722	722	722	722	722
R-sq	0.475	0.474	0.504	0.561	0.498	0.4809	0.4807	0.5099	0.5691	0.5021

t statistics in parentheses

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Note: The "l" attached to each variable name, except for the dummy variables, indicate that the variable is in logarithmic transformation

OLS reflects adjusted R-sq

Table 4. Factors Affecting People’s Vulnerability to Tropical Cyclones

Full model specification
Set 2: Dependent variable is laffectedp1

	Pooled OLS					Random Effects				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Hazard										
lrainfall	1.010***	0.992***	1.016***	1.014***	1.008***	1.031***	1.021***	1.019***	1.038***	1.030***
	(5.96)	(5.83)	(5.98)	(5.96)	(5.98)	(4.96)	(4.87)	(5.17)	(4.95)	(4.99)
lwind	1.500***	1.559***	1.514***	1.525***	1.504***	1.520***	1.579***	1.517***	1.543***	1.524***
	(3.65)	(3.77)	(3.69)	(3.68)	(3.66)	(3.72)	(3.87)	(3.70)	(3.74)	(3.71)
Exposed										
lpop	-0.0362	0.155	-0.474	-0.00238	0.196	-0.133	0.219	-0.477	-0.557	0.208
	(-0.10)	(0.40)	(-1.09)	(-0.00)	(0.37)	(-0.37)	(0.55)	(-1.22)	(-0.37)	(0.37)
Topography and Geography										
lslopeflat	-0.992	-0.978	-0.686	-0.970	-0.949	-0.949	-0.993	-0.684	-0.716	-0.981
	(-1.83)	(-1.85)	(-1.25)	(-0.97)	(-1.78)	(-1.85)	(-1.93)	(-1.38)	(-0.71)	(-1.89)
lslopesteep	-0.787	-1.082	-0.681	-0.787	-0.670	-0.714	-1.105	-0.680	-0.585	-0.656
	(-1.28)	(-1.66)	(-1.18)	(-0.90)	(-1.17)	(-1.33)	(-1.93)	(-1.39)	(-0.82)	(-1.38)
lelev0300	0.637	0.522	0.820*	0.718*	0.601	0.665	0.493	0.822**	0.704*	0.606
	(1.92)	(1.53)	(2.42)	(2.19)	(1.80)	(1.93)	(1.34)	(2.73)	(2.07)	(1.74)
lelev300a	0.378	0.511	0.197	0.326	0.296	0.340	0.550	0.200	0.392	0.330
	(0.88)	(1.21)	(0.49)	(0.76)	(0.76)	(0.82)	(1.41)	(0.55)	(0.90)	(0.89)
dl	-0.0461	0.253	-0.562	-0.0857	-0.183	-0.188	0.304	-0.564	-0.0478	-0.184
	(-0.07)	(0.34)	(-0.84)	(-0.12)	(-0.28)	(-0.28)	(0.43)	(-0.77)	(-0.06)	(-0.29)
dv	-1.228	-1.027	-1.471	-1.237	-1.295	-1.354	-1.052	-1.477*	-1.243	-1.347
	(-1.60)	(-1.30)	(-1.95)	(-1.56)	(-1.70)	(-1.89)	(-1.41)	(-2.01)	(-1.58)	(-1.91)
deast	-0.378	-0.470	-0.267	-0.375	-0.355	-0.500	-0.588	-0.279	-0.515	-0.470
	(-0.79)	(-0.97)	(-0.52)	(-0.78)	(-0.74)	(-1.15)	(-1.37)	(-0.61)	(-1.18)	(-1.05)
landlocked	-1.430*	-1.471*	-1.354*	-1.391*	-1.441*	-1.568**	-1.562**	-1.373*	-1.531**	-1.594**
	(-2.44)	(-2.52)	(-2.21)	(-2.39)	(-2.46)	(-3.00)	(-2.84)	(-2.56)	(-2.99)	(-3.01)
lriver	0.523**	0.552**	0.503**	0.484**	0.515**	0.523***	0.555***	0.503***	0.495***	0.519***
	(3.10)	(3.21)	(2.97)	(2.89)	(3.10)	(3.67)	(3.77)	(3.34)	(3.81)	(3.67)
Vulnerability										
lpercap	-0.809					-0.426				
	(-0.81)					(-0.44)				
lpovinci		0.758					0.917*			
		(1.50)					(2.07)			
llife			-1.726					-1.811		
			(-0.31)					(-0.29)		
lschoolm			5.613					5.718		
			(1.46)					(1.48)		
lbuiltden				0.180					0.203	
				(0.56)					(0.57)	
lpopden				-0.185					0.349	
				(-0.12)					(0.24)	
ltaxinct					-0.397					-0.406
					(-0.98)					(-0.92)
_cons	6.558	-2.789	-1.674	-0.748	-1.855	4.350	-4.133	-1.587	-0.154	-2.238
	(0.86)	(-0.48)	(-0.08)	(-0.11)	(-0.30)	(0.60)	(-0.74)	(-0.07)	(-0.03)	(-0.37)
N	628	628	628	628	628	628	628	628	628	628
R-sq	0.102	0.105	0.102	0.100	0.103	0.1202	0.1228	0.1225	0.1197	0.1211

t statistics in parentheses

* p<0.05   ** p<0.01   *** p<0.001

Note: The “l” attached to each variable name, except for the dummy variables, indicate that the variable is in logarithmic transformation

OLS reflects adjusted R-sq

B. Predicted values and the relative importance of the components of disaster risk

We use our model to gain understanding on the existing relative exposure, vulnerability and disaster risk of the provinces.[36] In Figure 7, we show the mean observed fatalities per province across all tropical cyclones and years (ijt). In Figure 8, we present the model's predicted fatalities using the mean of actual values of all variables we considered, covering the period 2005-2010.[37] The predicted values are estimated using Equation 7, with poverty incidence as the proxy for vulnerability[38]. The mean of observed fatalities is 3.81 per million population, while that of the predicted fatalities is 3.05 per million population.[39] In general, Figures 6 and 7 show that disaster impacts and current risks associated with tropical cyclones vary across provinces.

Using the same equation, we also estimate scenarios where we use one at time in separate regressions the observed minimum and maximum values of the proxies for hazard strength, exposed population, and vulnerability across *ijt*. Scenarios using these extreme values are not the most plausible assumptions, and therefore the corresponding estimates are not the most likely scenario to occur. However, these scenarios allow us to better appreciate which of the components of disaster risk have greater influence on the resulting disaster impacts in the context of the Philippine provinces. Table 5 below shows the summary of the observed and model-predicted fatalities for the various scenarios. For purposes of comparison, the table likewise shows the results for scenarios using mean values.[40]

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[36] Our model may not be appropriate to predict future fatalities, particularly as our dataset is a short panel only.
[37] Nine provinces have a difference between observed and predicted values of more than 2 fatalities per million population
[38] We choose poverty incidence, as it is the only vulnerability indicator that is found to be a significant determinant of both fatalities and affected persons. The variables and coefficients we use are as presented in Column 7 of Table 3. We ran separate estimates using only the variable found to be significant. They yield similar results as those using the full set of control variables.
[39] The test of means indicate that the two means not are significantly different.
[40] Table 23 in the Appendix shows the detailed values per province by scenario.

Figure 7

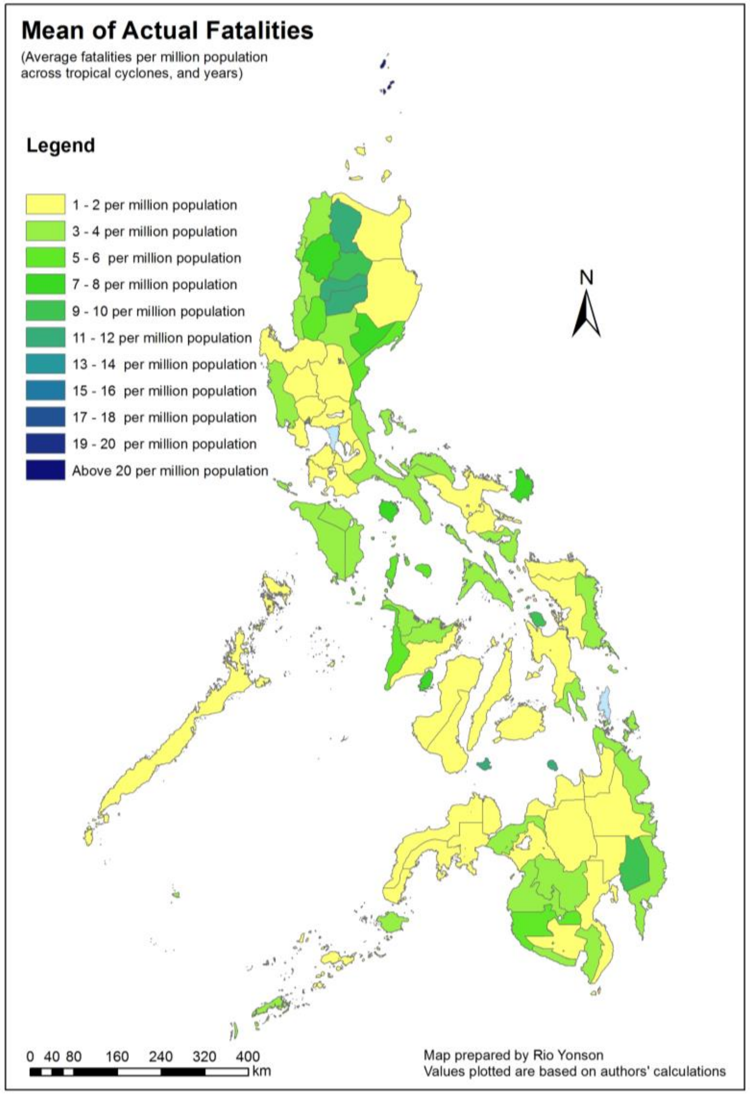
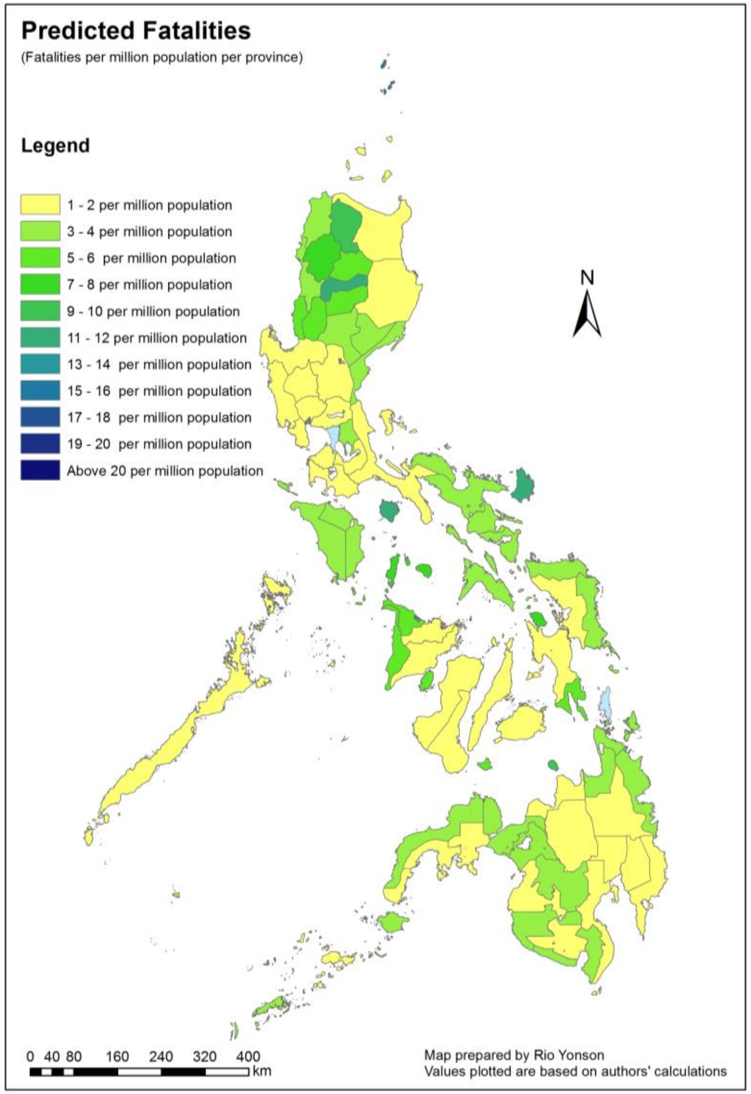


Figure 8



*The results presented in the maps are rounded up to the nearest whole number. Metro Manila and Dinagat Islands, which are shaded with light blue are not included in the sample.

Table 5. Observed and Predicted Fatalities by Scenario

Scenarios		Fatalities (per million population)
Observed Values		3.81
Base Case: Model Predicted Values		3.05
Scenario 1	Adjusted hazard strength using minimum rainfall volume	2.20
Scenario 2	Adjusted exposed population using minimum proportion of affected population	1.63
Scenario 3	Adjusted vulnerability using using minimum poverty incidence	0.67
Scenario 4	Adjusted hazard strength using using maximum rainfall volume	3.81
Scenario 5	Adjusted exposed population using maximum proportion of affected population	5.53
Scenario 6	Adjusted vulnerability using maximum poverty incidence	4.88
Scenario 7	Adjusted hazard strength using mean rainfall volume	3.11
Scenario 8	Adjusted exposed population using mean proportion of affected population	3.07
Scenario 9	Adjusted mean vulnerability using mean poverty incidence	2.74

In Figure 9, we present the results of the first six scenarios using the extreme values.[41] We use as base case scenario the model-predicted values presented in Figure 8. In Scenario 1, we set the rainfall volume for each province equal to the lowest recorded across *ijt*. Having set the hazard strength uniform across provinces and to the minimum, the intuition behind the results is that the fatalities are due more to a combination of exposed population, topography and vulnerability, than to the strength of the hazard. Under this scenario, the mean of the estimates across provinces in 2.20 fatalities per million population. Such results confirm a wealth of qualitative studies that have argued that people's vulnerability constitutes the main driver of disasters (e.g. Watts and Bohle, 1993; Lewis, 1999; Bankoff et al., 2004; Wisner et al., 2004).

In Scenario 2, we assign to each province the minimum observed level of exposed population, using as proxy indicator the number of affected persons per million population. The results under this scenario indicate that the relatively higher fatality rates are due mainly to a combination of

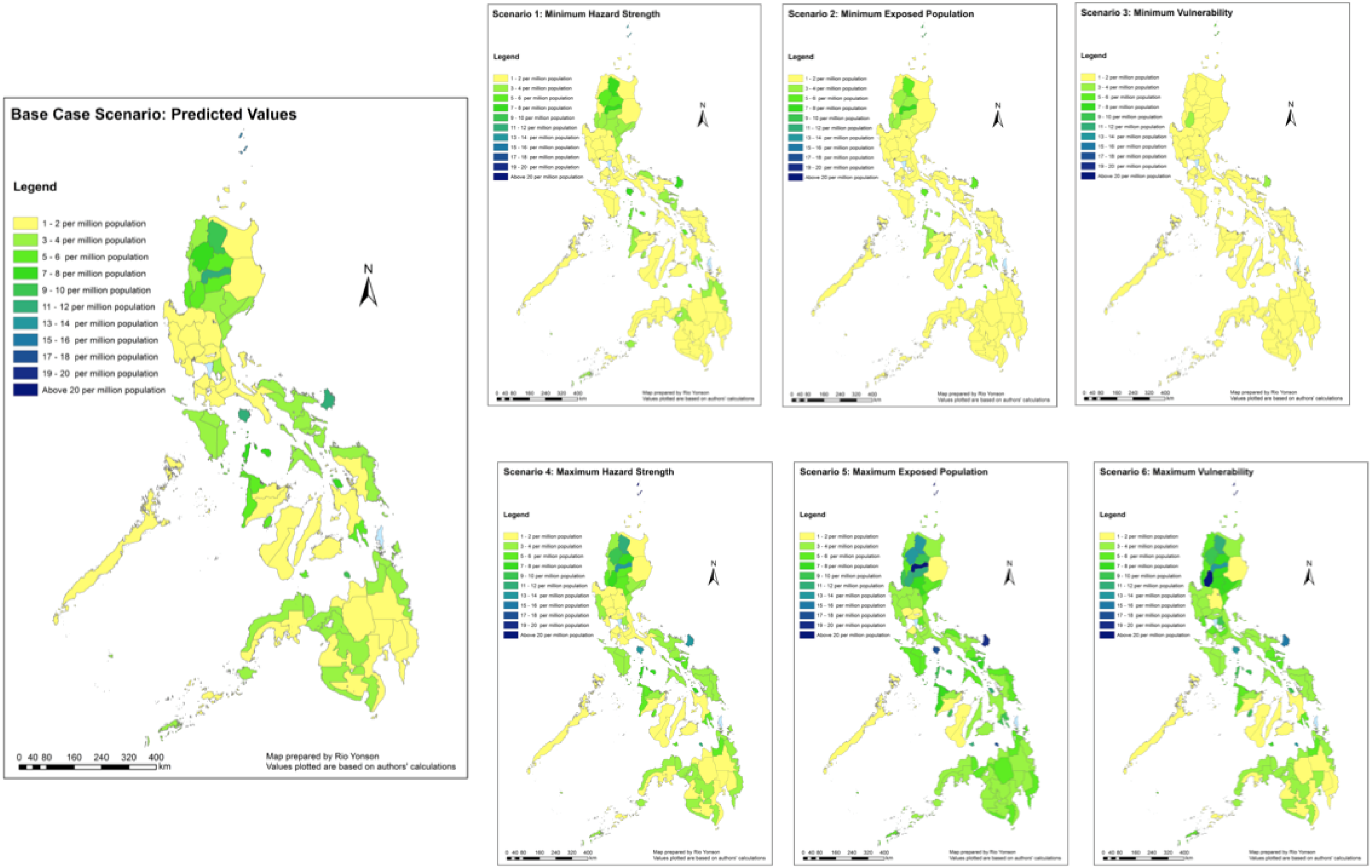
[41] The results presented in the maps are rounded up to the nearest whole number. Metro Manila and Dinagat Islands, which are shaded with light blue are not included in the sample.

vulnerability, topography, and the strength of the hazard, and only to a relatively lesser extent on exposure. This scenario bring the fatalities from 3.05 per million population in the base case scenario to only 1.63. Thus a changing in the exposure to tropical cyclones does alter the resulting disaster impacts.

Similarly, for the third scenario, we assign the same level of vulnerability to all provinces, using the minimum poverty incidence recorded across the provinces and years covered. With vulnerability kept to the minimum and uniform across provinces, the relatively higher fatalities can be attributed more to either hazard strength, exposed population and topography, or a combination of these, than to vulnerability. Among these three scenarios, it can be seen from the maps that it is the third scenario where the estimated fatalities are lowest, and with an overall mean that is substantially lower than that in the base case scenario. Under the third scenario, the average fatalities is only 0.67 persons per million population, compared to 3.05 under the base case scenario. This result indicates that only in three of the 79 provinces covered does vulnerability have a relatively weak influence on disaster impacts compared to hazard, exposed population, topography and geography. These three provinces are Batanes, Benguet and Catanduanes, all relatively more prosperous parts of the Luzon island group.

The important influence of vulnerability on disaster risk in the context of the Philippine provinces is more evident when we compare the results of scenarios using the minimum value of poverty incidence (Scenario 3), on one hand, and the maximum value of poverty incidence (Scenario 6), on the other hand. As can be gleaned, the predicted fatalities vary substantially as the level of vulnerability is adjusted, pointing to the important influence of vulnerability on disaster impacts. Scenarios 2 and 5 likewise show that the importance of exposure is more than that of hazard strength. The results provide initial indications that in the context of the Philippines, exposure and vulnerability have a greater relative importance than the hazard strength itself. This means that despite the Philippines' geographic and topographic setting – one that makes it prone to tropical cyclone hazards – grave impacts on people can be minimized through measures to reduce vulnerability and exposure.

Figure 10. Predicted Fatalities by Scenario



The results presented in the maps are rounded up to the nearest whole number. Metro Manila and Dinagat Islands, which are shaded with light blue are not included in the sample.

To systematically confirm this, we run separate sets of regressions using standardized variables in order to determine which among the components of risk have a greater influence on the resulting disaster impacts. The coefficients of the standardized variables indicate the relative importance of each control variable in determining the proportion of fatalities. The results are shown in the Appendix table 24. It can be seen that among the variables found to be significant in determining fatalities, rainfall volume and wind speed each have a lower coefficient than those of exposed population, topography, and vulnerability; fatalities are not mainly results of the destructive characteristics of the hazard, but more so of the exposure and vulnerability to the hazard.[42]

While we are not able to quantitatively identify which hazards associated with tropical cyclones affect each province more, we nonetheless attempt to extract insights from our results. Specifically, we consider the only three provinces with estimated fatalities of more than 2 per million population under Scenario 3. As noted earlier, these are the provinces whose exposure and hazard experience have a relatively more important influence on disaster fatalities. In Figure 10, we present the result of Scenario 3, this time juxtaposed with the maps on mean poverty (i.e. the proxy indicator for vulnerability), mean affected persons (proxy for demographic exposure), mean rainfall volume brought by tropical cyclones during the period (proxy for hazard strength), as well as mean slope and mean elevation (indicators of topography). As noted earlier, Scenario 3 depicts the provinces where vulnerability has a relatively less important determinant of disaster fatalities. This is confirmed for Benguet, which as shown in the mean poverty map, has one of the lowest poverty incidences across provinces. Poverty incidence in Benguet is only 6.23%, substantially lower than the average across provinces of 29.07%. On the other hand, the maps on topographic indicators show that Benguet has a combination of high mean elevation and high mean slope. In fact, Benguet has the highest mean elevation across provinces. In addition, the map on mean rainfall volume depicts that the province

[42] This is further confirmed in our preliminary regressions that control for hazard strength only; rainfall volume and wind speed together only explain a small proportion of the variation in the proportion of fatalities (R2 of less than 0. 05 in Columns 1 to 3 of Table 7 in the Appendix).

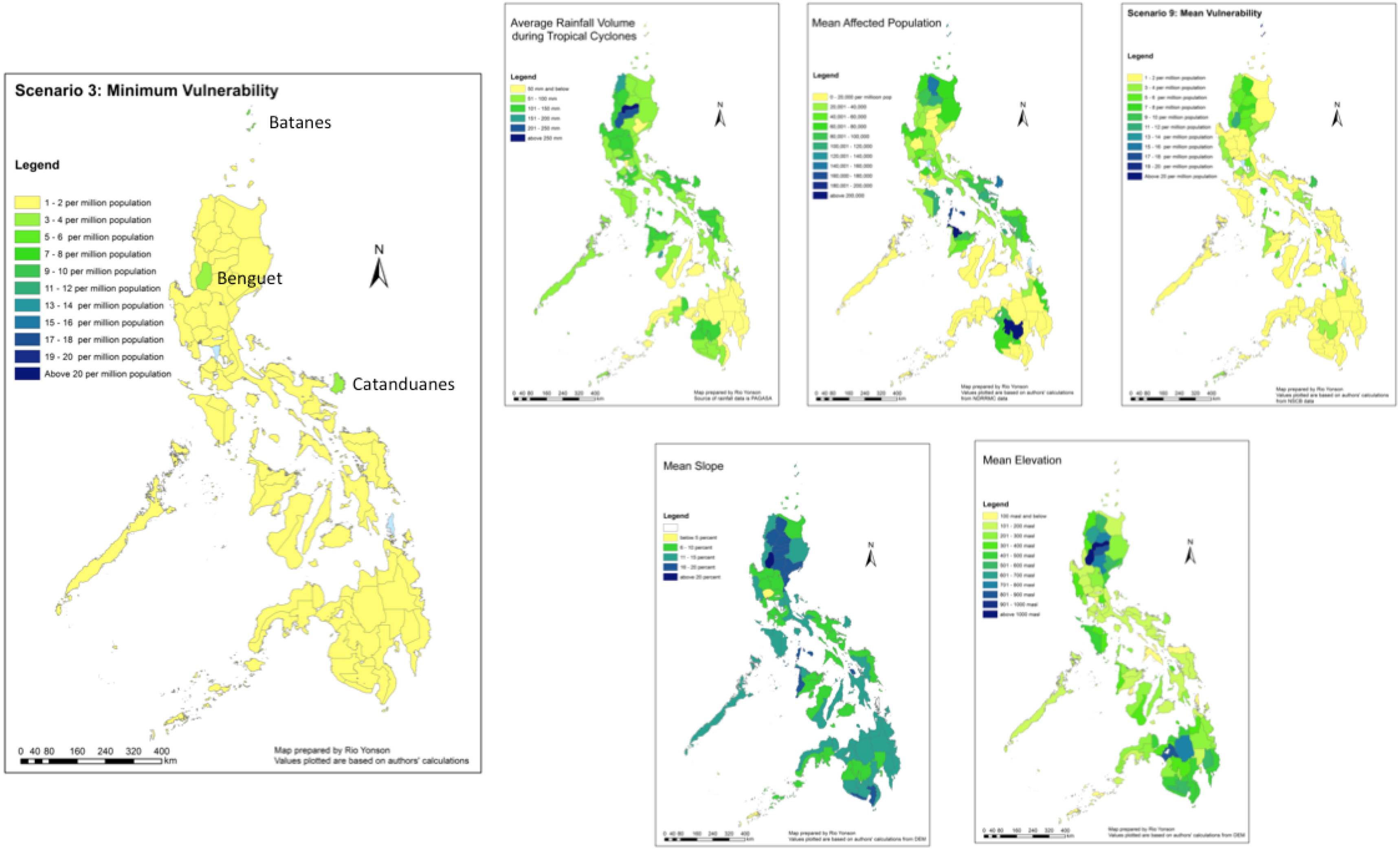
also experienced an average 24-hour rainfall of 245 mm during tropical cyclones, more than double the average of 101 mm across provinces. The combination of these topographic features and the relatively greater rainfall experienced by the province makes it susceptible to rain-induced landslides. Hence, it is a reasonable approximation that the fatalities in the province are likely brought about more by rain-induced landslides than the other associated hazards of tropical cyclones.

As for Catanduanes, an average of 145 persons per 1,000 population are affected during a tropical cyclone occurrence. This is almost thrice as much as the average across provinces of only 51 per thousand population. Similarly, Batanes' relatively higher fatalities is due to higher exposure. On average, there are 130 persons affected per thousand population. Like Benguet, poverty incidence in Batanes is low with an average of 14.76% during the period. Catanduanes though has high poverty incidence of 34.57%. Both Batanes and Catanduanes are small island-provinces that are detached from the main island of Luzon, and are located along the eastmost coastline facing the Pacific Ocean. Hence, it may be likely that storm surge and coastal flooding are the likely causes of a greater number of disaster-related fatalities in each of these provinces.

Overall, this comparison of various scenarios against the base case values reveals the following:

- Vulnerability and exposure, along with topography and geography, are relatively more important determinants of disaster impacts, more than hazard strength; and,
- The type of hazards that pose threat to the provinces vary, and this is influenced largely by the topographic and geographic characteristics of the province

Figure 10


Scenario 3: Minimum Vulnerability
Batanes
Legend
1 - 2 per million population
3 - 4 per million population
5 - 6 per million population
7 - 8 per million population
9 - 10 per million population
11 - 12 per million population
13 - 14 per million population
15 - 16 per million population
17 - 18 per million population
19 - 20 per million population
Above 20 per million population
N
Benguet
Catanduanes
0 40 80 160 240 320 400 km
Map prepared by Rio Yonson
Values plotted are based on authors' calculations
Average Rainfall Volume during Tropical Cyclones
Mean Affected Population
Scenario 9: Mean Vulnerability
Mean Slope
Mean Elevation

6. General Conclusions, Policy Implications and Next Steps

Our research is the first sub-national empirical work that combines the use of panel data econometric estimation methods with GIS tools to asses people's vulnerability and risk to disasters. These methods and tools allow us to systematically assess the dynamic nature of disaster risk and undertand the relative importance of its various components, and to capture the influence of the social, economic, institutional and physical dimensions of vulnerability. Together with our sub-national scale of assessment, these enable us to generate results that have direct usefulness into the integration of DRRM into the various stages of the provincial planning cycle.

The estimated disaster risk per province may serve as baseline values against which succeeding estimates are compared, and as a benchmark for use in the monitoring and evaluation of outcomes resulting from recently-implemented landmark DRRM laws and practices. As we use an evidence-based restrospective deductive approach, our results complement and add value of the existing inductive disaster risk assessement methodology used in the Philippines and elsewhere. Likewise, our findings on the factors affecting vulnerability and exposure provide broad yet systematically derived indications of a number of interventions that may be worthwhile to integrate into an investment programme for DRRM.

We find strong quantitative evidence of the linkage between several aspects of development and disaster-related fatalities, even in a country where the degree of hazard exposure is high. Having controlled for the three components of disaster risk, we are able to determine their relative importance in influencing the resulting disaster impacts. Broadly, we find that in the case of Philippine provinces, disaster impacts are generally influenced more by vulnerability and exposure, than by the hazard itself, thus confirming a number of qualitative studies conducted in different contexts across the archipelago (e.g. Bankoff, 2003; Gaillard, 2011; Porio, 2011; Cadag, 2013).

Our results reveal that the level of economic development, as proxied by income per capita, is negatively associated with fatalities. This indicates that adequacy of income allows people to afford their basic needs, including their needs to secure themselves from harm. In contrast, poverty, which we find to be positively associated with fatalities, deprives people from building safe dwellings and from acquiring legal access to settle in hazard-free areas. Poverty also forces people to forgo investments in human capital, particularly health and education, which we likewise found to be critical in building their capacity to survive disasters.

Good local development governance is associated with fewer disaster-related fatalities. Based on the presented results, improved governance may include the provision of services for public safety (such as early warning systems), as well as increased access to universal public basic education, and expanded and better quality public health services, particularly among the poor. Moreover, our result implies the need to strengthen accountability and effectiveness of the local government units in performing their mandated roles.

The positive and statistically significant coefficient for built-up density on disaster fatalities indicate that amidst unplanned and rapid urbanization, vulnerabilities are generated and exposure to hazards increased. This finding, along with the result that landlocked provinces and those with smaller areas of rivers have fewer affected persons, points to the need for better land use planning along with intensified enforcement of these plans and related laws and systems, such as zoning ordinances, water code, building code, and forestry code, as well as weather forecasting and monitoring, and early warning systems.

Overall, our results provide support for national and sub-national policy planning through the identification of priority regions and provinces, and critical DRRM interventions. Robust risk indexes, such as the one developed here, thus equip policy makers with tangible evidence to guide investments and actions. They encourage a development path that is carefully planned and which deliberately integrates into the development process the various components of disaster risk, particularly exposure and vulnerability. After all, apart from our findings that these components are found to be relatively more important, they are also the components of disaster risk that can be influenced by policy.

Econometric studies alone can hardly capture unequal power relations amongst individuals and the distant (in time and space) causes of vulnerability that facilitate or rather hinder access to resources and means of protection (Wisner et al., 2004). Studies at the national or subnational scales may also mask local inequalities and/or lead to further marginalisation of small vulnerable minorities in provinces and regions deemed less at risk when taken as a whole.

In the future, we plan to further examine the issues raised here, as additional relevant datasets become available for our use. We also note that due to data limitations, including the absence of maps on areas prone to other hazards induced by tropical cyclones, we are unable to further detail our vulnerability and risk assessment according to each of these associated hazards. In addition, we are not able to quantitatively explore the impact of environmental degradation on human vulnerability. Among other data on the environment, vector maps on the state of environmental quality or degradation (i.e. forest cover, etc.) will allow as to undertake such an assessment, using both spatial and statistical analysis tools. We likewise endeavour to cover these as we continue to pursue what we view as an important research agenda.

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