Development of Global Social Vulnerability Model for Earthquakes

by

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Abstract

Although earthquakes are one of the most devastating natural hazards that affect humanity, very few attempts have been made to consider the human elements that put populations at risk. Most researchers focus on the assessment of seismic hazard and the physical risk of a given area (i.e. potential for losses of life and infrastructure). But more integrated approaches that address both physical risk and social/human characteristics that place people at risk are needed to assess earthquake risk in a manner that is robust and holistic. Measurement of the concept of social vulnerability is one of the methods of addressing the human element of earthquake risk, which can be defined as characteristics or qualities within social systems that create the potential for loss or harm. There is no agreed-upon framework and established sets of data, however, to measure social vulnerability to earthquakes. It is within this context that the objective of this thesis is to take steps toward addressing the aforementioned area of opportunity by focusing on the human component of earthquake risk worldwide. The latter is accomplished by following a step-by-step methodology for producing composite indices representing the social vulnerability of countries to earthquakes within three topical areas (human impact potential, economic vulnerability, and recovery and reconstruction potential) that includes the development of a "wish list" of variables, missing data imputation, correlation anlysis, and global as well as geographically weighted regression analyses for variable validation and selection. Three research questions guide this work:

I) What metrics may provide the best comparative assessment of vulnerability to earthquakes from a societal perspective?

II) To what extent do these metrics predict measurable outcomes from earthquakes, including property losses, casualties, and displacement?

III) How does the predictability of metrics for measuring social vulnerability to earthquakes vary by world region?

The results show that a number of different indicators can be used to assess social vulnerability considering the human impact, economic vulnerability and recovery potential, and these indicators vary across space. Using earthquake losses, fatalities, homelessness and total population impacted by earthquakes as a dependent variable in the regression analyses, the results also demonstrate that some of the variables such as housing and commercial building density have higher associations with earthquake impacts than other variables.

Acknowledgments

The completion of this thesis is the culmination of many long hours of work, late-night coffee breaks and constant support of my mentors, family, and friends. Completion of this work has been a firm academic challenge and a test of my determination during my academic career. I have learned things not only about my research but about myself and my professional interests along the way.

I would like to first thank my major professor, Dr. Christopher G. Burton. I could not imagine where my carrier ambitions would be without his inputs. He has provided constant and positive support during the pursuit of my graduate degree with professional wisdom that I will continue to use for the rest of my life. He is an amazing scholar, educator and mentor. I look forward to our future collaborative work together and continue to learn from him after I move on from my time at Auburn.

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Chapter 1: Introduction

Earthquakes are one of the most devastating natural hazards that affect humanity (Sengar et al. 2013). Between 2000 and 2015, natural hazards accounted for 1,192,794 deaths of which 67% of these deaths were caused by earthquakes (USGS 2017). It is within this context that trends in population growth have resulted in rapid, and at times unplanned, urbanization that has considerably enhanced earthquake loss potential worldwide. It is becoming progressively obvious that threats to society from earthquakes will increase in parallel with global urbanization, and millions of people will be increasingly vulnerable to earthquakes in the coming decades (Voigt et al. 2007; Lantada et al. 2008; Cvetkovic et al. 2015). For these reasons, great emphasis is being placed by governments, stakeholders, and researchers on assessing and communicating the risk of people and places from earthquakes (Cardona 2003; Cutter et al. 2008; UNDRR 2015). Despite efforts undertaken by social scientists since the mid-20th century (e.g., White 1942; Kates 1971; Quarantelli 1988), however, systematic studies of earthquake risk have been primarily assumed by experts in the natural sciences and engineering (Cardona 2003). The latter has led to approaches for assessing earthquake risk that remain focused primarily on the hazard event itself in terms of potential for groundshaking, or on estimated damages to buildings, but not on social conditions that create a differential potential for loss or harm from earthquake events. This bifurication in earthquake risk studies has been exemplified by the Global Earthquake Model (GEM) Foundation and their publication of the world's first high resolution global earthquake hazard and risk maps (Figure 1.1) (GEM Foundation 2019). Although these maps aim to deliver a comprehensive global assessment of earthquake hazard and risk (defined as the potential for losses), they fail to capture spatial patterns of differential capacities of populations to reduce earthquake loss, to respond to seismic emergencies, and to recover from damaging earthquake events when they occur.

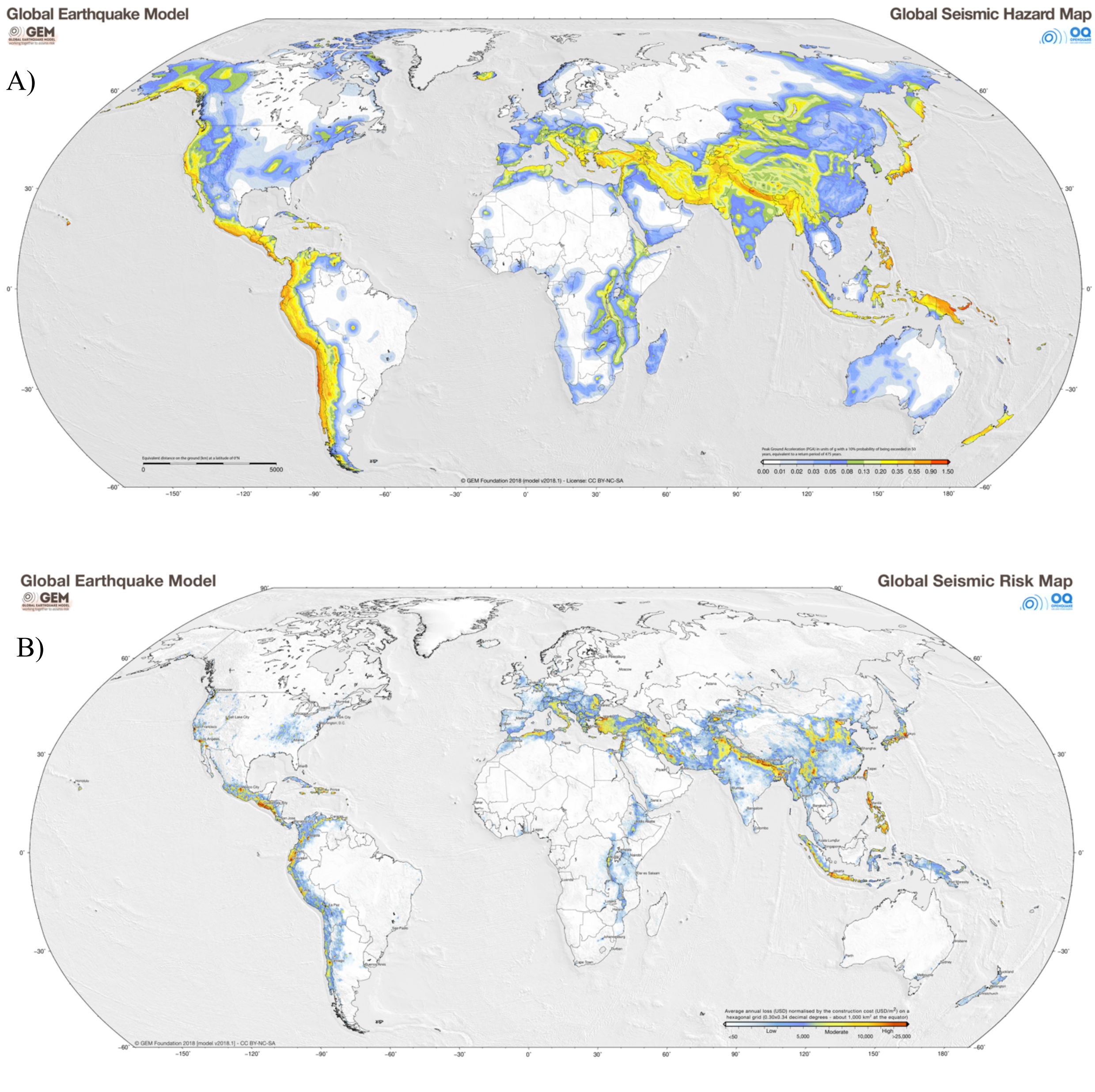

Figure 1.1: Example of A) global earthquake hazard and B) global earthquake risk model. [Adapted from GEM Foundation (2019)]

To promote earthquake resilient societies, and to address the area of opportunity outlined above, a paradigm shift is needed that diverges from focusing heavily on assessing earthquake hazard and risk towards the identification, assessment, and ranking of various vulnerabilities to earthquakes within social systems (Maskrey 1993; Lavell 1996; Bogardi and Birkmann 2004; Burton and Silva 2016). It is within this context that the purpose of this research is to take steps toward addressing the aforementioned area of opportunity by addressing the human component of earthquake risk. Addressing the human component of earthquake risk can be accomplished through the measurement of the concept of social vulnerability which is often defined as characteristics or qualities within social systems that create the potential for loss or harm (Cutter 1996; Cutter et al. 2003). However, there is no agreed-upon framework and established sets of data for measuring, understanding, and communicating social vulnerability to earthquakes (Burton and Silva 2016). This is partially due to a lack of attempts to validate the social vulnerability concept as well as a need to account for the context of the natural hazard itself, i.e., characteristics that result in populations being vulnerable to an earthquake may be different from characteristics that result in populations being vulnerable to other hazards such as a drought or flood (Rufat et al. 2015).

Three research questions guide this work:

I) What metrics may provide the best comparative assessment of vulnerability to earthquakes from a societal perspective?

II) To what extent do these metrics predict measurable outcomes from earthquakes including property losses, casualties, and displacement?

III) How does the predictability of metrics for measuring social vulnerability to earthquakes vary by world region?

Using the aforementioned research questions as a guideline, the objective of this thesis is to produce a validated set of composite indices (also known as composite indicators) that represent the social vulnerability concept applied to earthquakes for the world. Here, the term "composite indicator" is used to designate the manipulation of individual data to produce an aggregate measure of social vulnerability. An indicator is a quantitative or qualitative measure derived from observed facts that model the reality of a complex situation (Freudenberg 2003). A composite indicator is the combination (mathematically) of individual data (also referred to as variables) or thematic sets of data that represent different dimensions of a concept that cannot be fully captured by any individual indicator alone (OECD 2008; Cutter et al. 2010).

The development of the composite indicators for this research was accomplished as part of a larger project conducted by the GEM Foundation. The purpose of the GEM project is to supplement the global earthquake hazard and risk maps demonstrated in Figure 1.1 with maps depicting the global social vulnerability of populations. This work contributes to GEM's effort by mapping worldwide social vulnerability using metrics that compare countries to one another, but also by highlighting variables that could be most appropriate for measuring the social dimensions of earthquake risk at sub-national levels of geography where public policies to reduce earthquake risk are enacted.

Chapter 2: Literature Review

2.1 Defining Social Vulnerability

Vulnerability can be broadly defined as the potentiality of being negatively affected by any event. The word "vulnerability" is derived from the Latin word *vulnerare*, meaning "to wound" (Kates1985; Dow1992). At a very basic level, vulnerability can be defined as "the capacity to be wounded" (Kates1985; Dow1992) or the "potential for loss" (Cutter 1996). The concept of vulnerability evolved out of the social sciences and was introduced as a response to predominantly hazard-oriented studies on disaster risk in the 1970s (Schneiderbauer & Ehrlich, 2004). Although there are debates as to how to define vulnerability within social systems, it is almost always considered a concept for understanding conditions of people that enable a hazard impact to become a disaster (Tapsell et al. 2005; Cutter et al. 2003; Bankoff et al. 2004; Adger 2006). Here, the concept is used to describe the susceptibility of social groups (or society at large) to potential losses from hazard events rather than the individual potential for losses (termed as individual vulnerability) (Cutter 1996), and there are many definitions of it in the literature (Table 2.1). These definitions generally include the components of exposure, susceptibility, and adaptive capacity. Exposure is the degree to which people and the natural and constructed environment which contact with a hazard event (Cutter et al. 2006; Burton et al. 1993; Pelling 2003). Susceptibility is the tendency of exposed people and places to suffer the adverse effects of a hazard (Burton et al. 2018). Adaptive capacity and coping capacity refer to the ability of people, communities, and systems to adjust to adverse hazard impacts (Cutter et al. 2006; Blaikie et al. 1994).

Table 2. 1: Selected vulnerability definitions

Source	Definition
Mileti 1999	Measure of the capacity to weather, resist, or recover from the impacts of a hazard in the long term as well as the short term.
Alexander 2002	Susceptibility of people and things to losses attributable to a given level of danger, a given probability that a hazard will manifest itself at a particular time or place, in a particular way, and with a particular magnitude.
Bohle et al. 1994	Aggregate measure of human welfare that integrates environmental, social, economic, and political exposure to a range of harmful perturbations.
Wisner et al. 2004	Characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard.
Turner II et al. 2003	The degree to which a system, subsystem, or system component is likely to experience harm due to exposure or hazard; either a perturbation or stress/stressor.
Adger 2006	State of susceptibility to harm from exposure to stresses associated with environmental and social change, and from the absence of capacity to adapt.
Dow 1992	Vulnerability is the differential capacity of groups and individuals to deal with hazards, based on their positions within physical and social worlds.
Timmerman 1981	Vulnerability is the degree to which a system acts adversely to the occurrence of a hazardous event. The degree and quality of the adverse reaction are conditioned by a system's resilience (a measure of the system's capacity to absorb and recover from the event).
Susman et al. 1984	Vulnerability is the degree to which different classes of society are differentially at risk.
Kates 1985	Vulnerability is the 'capacity to suffer harm and react adversely.'
Bogard 1989	Vulnerability is operationally defined as the inability to take effective measures to ensure against losses. When applied to individuals, vulnerability is a consequence of the impossibility or improbability of effective mitigation and is a function of our ability to detect the hazards.
Liverman 1990	Distinguishes between vulnerability as a biophysical condition and vulnerability as defined by political, social, and economic conditions of society. She argues for vulnerability in geographic space (where vulnerable people and places are located) and vulnerability in social space (who in that place is vulnerable).
Downing 1991	Vulnerability has three connotations: it refers to a consequence (e.g., Famine) rather than a cause (e.g., drought); it implies an adverse consequence (e.g., maize yields are sensitive to drought; households are vulnerable to hunger);

	and it is a relative term that differentiates among socioeconomic groups or regions, rather than an absolute measure of deprivation.
Dow and Downing 1995	Vulnerability is the differential susceptibility of circumstances contributing to vulnerability. Biophysical, demographic, economic, social, and technological factors such as population ages, economic dependency, racism, and age of infrastructure are some factors which have been examined in association with natural hazards.

2.2 Conceptualizing Social Vulnerability

The ability to measure social vulnerability is considered a key step towards efficient risk management and the promotion of societies that are resilient to natural hazards such as earthquakes. It is within this context that the social vulnerability of populations can vary significantly across social and geographic space (Bohle et al., 1994; Cutter, 1996; Liverman, 1990) leading to populations that are differentially exposed to and affected by natural hazard impacts. Social space refers to who is vulnerable and is defined by the political, economic, and institutional capabilities of people at a specific time and place (Bohle et al., 1994; Wisner et al., 2004). Conversely, geographic space describes the location and scale at which people and places are vulnerable (Cutter, 1996). Predominant theoretical frameworks that have helped guide our understanding of the social vulnerability concept have been categorized into three distinct framings (Burton et al. 2018). These include risk-hazard, political economy and ecology, and the hazard of place framework. These frameworks are described in the following section since adopting a relevant framework will provide the basis for the selection and combination of single indicators into a meaningful composite indicator under a fitness-for-purpose principle for measureing social vulnerability to earthquake events (OECD 2008).

2.2.1 Risk-Hazard

The Human Adjustment to Natural Hazards model (Kates 1971) is one of the earliest theoretical models that incorporates what is now refered to as the risk-hazard approach for natural hazard vulnerability assessments (Figure 2.1). Social vulnerability from the risk-hazard perspective is defined as the potential for loss or other adverse impacts, or the capacity to suffer harm (Cutter 1996). Some experts have expressed it mathematically in a risk equation: 'Risk = Hazard x Exposure x Vulnerability' (Schneiderbauer and Ehrlich 2004). Although natural hazard risk is often viewed as a function of coupled physical, social, and economic factors, in the risk-hazard method, it is assumed that the hazard plays the central role. Thus, the degree of the vulnerability of a population depends on the exposure to a hazard event. As the risk-hazard approach depends on exposure to hazard events, the model posits that by modifying exposure to through land-use-planning, engineering, and monitoring the existing condition, disaster impacts can be reduced (Hewitt 1983). The Human Adjustment to Natural Hazards model and its accompanying risk-hazrd approach for understanding vulnerability has been criticized, however. This is primarily because the model poorly describes human actions which affect hazard impacts and also does not consider political and economic components that put people and places in harm's way. For these reason's the model was not adopted as a means to guide this research.

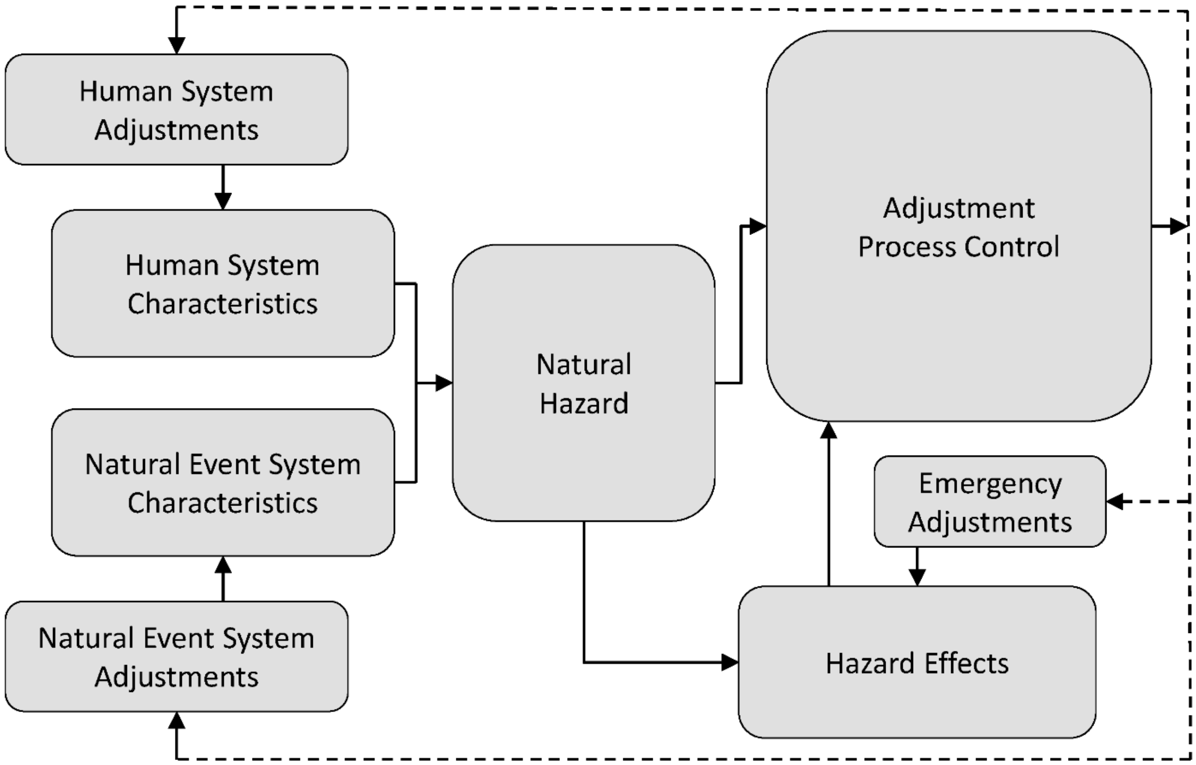

Figure 2. 1: Human adjustment to natural hazards [Adapted from Kates (1971)]

2.2.2 Political Economy and Ecology

Social determinants of vulnerability help us to understand why people who might have the same level of exposure to a hazard may face different, and differential, levels of adverse impacts when damaging events occur. The concept of social vulnerability to natural hazards has its roots in the domains of political economy and political ecology (Burton et al. 2018). Political economy researchers generally focus on how political (strength of democratic system, human rights, corruption, legitimacy of government action, citizen participation in decision making etc.), economic (income, wealth, debt, credit access, trade policy etc.), social (class, gender, ethnicity, age, religion, immigration status, literacy, education, health etc.), and institutional (rules, regulations, programs, decision making procedure etc.) factors produce differential exposure and susceptibility to hazard events (Burton et al. 2018). Political ecologists/economists extend the concept by examining how these structural determinants within societies generate, exacerbate, and attenuate environmental hazards (Collins, 2008). From both the political ecology and economy perspectives, disasters result from failures of political and economic systems, producing inequality, marginality, and lack of opportunities for individuals. Societal issues such as policy agendas, resource management, land-use patterns, wealth distribution, and economic development may overlap with natural events, combining with place and time to make individual hazards unique (Mitchell et al. 1989; Tobin and Montz 1997). There is also a potentiality of multiple stress factors occurring simultaneously. For example, the occurrence of an extreme natural event concurrent with economic marginality can result in double exposure (O'Brien et al. 2004). Therefore, in order to truly understand impacts from natural hazards, stress factors cannot be considered in isolation (Tobin and Montz 1997).

The Pressure and Release (PAR) model is a framework developed under the Political Economy/Ecology paradigm for showing how disasters occur when natural hazards affect people (Blaikie et al. 1994). Here, vulnerability is rooted in social processes and underlying causes, which may ultimately be not directly related to the hazard itself such as the development of public policies that foster social inequalities and occupation of high hazard zones. The basis for the PAR is that a disaster is the intersection of two opposing forces: those processes generating vulnerability on one side (pre-existing socio-economic or biophysical conditions), and the natural hazard event (or sometimes a slowly unfolding natural process) on the other. The image portrayed by Figure 2.2 resembles a nutcracker where increasing pressure from the "progression of vulnerability" on the left side of the figure and the "hazard" on the right side of the figure produces the disaster potential (Wisner et al. 2003). The 'release' idea is incorporated to conceptualize the reduction of disaster vulnerability: to relieve the pressure; vulnerability has to be reduced.

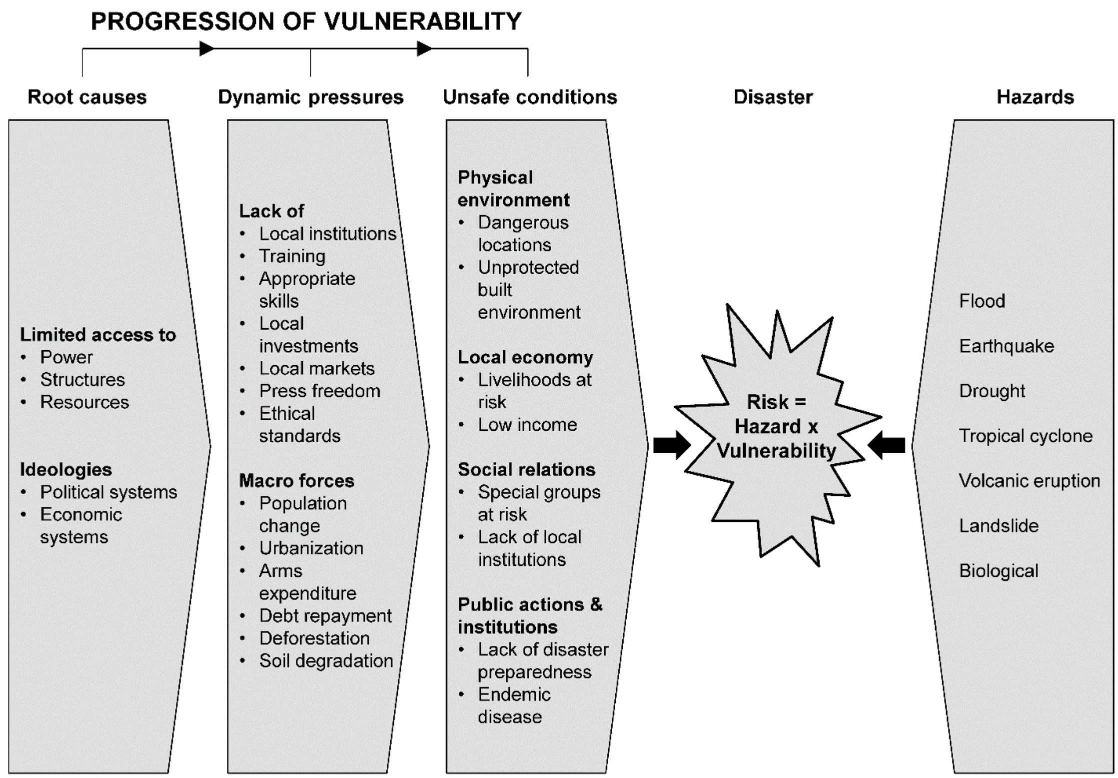

Figure 2. 2: Pressure and release (PAR) model [Adapted from Blaikie et al. (1994)]

The PAR model has been criticized for downplaying physical aspects of natural-human systems interactions and underemphasizing system feedbacks common in human adjustment models (Turner II et al. 2003). Other critics of the model argue that the PAR is well suited for descriptive analysis via qualitative methods only. Conversely, it is not very suitable for quantification, and thereby not appropriate for this research, because the root causes and dynamic pressures portion of the model are nearly impossible to measure consistently using secondary source data such as those from country censuses (Burton et al. 2018). For example, it is difficult to define and measure characteristics that affect vulnerability such political ideologies or cultural attitudes towards risk (Burton et al. 2018).

2.2.3 Hazards-of-Place Model of Vulnerability (HoP)

To fully understand the effects of potential hazards and associated impacts from them, some researchers argue that the analysis of natural hazards and disasters should expand from a focus on single hazards to all hazards that affect a place (Hewitt and Burton 1971). The Hazards-of-Place Model of Vulnerability (HoP) (Cutter 1996) addresses this "all hazards" approach by combining vulnerability from biophysical and social systems to produce vulnerability assessments specific to a particular place and time (Figure 2.3). In the model, risk and hazard mitigation interact to determine the initial hazard potential for a place. The hazard potential then interacts with the geographic context of a place to produce the place's biophysical vulnerability (i.e. multi-hazard impact potential). In addition, the hazard potential interacts with a place's social fabric. Understanding the social fabric of a place is important within the context of this thesis because the starting point for measuring social vulnerability is to capture contextual conditions within a study area's social fabric that could create the potential for harm and loss. It is within this context that there is a tradition of research focused of factors that either increase or decrease the adverse impacts of natural hazard events on populations. These characteristics include age, gender, and the distribution of income (Tierney et al. 2001; Cutter et al. 2003; National Research Council 2006; Burton and Silva 2016). These characteristics also include access to education, governance, healthcare access, and employment access (Cutter et al. 2003; Burton and Silva 2016). It is the underlying social fabric of a place that can be quantified to measure the social vulnerability of populations to earthquakes. When combined with hazard metrics (the biophysical vulnerability portion of the model) using map overlays or mathematical convolution, a total vulnerability of a place can be obtained.

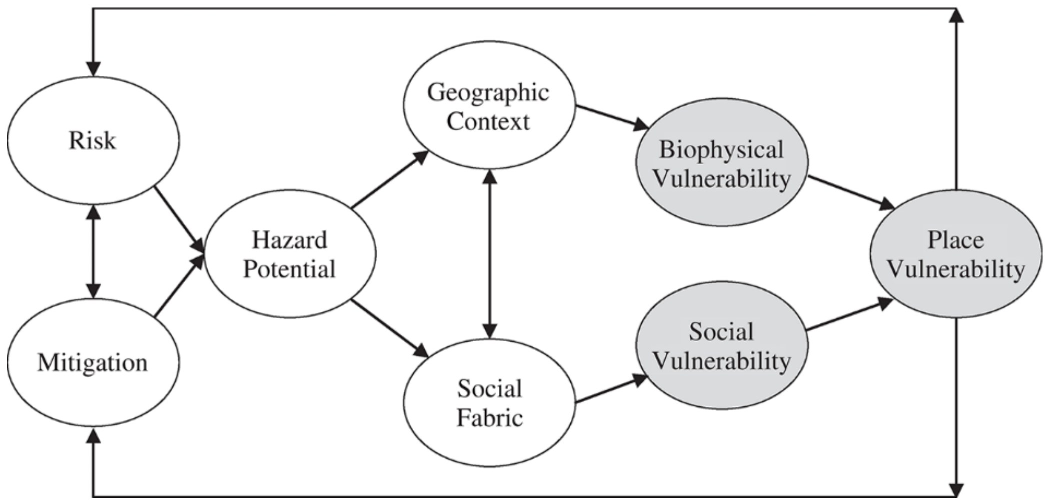

Figure 2. 3: Hazard of place model of vulnerability [Adapted from Cutter et al. (1996)]

This place-based approach has been applied in a myriad of studies to date (e.g. Jones and Andre 2007; Burton and Cutter 2008; Fekete et al. 2009, Khazai et al. 2014), and the framework has been modified to be suitable for earthquake risk assessments. Of significance for this thesis is the Integrated Earthquake Risk Framework (Burton and Silva 2016) that builds heavily upon the HoP model. This framework is discussed directly below in the Sub-section 2.2.4.

2.2.4 Integrated Earthquake Risk Framework

An integrated approach to identify the adverse effects from earthquakes, as delineated within the Integrated Earthquake Risk Framework (Burton and Silva 2016), is the combination of calculating physical risk (i.e., estimates of losses of life or infrastructure) for earthquakes coupled with quantified metrics of social vulnerability (Figure 2.7). As with the HoP model, the social vulnerability of populations refers to preexisting conditions within a community's social fabric that make some people more vulnerable than others given equal exposure to a damaging event. Burton and Silva (2016) developed the Integrated Earthquake Risk Framework to assess earthquake risk for Portugal using the HoP Model (Cutter 1996 and Cutter et al. 2000) as a starting point. The Integrated Earthquake Risk Framework diverges from the HoP model in that: 1) the starting point for the Integrated Earthquake Risk Framework is the calculation of seismic hazard (either probabilistically or deterministic); 2) physical risk from earthquakes (i.e. calculations of potential damages and financial loss to buildings) is calcualted in lieu of multi-hazard biophysical vulnerability; and 3) the ability to mitigate against hazard events is captured within the social vulnerability portion of the model.

The risk for Portugal was calculated using the GEM OpenQuake-engine (Pagani et al. 2014; Silva 2014). The OpenQuake-engine is a python-based module which comprises a series of workflows that have been used to calculate both earthquake hazard and physical risk (Pagani et al. 2014). The social vulnerability of populations within Portugal was assessed by constructing a composite indicator of social vulnerability. A total risk index was then constructed to estimate integrated risk by the convolution of social vulnerability index with the estimates of average annual loss. The amenability of a place's social fabric to qualtification and the theoretical ability to combine the social vulnerability maps with metrics of earthquake hazard and risk, such as those delineated in Figure 1.1, make the Integrated Earthquake Risk Framework ideal to guide the development of social indicators for this thesis.

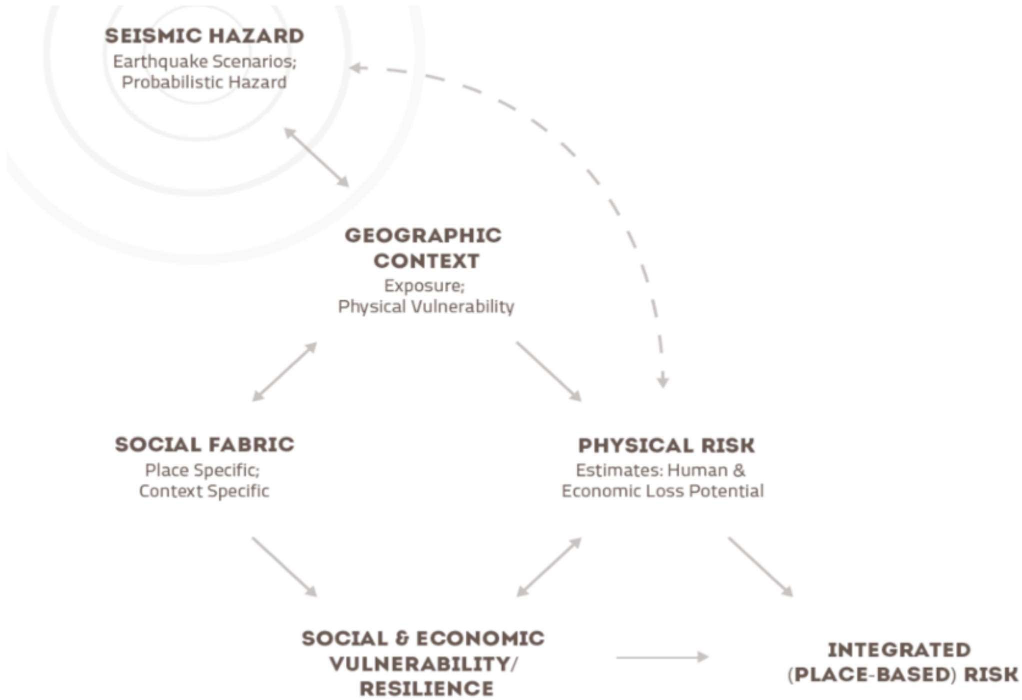

Figure 2. 4: Framework for integrated risk assessment in OpenQuake [Adapted from Burton and Silva (2016)]

2.3 Summary

A sound theoretical framework is the starting point for constructing composite indicators which is one of the outcomes of this work. This is because the theoretical framework provides the means for researchers to get a clear understanding and definition of the multidimensional phenomenon to be measured and to develop a selection criterion for culling variables that will make up the composite indices of social vulnerability (OECD 2008). In other words, the theoretical framework provides the basis for the selection and combination of variables into a meaningful composite indicator.

The frameworks discussed in this section are attempts to define, understand, and provide the basis for the measurement of social vulnerability in different ways. The risk-hazard approach puts more emphasis on the hazard event and exposure but fails to incorporate human actions contributing to vulnerability and socio-economic conditions of the affected population. On the other hand, the PAR put more importance on preexisting socio-economic conditions rather than the physical aspects of nature-human system interactions, but it is nearly unquantifiable. The HoP model addresses the problems inherent within the two previous models and posits that both social and biophysical systems cause vulnerability at particular places and times. Although the Hazard of Place model has been utilized widely in the literature, and in a variety of studies, a more applicable framework designed explicitly for earthquakes was adopted here. This thesis makes use of the Integrated Earthquake Risk Framework (Burton and Silva 2016) as discussed is Section 2.2.4 for its theoretical background. This framework uses the procedure of constructing social metrics using best practices outlined in the earthquake risk literature.

Chapter 3: Methodology

3.1 Study Area

As the outcome of this thesis is to construct metrics to quantify global social vulnerability to earthquakes, the study area is the whole world. This thesis accounts for all countries with populations of 200,000 or more (*N*=193). Countries not meeting the designated population threshold were deleted due to data limitations that occurred where some small countries and Island States had no data reported. Since drivers of the social vulnerability of populations are likely regional and dependent on similarities and differences in culture and the socio-economic standing of countries, a regionalization scheme was utilized as not to compare countries in which cultural and economic situations diverge in statistical analyses and for the imputation of missing data (discussed in the sub-sections below). As a result, data processing and analysis were at both the global and regional level. To classify the world into regions of similarity, World Bank Country and Lending Groups were utilized (The World Bank 2018). Here, the World Bank classified countries into regions based on :1) cultural similarities and geography, and 2) by similarities in income. The cultural/geographical regions (Figure 3.1) are:

1. East Asia and Pacific;
2. Europe and Central Asia;
3. Latin America & the Caribbean;
4. Middle East and North Africa;
5. North America;
6. South Asia; and

7. Sub-Saharan Africa

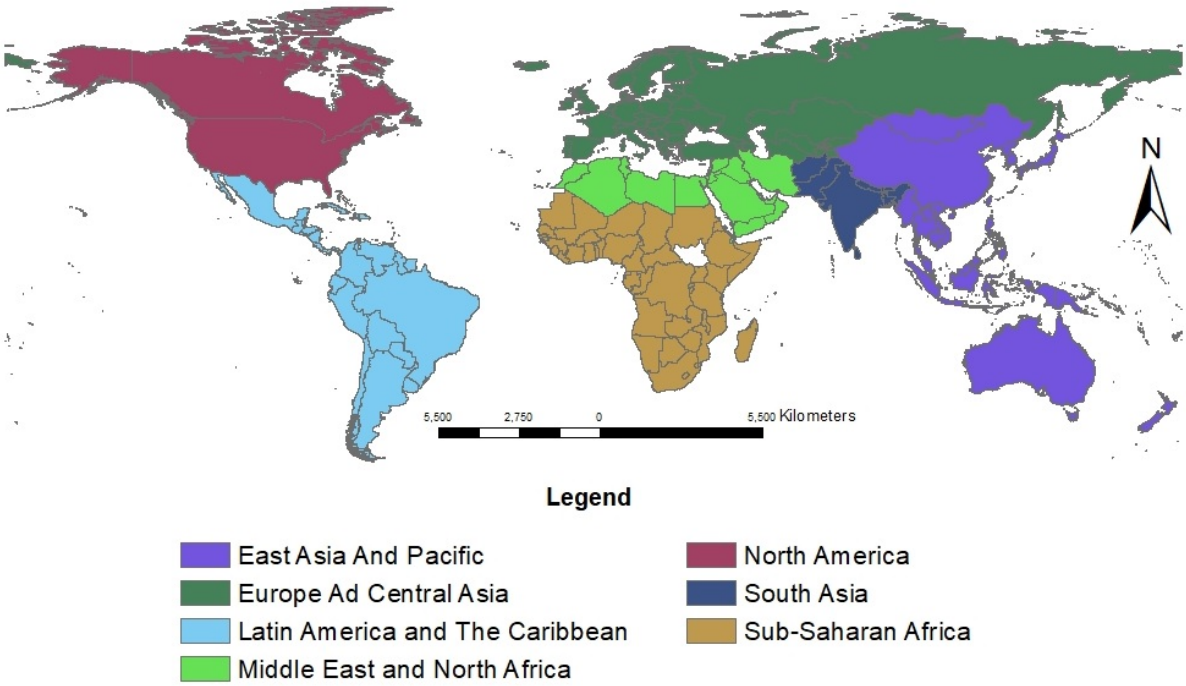

Figure 3. 1: World bank geographic regions. [Adapted from world bank (2018)]

Regionalization by income (Figure 3.2) includes:

1. Low-income economies (Gross national income per capita of $1,025 or less);
2. Lower-middle-income economies (Gross national ncome per capita between $1,026 and $3,995);
3. Upper-middle-income economies (Gross national income per capita between $3,996 and $12,375); and
4. High-income economies (Gross national income per capita of $12,376 or more)

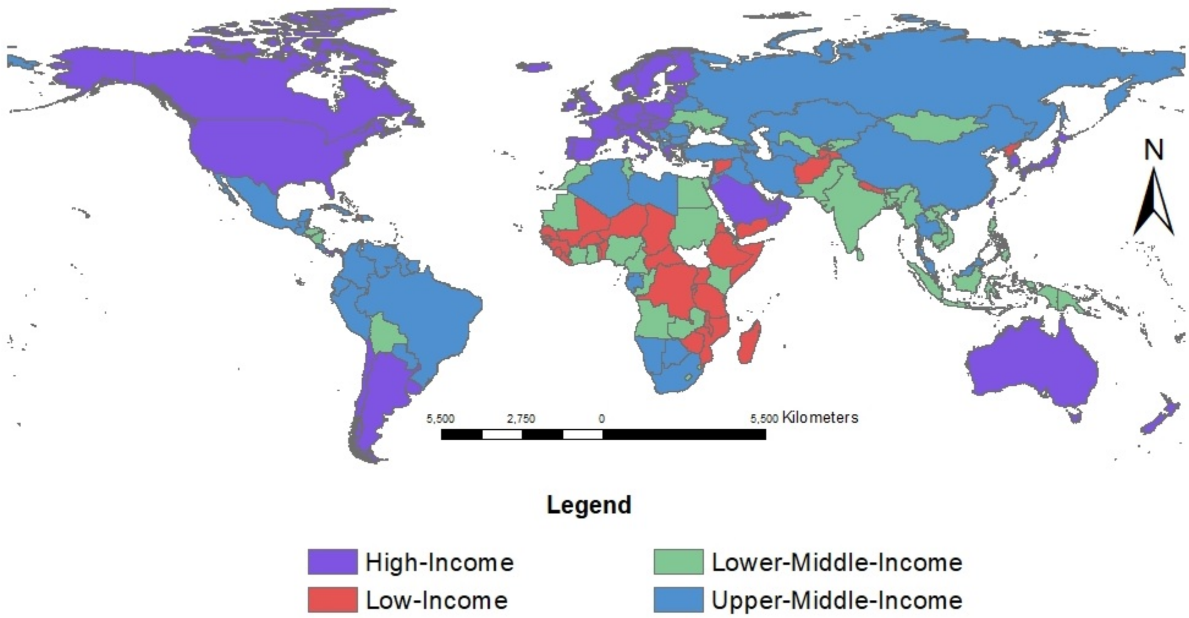

Figure 3. 2: Word bank income regions. [Adapted from world bank (2018)]

3.2 Overview of the Methodology

The intent of this thesis is to provide a rough set of composite indicators that are capable of offering a broadly brushed approach for measuring, comparing, and communicating the social vulnerability of countries throughout the world to earthquakes. The methods entail the development and testing of a robust and validated set of indicators that make up the composites. A composite indicator generally measures multi-dimensional concepts which cannot be captured with a single indicator, and composite indicators have been considered ideal tools to quantify social vulnerability (Cutter et al. 2010). The literature outlines several steps for the development of a composite indicator. These include: 1) data selection; 2) imputation of missing data; 3) multivariate analysis; 4) normalization; 5) weighting and aggregation; and 6) presentation and visualization (OECD 2008). Each step helped to make up the methodology of this thesis which includes a 5-step workflow (see Figure 3.3).

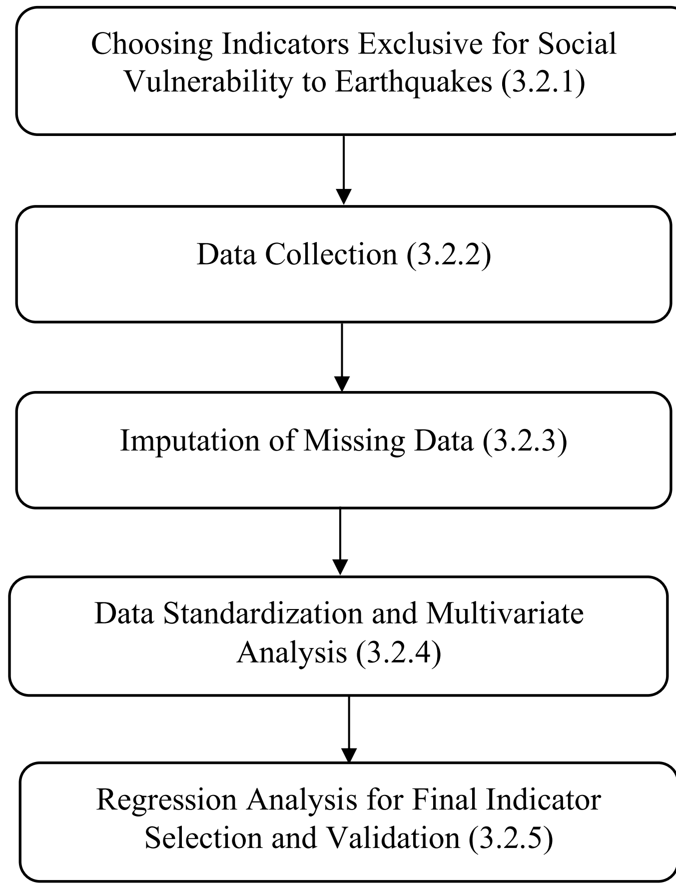

Figure 3. 3: Workflow for social vulnerability indicator selection

3.2.1 Choosing Indicators Exclusive for Social Vulnerabilty to Earthquakes

To choose indicators exclusive for modeling social vulnerability to earthquakes, the starting point was an exhaustive review of the social vulnerability literature. This review of the literature was conducted in collaboration with social vulnerability scientists at the Global Earthquake Model to develop a "wish list" of variables that can be applied exclusively to measure social vulnerability to earthquakes. For this, more than three hundred papers were collected and compiled into a digital library. These papers were then reviewed to identify characteristics identified in the literature as either contributing to or reducing the social vulnerability of populations to natural hazard events, earthquakes in particular.

Appendix A constitutes the wish list of approximately 440 indicators that were derived from the literature and that were considered for the work conducted for this thesis. For a variable to be considered appropriate and collected, three equally important criteria were met. First, it was essential that variables were justified based on the literature and regarding the variable's relevance to social vulnerability within three categories that are intended to measure pre-existng conditions within a country's social fabric that affect the vulnerability of populations (see Figures 2.3 and 2.4). The three major categories are outlined in Cutter (1996) and Cutter et al. (2003) and include: 1) human impact potential, 2) economic vulnerability, and 3) recovery/reconstruction potential.

The first theme, human impact potential, was designed to measure characteristics that exclusively pertain to social systems and that make populations and individuals vulnerable to loss of life and property (Cutter et al. 2003). This theme uses demographic attributes to capture the diffential capacities of populations to reduce the risk from earthquakes where the linking of social capacities with demographic attributes (see Appendix A) suggests that communities with higher percentages of age dependent populations (the very young and the old), homeless, disabled, under-educated, and foreign migrants are likely to exibit higher social vulnerability than communities lacking these characteristics (Tierney et al. 2001; Cutter et al. 2003; National Research Council 2006). Other relevant indicators include in-migration from foreign countries and population density (Cutter et al. 2000).

The economic vulnerability theme is the second sub-component. The economic vulnerability theme was designed to measure the exposure of a country's economy to exogenous shocks (Briguglio et al. 2009). It is also intended that the economic vulnerability theme be an appraisal of the state of economic health of countries. Here, relevant indicators include employment status, imports/exports, income, and purchasing power (Cutter et al. 2003). Other indicators are related to economic stability and include measures of single-sector economic dependence such as the percentage of population employed in tourism (Cutter et al. 2003).

The third theme, recovery and reconstruction potential, was designed to measure: 1) potential for rescue and relief operations, including the construction of emergency shelters and temporary housing; and 2) the ability to reconstruct buildings, housing, and critical infrastructure (Ghafory-Ashtiany and Hosseini 2008). The recovery and reconstruction theme is therefore closely coupled with the concept of community resilience to natural hazards and disasters, i.e. characteristics within communities that allow them to prepare for, respond to, and recover from damaging hazard events (Burton 2015). Measures of community resilience include preparedness (such as the percentage of the workforce employed in emergency services), access and evacuation potential (such as the density of roads and rail lines), and social capital (such as the prevelance of civic and social advocacy organizations within a country) (Burton 2015).

The second criterion for the selection of variables was that they must be of consistent quality and freely available from sources distributing national and sub-national data such as the World Bank, the United Nations, and country censuses. The third criterion was that variables must be scalable or available at varying scales. The concept of scalability was important for this thesis because the parameters that affect the social vulnerability of populations are unevenly distributed across space and should be reflected at the sub-national level where public policies to reduce risk and increase resilience are generated. Out of approximately 440 variables on the wish list, 85 of them were available and deemed fitting to measure social vulnerability to earthquakes based on the three criteria identified (Table 3.1). These variables were collected for further analysis. Since it is nearly impossible to measure social vulnerability in absolute terms, these variables were collected as proxy measures of social vulnerability.

Table 3. 1: Initial variable set for social vulnerability by theme and the number of references citing the variables within each theme

Indicator Names	***Human Impact Theme***	***Economic Impact Theme***	***Reconstruction and Recovery Theme***	**Total References all themes**
Population density (p/km2)	8	2	0	10
Slum population in urban areas	2	0	1	3
Years of health lost due to disability	14	1	6	21
Unemployment Rate	23	10	16	49
Average GDP growth rate (%)	0	5	2	7
Road density (km roads/100km2 of Area)	2	0	1	3
Adult mortality rate (Deaths per 1000 population)	3	0	1	4
Population proportion under 15 (%)	36	5	15	56
Population proportion over 60 (%)	36	5	15	56
Hospital beds (per 10 000 population)	4	0	2	6
Labor force participation rate, female (% of female population ages 15+)	3	0	1	4
Governance, voice and accountability	1	0	0	1
Median wealth per adult (US$)	0	1	1	2
Avg Debt per adult (US$)	1	2	0	3

% Commercial development (number of buildings)	8	0	0	8
% Industrial development (number of buildings)	0	3	2	5
Total building density per country (blds/km2)	0	0	2	2
Average household size (number of members)	9	2	2	13
Female headship %	14	2	4	20
Universal Health Care service coverage index	2	0	3	5
At least basic sanitation (%)	3	0	3	6
Age dependency ratio	5	0	4	9
Percent of population illiterate	9	2	1	12
Net migration rate	3	1	2	6
Government Effectiveness	1	1	1	3
Birth rate	4	0	2	6
Crime rate (Losses due to Theft, robbery, vandalism)	2	0	0	2
Gross Fixed capital formation	1	2	0	3
Environmental sustainability index	0	0	2	2
Foreign direct investments	0	3	2	5
GDP per capita	6	13	3	22
GINI index	7	11	3	21
International tourism receipts as a percent of GDP	1	1	2	4
Population with access to electricity	2	1	2	5
Life expectancy at birth	2	0	0	2

Inflation rate (consumer prices)	1	1	1	3
Merchandise exports FOB	1	1	0	2
Merchandise imports CIF	1	1	0	2
General government gross debt	1	2	0	3
General Government Revenue	1	2	0	3
Research and development expenditure	0	0	4	4
Foreign born migrants	1	1	0	2
Income payments	1	6	1	8
Crude death rate	3	0	1	4
GDP composition by sector - industry	1	5	1	7
Education expenditures	2	0	1	3
GDP - composition by sector - services	2	0	0	2
Population below national poverty line	12	3	6	21
GDP at purchasing power parity per capita	1	2	0	3
Prevalence of undernourishment	3	0	2	5
Percentage of the population below income poverty line	24	7	12	43
Male population without secondary education or higher	3	0	3	6
Female population without secondary education or higher	3	0	3	6
Remittance Inflows	0	2	1	3

Voter Turnout at last parliamentary Election	1	0	1	2
Employment in industry	2	0	1	3
Employment in services	2	0	1	3
Motor vehicles	5	1	2	8
Mobile cellular subscriptions	1	0	1	2
Fixed broadband Internet subscribers	1	0	0	1
Under 5 years mortality rate	2	0	0	2
Mean Years of Schooling	3	0	1	4
Children out of school, primary	1	0	0	1
Ratio of young literate males to females ages 15-24	5	0	0	5
Primary School Completion Rate	2	0	1	3
Refugees (country of origin)	3	0	1	4
Rural population	1	0	0	1
Population access to improved sanitation facilities	6	1	2	8
Population access to improved water source	6	1	3	9
Health expenditure per capita	3	1	0	4
Number of Physicians for 1000	2	0	4	6
International tourism arrivals	1	0	0	1
Gross national savings	1	2	1	4
GDP Nominal per Capita	6	13	3	22
Infant Mortality	3	0	0	3

Gross enrollment ratio, secondary	2	0		
Gross enrollment ratio, primary	2	0	1	3
Gross enrollment ratio, tertiary	2	0	1	3
Adult Mortality Rate	2	0	0	2
Labour force	5	1	2	7
Average Population Density (areas over 400 ppl/km2)	28	6	7	41
International Tourism Receipts as Percentage of total Exports	1	1	2	4
Ratio of Males to Females	19	1	11	31
Reference count per theme	**390**	**134**	**182**	**706**

3.2.2 Data Collection

Once the "wish list" of potential indicators was derived, data was collected. The primary source of data was the Global Earthquake Model's Socio-economic Vulnerability database (Power et al. 2014). This database contains 216 indicators linked to 197 countries. The database was compiled from 44 different publicly available sources providing indicators that directly represent the social vulnerability concept. Figure 3.4 illustrates the data sources and the different proportions they contributed to the socio-economic database. As can be seen in Figure 3.4, nearly 75% of the data comes from 4 primary data sources with the United Nations data making up 25.7% of the data. The variables cover a wide range of different aspects of country specifics such as demography, economics, health, and infrastructure.

In addition to the socio-economic data collected to measure the social vulnerability concept, earthquake outcome data was collected to be used in a validation step (see Section 3.2.5).

The earthquake loss data needed for validation of the indicators was collected from the EM-DAT Emergency Events Database (https://www.emdat.be/). EM-DAT was created with the initial support of the World Health Organization (WHO) and the Belgian Government and contains essential core data on the occurrence and effects of over 22,000 mass disasters in the world from 1900 to the present day. The database is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutes, and press agencies.

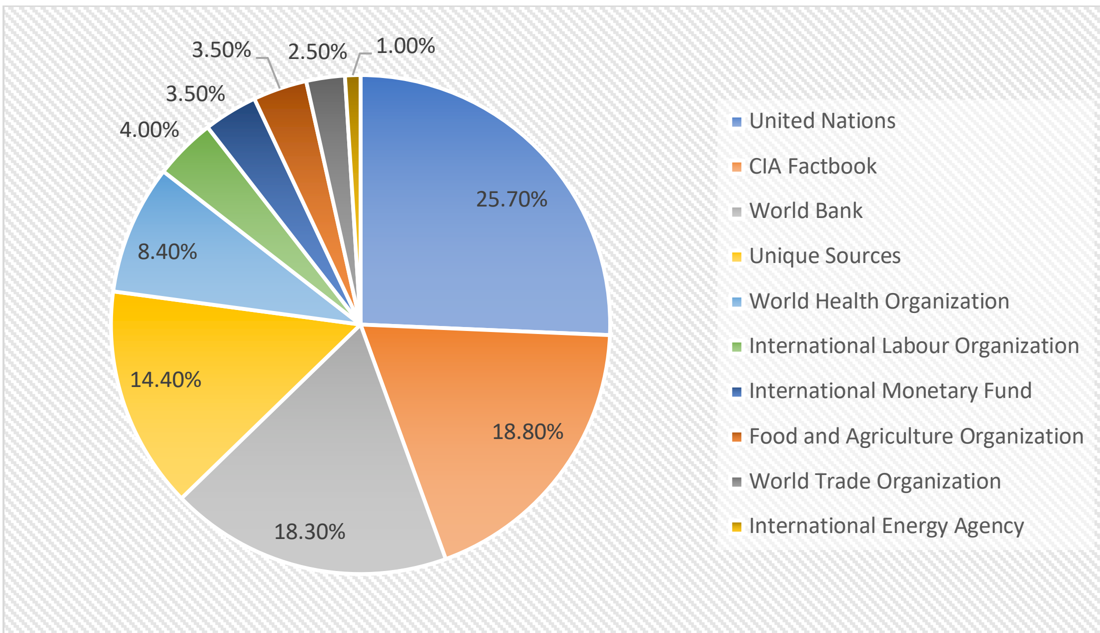

Figure 3. 4: Different source and contribution to the country-level database [Adapted from Power et al. (2014)]

3.2.3 Imputation of Missing Data

Once all the data were collected, a subsequent step had to be taken to address countries containing missing data entries for certain variables. Missing data can hinder the development of robust composite indicators, and steps had to be taken in this thesis to account for missing data values for certain countries. The literature on composite indicators development (e.g. Freudenburg 2003; Nardo et al. 2005; OECD 2008) outlines methods for imputing missing data. Here, data used for the development of composite indicators can be missing in a random or non-random fashion and include Missing Completely at Random (MCAR), Missing at Random (MAR), and Not Missing at Random (NMAR) cases. For MCAR cases, the missing values do not depend on the variable of which the missing data is from or on any other observed variables in the data set. For MAR cases, missing values do not depend on the variable of interest but are conditional on other variables in the data set. But in NMAR cases, missing values depend on the values themselves (OECD 2008).

In this study, the missing data constitute the MAR type. For example, the variable per capita income for any country can be unreported, but it has a relationship with other economic variables (GDP, Economic growth, demographic data, etc.). Thus, the missing values can be imputed using statistical methods and/or values derived by using values from neighboring countries. It is within this context that three methods are used for the imputation of MAR type missing data: (i) case deletion, (ii) single imputation or (iii) multiple imputations (OECD 2008). In the case of deletion, the missing records are simply omitted from the analysis. As a rule of thumb, if a variable has more than 5% missing values, cases are not deleted (Little & Rubin 2002) leaving analysts to fill in missing data values using single imputation (*e.g.,* mean/median/mode substitution, regression imputation, hot-and-cold-deck imputation, expectation-maximization imputation) or multiple imputations (*e.g.*, Markov Chain Monte Carlo algorithm). In this study, a single imputation method utilizing a combination of means and a hot-deck approach was used. Here, the hot-deck approach facilitated the filling in of blanks cells with individual data that were drawn from "similar" reporting units (countries in this case). Here, missing values were derived using the average values from countries within the same World Bank economic region. It was assumed that countries fall within the same economic region have similar socio-economic conditions and can thus be compared.

3.2.4 Data Standardization and Multivariate Analysis

Once all variables were collected with missing data imputed, subsequent steps were taken to develop what is referred to as a parsimonious dataset, parsimonious being defined here as the simplest plausible model with the fewest number of variables. First, when necessary, raw data was transformed into variables using percentage (e.g., percentage of population in poverty), per capita (e.g., number of hospital beds per capita), and density functions (e.g., housing units per square kilometer). The data were then normalized using a Z-score standardization method that attempts to redistribute the data normally by converting the values to a common scale with mean of zero and a standard deviation of one. A value, v, can be normalized to v' by computing:

$$v' = \frac{v - \overline{F}}{\sigma_F}$$

where $\overline{F}$ and σ_F are the mean and standard deviation of feature F, respectively.

To analyze the 85 proxy variables selected to represent the social vulnerability of countries to earthquakes for significantly high correlations, a 85 x 85-dimension correlation analysis (Spearman's Rho) was utilized. The correlation analysis was useful in reducing the data from 85 to 55 variables. Table 3.2 presents the refined variable set that was considered parsimonious from a statistical viewpoint and that was appropriate for the next step, validation. This variable set was validated using a regression analysis outlined in the following subsection.

Table 3. 2: Refined variable set for global social vulnerability

Variable	***Analysis Abbreviation***

% population aged 5 and younger and 65 and older	POPPPSADP
Population density	POPPPSPDE
% population that is a minority	POPPPSRCE
% population under poverty line	ECOIDPPPL
% population with a disability or special needs	HEAHSTDST
Gender ratio	POPPPSSRI
Unemployment rate	ECOLAMUEP
Education expenditures	EDUEACEEG
% of population that is illiterate	EDUEOCLTP
% of the population without healthcare access	HEAHCRUHC
Household size	POPPPSPPH
GDP per capita	ECOEACGDP
GDP Growth rate	ECOEACGRW
GINI Index of Inequality	ECOIDPGIN
% female labor force participation	POPPPSLPF
% population with no access to electricity	INFEWSACE
% population with no access to improved sanitation facilities	INFEWSISP
% population with no access to potable water	INFEWSIWP
Density of housing units	INFHOUDEN
Tourism receipts	ECOEACTR
Net migration rate	POPPPSNMR
Government effectiveness index	GICGEFGEF
Government gross debt	ECOEREGGD
Birth rate	HEAHSTBRC
Hospital beds per capita	HEAHCRHBE
Losses due to Theft, robbery, vandalism	GICAVTLCP
Gross fixed capital formation	ECOEACGFC
% of the working aged population that is unemployed	ECOLAMLAF

Environmental sustainability index	INXXXXESI
Foreign direct investments	ECOEACFDP
Life expectancy	HEAHSTLEX
Under 5-year child mortality rate	HEAHSTMUF
Road density	INFTCORDE
Inflation rate	ECOEREIRP
Gross imports and exports	ECOEACPEE
Government debt	ECOEREGGD
% electorate voting in local elections	GICLRVVTE
% employed in the low-skill service sector	ECOLAMEST
Mortality rate	HEAHSTADT
Net debt as percentage of gross revenue	ECOEACGRB
Per capita consumption	ECOECPSER
Physicians per 100,000 population	HEAHCRPHY
Gross national savings	ECOEREGNS
Share of budget spent on research and development	ECOERERDE
% of population living in slums-squatter neighborhoods	POPVNPSLP
% of households with vehicle access	INFTCOMVC
Voice and accountability index	GICGEFGVA
Median wealth per adult (US$)	ECOEACWPA
% economic decline	ECOEREDEC
Commercial building density	INFEXPDEN
% population that is a foreign-born migrant	POPPPSIMP
Household income	ECOEACIPD
Prevalence of undernourishment	HEAHSTPUP
Merchandise exports FOB	ECOTREEEE
Merchandise exports FOB	ECOTREMIC

3.2.5 Regression for Final Indicator Selection and Validation

One of the main problems with the development of social vulnerability indicators is the finding of data that is an agreed upon representation of the phenomena being measured. In other words, each index cited in the literature typically has its own variable set, and little justification for the conclusion of indicators in a particular analysis exists. The need to validate variables within a social vulnerability index is therefore particularly great given the multidimensional nature of the social vulnerability concept and the lack of studies that have performed validation. By calibrating a series of regression models using the proxies selected to measure social vulnerability as predictor variables and data representing adverse impacts from earthquakes as response variables, a refined dataset for measuring social vulnerability is proposed in the results section. The earthquake impact data used as independent variables were collected from the EM-DAT Emergency Events Database (https://www.emdat.be/) (described in data collection sub-section 3.2.2). Four different types of earthquake impact variables from EM-DAT were collected on a country by country basis from 2000 to 2018: 1) total deaths, 2) total population homeless, 3) total population affected, and 4) total damage in $USD per country.

Utilizing the earthquake impact data, a series of multivariate regression analyses were utilized to gauge the statistical significance, strength, and direction of the association between the social vulnerability indicators and real-world earthquake impacts. A multivariate regression analysis was chosen since it provides a simplistic view of the relationship between variables and a means for evaluating the importance of variables. For this, Ordinary Least Square (OLS) regression was used. Ordinary least squares (OLS) regression is a statistical method of analysis that estimates the relationship between one or more independent variables and a dependent variable. The method estimates relationships between the dependent and independent variables by minimizing the sum of the squares in the difference between the observed and predicted values (Rogerson, 2006) (Ray 2015). The formula for OLS regression is:

$$Y' = a + b_1X_1 + b_2X_2 + \ldots\ldots$$

where Y' = a predicted value of Y (which is dependent variable)

a = the 'Y intercept.'

b_1 = the changes in Y for each 1-unit change in X_1

b_2 = the changes in Y for each 1-unit change in X_2

X_1 = value of the first independent variable

X_2 = value of the second independent variable

For this thesis, a series of OLS regression models were calibrated in which the impacts data for the earthquakes were taken as dependent variables, and the social vulnerability indicators were taken as independent variables. The regression results helped to answer the question, "What metrics may provide the best comparative assessment of vulnerability to earthquakes from a societal perspective?" and "To what extent do these metrics predict measurable outcomes from earthquakes including property losses, casualties, and displacement?" Here, all variables found statistically associated with the earthquake outcome data due to their statistical significance ($p <= 0.05$) were deemed appropriate to measure social vulnerability and were included in the final results. The extent to which these metrics predict measurable outcomes from earthquakes was evaluated using the strength and direction of the regression's beta coefficients.

It is important to note that when calibrating a regression model, there are a number of critical assumptions that may affect the outcome of the model prediction. These are outlined in Rogerson (2006) and a multitude of sources elsewhere. The first assumption is that a linear relationship between the dependent and independent variables must exist. Moreover, conditions of multivariate normality, little or no multicollinearity, no autocorrelation, and homoscedasticity must exist. It is within this context that no real-world data will conform exactly to linear regression’s assumptions, and some minor violations of the linearity and normality assumptions were found to exist when testing the data for this research. With the latter being said, the results should be considered suggestive at best and were not used to make inferences regarding the relationship between adverse earthquake impacts and characteristics in societies that make people vulnerable to them. Simply, the analysis was used to explore which variables are associated (statistically) with the adverse impacts and which direction and order of magnitude that association might be. The use of machine learning (Artificial Neural Networks and Random Forest) have been applied to further explore the relationships between the independent and dependent variables using non-linear and non-parametric algorithms with similar results. These results analyses were not conducted as part of this thesis, are a work in progress, and thus, not reported upon here. The final list of variables is shown in the results section of this thesis.

3.3 Geographically Weighted Regression

Results from the OLS regressions revealed important relationships between the social vulnerability indicators and earthquake impacts. However, these reflect a stationary model (also referred to as a global model) where only one measure of the association between each social vulnerability variable and the earthquake outcome indicators are provided for the entire world. The latter is likely untenable, however, given the dynamic nature of earthquake impacts across a study area as large as the world. It is within this context that, a series of Geographically Weighted Regressions (GWR) were applied (Anselin 1995; Brundson et al. 2002; Fotheringham et al. 2002). GWR was chosen because it is a type of spatial analysis aimed specifically at capturing relationships that vary intrinsically across space. The main output of a GWR is a set of local regression estimates (i.e. parameter estimates for each country) to define the relationship between the indepent and dependent variables. For this thesis, GWR was used to explore the spatial variability of the relationships between the social vulnerability variables and the earthquake outcome variables, thereby helping to answer the question "How does the predictability of metrics for measuring social vulnerability to earthquakes vary by region?". Answering this question is possible because GWR allows regression coefficients to vary across space in terms of Tobler's (1970) first law of geography. Brunsdon et al. (2001), Brunsdon et al. (1996), Fotheringham and Charlton (1998), and Fotheringham et al. (2002) have defined the GWR model with the equation:

$$y_i = \beta_0 + \Sigma_k \beta_k x_{ik} + e_i.$$

where GWR extends OLS regression by allowing local rather than global parameters to be estimated so that the model is rewritten as:

$$y_i = \beta_0(u_i, v_i) + \Sigma_k \beta_k(u_i, v_i) x_{ik} + e_i$$

where (u_i, vi) represent the coordinates of the *i* th point in space and $\beta_k(u_i, v_i)$ is the result of the continuous function $\beta_k(u,v)$ at the point *i* (Fotheringham et al., 2002). The result is a continuous surface of parameter estimates where measurements are taken at certain points denoting the spatial variability of the surface by allowing local variations in the coefficients of the model specific to location *i*.

3.4 Summary

A primary purpose of this study was to identify indicators which may provide the best comparative assessment of human and economic vulnerabilities and recovery potential of countries from earthquake hazards within a social vulnerability framework. For this, more than three hundred pieces of literature were reviewed to find potential proxy indicators that could be used to model social vulnerability to earthquakes. As a first step, a wish list of potential indicators was developed, and data was collected for indicators that met three inclusion criteria. Upon the collection and preprocessing of the data, a correlation analysis was conducted to address the multicollinearity problem and to reduce the data to a parsimonious set of metrics suitable for regression analysis. Loss data for earthquakes were also collected for all the countries of the world, and for different time periods. OLS regression models were then calibrated to validate the data and to further reduce the selection of variables to those only statistically associated with earthquake impacts. Finally, a series of GWR analyses were performed to better understand how the association between the social vulnerability and impact variables vary by region.

Chapter 4: Results and Discussion

4.1 OLS Regression Results for Earthquake Losses

To determine which variables might be appropriate for measuring social vulnerability to earthquakes, a series of Ordinary Least Square (OLS) regression models were calibrated by taking social vulnerability indicators as independent variables and earthquake impact data (total damage, tatal fatalities, total homeless and total people affected) as dependent variables. A regression model was generated for four different time periods (years 2000 to 2018, 2000 to 2009, 2005 to 2014, and 2009 to 2018) to capture the effect of temporal variability in the model, i.e., variables found statistically significant during one time period may not be statistically significant during another.

The results show that more indicators are statistically significant considering years 2000 to 2018 than other time periods for total damage and total fatalities. The latter is likely due to the larger sample of earthquake events taking place over the 18-year time period. However, for total homeless and total people affected dependent variables, more indicators are statistically significant for the year 2009 to 2018. Only statistically significant results are being demonstrated in this section due to the large size of the output tables. For access to the complete table of results, see Appendix B. The R-square statistics for the different modeling runs range from 0.270 to 0.519, leaving between 0.481 and 0.730 percent of the variance unexplained.

4.1.1 Regression Results of Total Damage

Table 4.1 shows the OLS regression results for total damages in $USD from earthquakes as the dependent variable and the indicators chosen to represent the social vulnerability concept as independent variables. The results of the model show that 31 indicators out of 39 are statistically associated with total damages from earthquakes from 2000-2018 (Tabel 4.1). For the shorter time periods (i.e. 2000 to 2009, 2005 to 2014, 2009 to 2018), considerably fewer indicators are significantly associated with earthquake damage. In an OLS regression, it is the standardized beta coefficients (Beta) that compares the strength of the effect of each individual independent variable on the dependent variable. The higher the absolute value of the beta coefficient, the stronger the effect between the two variables exists. In table 4.1, the beta coefficient for Commercial building density (INFEXPDEN) (*B* = 0.422 in 2000 to 2018; .0.475 in 2000 to 2009, 0.487 in 2005 to 2014) is higher than any other indicator. That means that commercial buildings density, which is measuring the number of buildings per square kilometer, is the strongest predictor of damage for the 2000 to 2018 time period. Noteworthy statistically significant relationships also exist between earthquake damage and % population with no access to electricity (INFEWSACE) (*B* = 0.237 in 2000 to 2018) and % of population aged 5 and younger and 65 and older (POPPPSADP) (*B* = 0.230 in 2000 to 2018). Here, critical infrastructure (CI), which includes electricity and water supply, plays a key role in shaping a society's vulnerability towards natural hazards and the resulting risk of disasters (Garschangen and Sandholz 2018). This is because the measurement of critical infrastructure provides a measurement of the state of economic health of the community (Cutter et al. 2003). In addition, the loss of critical infrastructure may place an insurmountable financial burden on developing countries or small communities that lack the financial resources to rebuild. Regarding age, extremes of the age spectrum affect movement out of harm's way in addition to mobility concerns or constraints that affect the ability to prepare for, respond to, and recover from disasters (Cutter et al. 2003).

Table 4. 1: Regression results for total damage as the dependent variable

Year 2000 to 2018			Year 2000 to 2009		
Indicators	Sig	Beta	Indicators	Sig	Beta
ECOERERDE	.000*	.111	GICLRVVTE	.010*	-.199

ECOEREGGD	.000*	.173	HEAHCRHBE	.037*	.231
ECOIDPGIN	.000*	.112	GICGEFGVA	.034*	-.297
INFEWSACE	.000*	.237	INFEXPDEN	.000*	.475
POPPPSADP	.000*	.230			
POPPPSIMP	.000*	-.068			
ECOLAMLAF	.000*	.091			
ECOEACGFC	.000*	.138			
GICAVTLCP	.000*	-.037			
GICLRVVTE	.000*	-.186			
INFEWSIWP	.000*	-.092			
POPVNPPIP	.000*	-.154			
HEAHCRHBE	.000*	.290			
POPPPSNMR	.003*	-.030			
POPPPSPDE	.000*	-.124			
POPVNPSLP	.000*	.094			
INFTCORDE	.002*	.092			
POPPPSLPF	.000*	.162			
GICGEFGVA	.000*	-.249			
INFEXPDEN	.000*	.422			
INFEXPIND	.014*	.021			
ECOEACPEE	.000*	-.056			
ECOTREEEE	.000*	-.223			
ECOTREMIC	.000*	.069			
ECOEREGNS	.000*	.114			
ECOEACTRE	.000*	-.155			
EDUEACEEG	.000*	-.081			
EDUEEOCCT	.007*	.041			
HEAHSTPUP	.000*	-.130			
POPVNPITA	.000*	.096			

POPPPSRPP	.000*	.064			
R-Square = 0.483, Variables Significant at 5% (0.05) *, 1% (0.01) **			R-Square = 0.519, Variables Significant at 5% (0.05) *1% (0.01) **		
Year 2005 to 2014			Year 2009 to 2018		
Indicators	Sig	Beta	Indicators	Sig	Beta
ECOEACGFC	.040*	.183	ECOEREGGD	.028*	.206
GICLRVVTE	.017*	-.199	HEAHCRHBE	.028*	.301
INFEXPDEN	.000*	.487			
R-Square = 0.437, Variables Significant at 5% (0.05) *1% (0.01) **			R-Square = 0.270, Variables Significant at 5% (0.05) *1% (0.01) **		

4.1.2 Regression Results of Total Fatalities

Table 4.2 shows the results of regression analysis for total fatalities caused by earthquakes as the dependent variable, and the indicators of social vulnerability as independent variables. The results show that the R-square statistics for the respective time periods vary from 0.689 to 0.429. Between 2000 and 2018, six out of the 38 social indicators might be a good fit for measuring social vulnerability due to their statistical significance with fatalities. These include the prevalence of undernourishment (HEAHSTPUP) (B = 0.392) and crude death rate (HEAHSTDRC) (B = -0.286). The prevalence of undernourishment is an estimate of the proportion of the population whose habitual food consumption is insufficient to provide the dietary energy levels that are required to maintain a normal active and healthy life (FAO 2017). Undernourishment has a direct association with poverty (FAO 2017), so it is highly likely that undernourished populations will exhibit a degree of social vulnerability. In addition to crude death rate which captures the entirety of the population, the mortality rate for children under 5-years of age was also found to be statistically significant.The standardized beta coefficients show that under 5 years child mortality rate

(HEAHSTMUF) has the strongest relationship with total earthquake deaths (B = 0.951) in 2000 to 2018.

Table 4. 2: Regression result for total death as the dependent variable

Year 2000 to 2018			Year 2000 to 2009		
Indicators	Sig	Beta	Indicators	Sig	Beta
POPPPSADP	.024*	-.368	GICLRVVTE	.008**	-.217
GICLRVVTE	.002**	-.251	INFEXPDEN	000**	.465
INFEXPDEN	.022*	.182			
HEAHSTMUF	.000**	.951			
HEAHSTDRC	.031*	-.286			
HEAHSTPUP	.001**	.392			
R-Square = 0.689, Variables Significant at 5% (0.05) *, 1% (0.01) **			R-Square = 0.462, Variables Significant at 5% (0.05) *1% (0.01) **		
Year 2005 to 2014			Year 2009 to 2018		
Indicators	Sig	Beta	Indicators	Sig	Beta
POPPPSADP	.032*	-.360	POPPPSADP	.018*	-.404
GICLRVVTE	.003**	-.251	GICLRVVTE	.044*	-.169
HEAHSTMUF	.000**	.947	ECOEACPEE	.016*	.230
EDUEOCLFM	.014*	-.267	HEAHSTMUF	.000**	1.059
HEAHSTDRC	.039*	-.282	EDUEOCLFM	.005**	-.314
HEAHSTPUP	.002**	.394	HEAHSTDRC	.022*	-.316
			HEAHSTPUP	.001**	.400
			HEAHSTPUP	.001**	.400
R-Square = 0.442, Variables Significant at 5% (0.05) *1% (0.01) **			R-Square = 0.429, Variables Significant at 5% (0.05) *1% (0.01) **		

4.1.3 Regression Result for Total Homeless

Table 4.3 shows the results of regression analysis for total homelessness caused by earthquakes as the dependent variable and the social vulnerability indicators as independent variables. The R-square statistics for the time periods vary from 0.561 to 0.184. The results demonstrate that for all time periods, Commercial building density (INFEXPDEN) (B = 0.432 in 2000 to 2018) is the strongest predictor. It is within this context that high density commercial development increases potential losses in the business community (Cutter et al. 2003), and commercial business development is often juxtaposed with high density residential development within cities. With more property in harm's way, the chances of being displaced from a hazard event increased markedly (Burton 2015). Other than the commercial development indicator, % population with no access to potable water (INFEWSIWP) (B = 0.297 in 2005 to 2014, 0.582 in 2009 to 2018, and 0.419 in 2000 to 2009) has a noteworthy effect on total homelessness for earthquakes. Here, access to potable water may directly related to the socioeconomic status of populations. A high socioeconomic status increases the ability of a population to absorb and recover from losses. People with a low socioeconomic status, however, are economically and often socially marginalized and require support in pre- and post-disaster periods (Morrow 1999; Cutter et al. 2003; Burton 2015).

Table 4. 3: Regression results for total homeless as dependent variable

Year 2000 to 2018			Year 2000 to 2009		
Indicators	Sig	Beta	Indicators	Sig	Beta
INFEXPDEN	.000**	.432	INFEWSIWP	.050*	.285
			INFEXPDEN	.000**	.419
R-Square = 0.376, Variables Significant at 5% (0.05) *, 1% (0.01) **			R-Square = 0.364, Variables Significant at 5% (0.05) *1% (0.01) **		

Year 2005 to 2014			Year 2009 to 2018		
Indicators	Sig	Beta	Indicators	Sig	Beta
INFEWSIWP	.070	.297	GICLRVVTE	.026**	-.164
			INFEXPDEN	.000**	.582
R-Square = 0.184, Variables Significant at 5% (0.05) *1% (0.01) **			R-Square = 0.561, Variables Significant at 5% (0.05) *1% (0.01) **		

4.1.4 Regression Results for Total Affected

Table 4.4 shows the results of the regression analysis for the total people that were affected by earthquakes as the dependent variable and the social indicators as independent variables. The results show that the R-square statistics for these time periods vary from 0.550 to 0.482. For the time period of 2000 to 2018, the R-square value of the model is highest (0.550), which implies that 45% of the variability in the model is left unexplained. The results demonstrate that Commercial building density (INFEXPDEN) (*B* = 0.582) is also the strongest predictor of the total affected by earthquakes. The latter is likely the result of the number of people and property in harm's way where earthquake damages have affected populations in high-density areas of cities where commerce and personal interaction takes place. Gross fixed capital formation (ECOEACGFC), a measure of wealth, is also a statistically significant variable (*B* = 0.158). The latter measures the value of a country's fixed assets, such as dwellings, the premise being that the more assets a country has exposed to an earthquake threat, the more it could lose (Burton and Silva 2016). The percent of the electorate voting in local elections (GICLRVVTE) is also a statistically significant variable, but with a negative beta coefficient. This implies that increased political participation may be an effective means of reducing earthquake losses by offering populations an increased voice and accountability when considering their earthquake risk (Burton 2015).

Table 4. 4: Regression results for total affected people as the dependent variable:

Year 2000 to 2018			Year 2000 to 2009		
Indicators	Sig	Beta	Indicators	Sig	Beta
ECOEACGFC	.046*	.158	ECOEACGFC	.048*	.158
GICLRVVTE	.008*	-.198	GICLRVVTE	.012*	-.189
INFEXPDEN	.000*	.582	INFEXPDEN	.000*	.602
R-Square = 0.550, Variables Significant at 5% (0.05) *, 1% (0.01) **			R-Square = 0.545, Variables Significant at 5% (0.05) *1% (0.01) **		

Year 2005 to 2014			Year 2009 to 2018		
Indicators	Sig	Beta	Indicators	Sig	Beta
ECOEACGFC	.041*	.175	INFEWSACE	.026*	.405
GICLRVVTE	.008*	-.213	GICLRVVTE	.027*	-.177
INFEXPDEN	.000*	.519	POPVNPSLP	.008*	.394
			INFEXPDEN	.000*	.361
			ECOEACPEE	.006*	.249
R-Square = 0.482, Variables Significant at 5% (0.05) *1% (0.01) **			R-Square = 0.481, Variables Significant at 5% (0.05) *1% (0.01) **		

4.1.5 Final Variable Selection

The regression analyses conducted for this thesis delineated a set of indicators statistically associated with adverse earthquake impacts and loss. It is within this context that all variables statistically associated with the earthquake outcome variables were deemed valid and appropriate to measure the social vulnerability concept. Thus, only statistically significant variables were selected and carried over to the final stages of analyses for this work (Table 4.5). All other variables that were not statistically significant in the regression models were not considered for further analyses. Variables such as the percent of the population that is illiterate (EDUEOCLTP) and crude death rate (HEAHSTDRC) provide examples. The full table of regression results are shown in the Appendix B.

Tables 4.6 – 4.8 delineate the individual statistically significant variables chosen for each theme (i.e., human impact potential, economic vulnerability, recovery and reconstruction). The allocation of variables by theme were based on: 1) how the variables were reported in the literature; e.g., variables cited as contributing to economic vulnerability were assigned to the economic vulnerability theme; and 2) consultations with GEM scientists. Under these circumstances, an overlap between variables and sub-indices exists, and it is important to note that the selection of variables within each theme was subjective. The latter implies that, when aggregated into composite indices, the ranking of each country in terms of their final index scores could change considerably as the input variables are changed.

Table 4. 5: Final list of statistically significant variables

Code	**Variable Name**
POPPPSPDE	Population density (people/km^2)
INFEXPDEN	Commercial building density (buildings/km^2)
POPVNPSLP	% of population living in slums-squatter neighborhoods
ECOLAMUEP	Unemployment Rate
INFTCORDE	Road density (km roads/100km^2 of Area)
HEAHCRHBE	Hospital beds (per 10 000 population)
POPPPSLPF	Labor force participation rate, female (% of female population ages 15+)
GICGEFGVA	Governance (voice and accountability index)
INFEXPDEN	Commercial building density (number of buildings/km^2)
INFEXPIND	% Industrial development (number of buildings/km^2)
POPPPSPPH	Average household size (number of members)
POPPPSADP	Age dependency ratio (% population aged 5 and younger and 65 and older)

EDUEOCLTP	% of population that is illiterate
POPPPSNMR	Net migration rate
GICAVTLCP	Crime rate (Losses due to Theft, robbery, vandalism)
ECOEACGFC	Gross fixed capital formation
ECOEACGDP	GDP per capita
ECOIDPGIN	GINI index of inequality
ECOEACTRE	International tourism receipts as a percent of GDP
INFEWSACE	% population with no access to electricity
ECOTREEEE	Merchandise exports FOB
ECOTREMIC	Merchandise imports CIF
ECOEREGGD	General government gross debt
ECOERERDE	Share of budget spent on research and development
POPPPSIMP	% population that is a foreign-born migrant
HEAHSTDRC	Crude death rate
EDUEACEEG	Education expenditures
HEAHSTPUP	Prevalence of undernourishment
POPVNPPIP	Percentage of the population below income poverty line
ECOEACPEE	Remittance Inflows
GICLRVVTE	% electorate voting in local elections
HEAHSTMUF	Under 5 years mortality rate
EDUEEOCCT	Primary School Completion Rate
POPPPSRPP	Rural population
INFEWSIWP	% population with no access to potable water source
POPVNPITA	International tourism arrivals
ECOEREGNS	Gross national savings
ECOLAMLAF	% of the working aged population that is in labor force

Table 4. 6: Variables that construct human impact theme

Code	**Variable Name**
POPPPSPDE	Population density (people/km^2)
POPVNPSLP	% of population living in slums-squatter neighborhoods
ECOLAMUEP	Unemployment Rate
HEAHCRHBE	Hospital beds (per 10 000 population)
POPPPSPPH	Average household size (number of members)
POPPPSADP	Age dependency ratio
EDUEOCLTP	Percentage of illiteracy
POPPPSNMR	Net migration rate
GICAVTLCP	Crime rate (Losses due to Theft, robbery, vandalism)
ECOEACGDP	GDP per capita
ECOIDPGIN	GINI index
POPPPSIMP	Foreign-born migrants
HEAHSTDRC	Crude death rate
EDUEACEEG	Education expenditures
HEAHSTPUP	Prevalence of undernourishment
POPVNPPIP	Percentage of the population below income poverty line
HEAHSTMUF	Under 5 years mortality rate
EDUEEOCCT	Primary School Completion Rate
INFEWSIWP	Population access to an improved water source
POPVNPITA	International tourism arrivals
ECOLAMLAF	% of the working aged population that is in labor force

Table 4. 7: Variables that construct economic impact theme

Code	**Variable Name**
INFEXPDEN	Total building density per country (buildings/km^2)
ECOERERDE	Share of budget spent on research and development

ECOLAMUEP	Unemployment Rate
POPPPSADP	Age dependency ratio (% population aged 5 and younger and 65 and older)
INFEXPDEN	Commercial building density (number of buildings/km^2)
INFEXPIND	% Industrial development (number of buildings/km^2)
EDUEACEEG	Education expenditures
ECOEACGFC	Gross Fixed capital formation
ECOEACGDP	GDP per capita
ECOEREGNS	Gross national savings
HEAHCRHBE	Hospital beds (per 10 000 population)
ECOIDPGIN	GINI index
ECOEACTRE	International tourism receipts as a percent of GDP
ECOTREEEE	Merchandise exports FOB
ECOTREMIC	Merchandise imports CIF
ECOEREGGD	General government gross debt
POPVNPITA	International tourism arrivals
ECOLAMLAF	% of the working aged population that is labor force
POPPPSLPF	Labor force participation rate, female (% of female population ages 15+)

Table 4. 8: Variables that construct reconstruction and recovery theme

Code	**Variable Name**
ECOLAMUEP	Unemployment Rate
INFTCORDE	Road density (km roads/100km^2 of Area)
HEAHCRHBE	Hospital beds (per 10 000 population)
GICGEFGVA	Governance (voice and accountability)
POPPPSPPH	Average household size (number of members)
POPPPSADP	Age dependency ratio
EDUEOCLTP	Percentage of illiteracy

POPPPSNMR	Net migration rate
ECOEACGDP	GDP per capita
ECOIDPGIN	GINI index
ECOEACTRE	International tourism receipts as a percent of GDP
INFEWSACE	Population with access to electricity
ECOEREGGD	General government gross debt
ECOERERDE	Research and development expenditure
POPPPSIMP	Foreign-born migrants
EDUEACEEG	Education expenditures
POPVNPPIP	Percentage of the population below income poverty line
ECOEACPEE	Remittance Inflows
GICLRVVTE	Voter Turnout at last Parliamentary Election
EDUEEOCCT	Primary School Completion Rate
POPPPSRPP	Rural population
ECOEREGNS	Gross national savings
ECOLAMLAF	% of the working aged population that is labor force

4.2 Spatial Distribution of Social Vulnerability by Themes:

Up until this point, this research has been concerned primarily with the identification of a validated set of variables for measuring global social vulnerability. To map the relative social vulnerability of countries to earthquakes using the respective themes, composite indicators were developed using the variables indentified as being statistically accociated with earthquake impacts. As a first step, and as opposed to utilizing the variables standardized as Z-scores to make them suitable for statistical analyses, the data was standardized using a Min-Max rescaling scheme to create indicators on the same measurement scale. Min-Max rescaling rescales each variable into an identical range between 0 and 1 (a score of 0 being the best rank for an indicator and 1 being the worst rank) making this type of transformation ideal for displaying or aggregating social vulnerability variables in a manner that is straight forward and easy to understand. The method of aggregation to derive the final social vulnerability scores for each respective theme is the average of equally weighted variables within each theme (Cutter et al. 2010; Peacock et al. 2010; Sherrieb et al. 2010; Burton 2015; Burton and Silva 2016). In other words, the transformed variable scores within each theme were averaged to reduce the influence of a differential number of variables within each theme contributing unevenly to the output score. The outcomes of these aggregations vary between 0 and 1, and these were mapped using an equal interval classification. The results are demonstrated in the subsections below.

4.2.1 Global Human Impact Potential

The aggregated index scores provide a comparative assessment of the potential for human impacts throughout the world. The results in Figure 4.1 demonstrate that a number of African countries and Afghanistan have the highest potential for adverse human impacts from earthquakes. Some South Asian countries such as Pakistan, India, Bangladesh and Myanmar are also showing high human vulnerabilities. It is within this context that countries with high human impact potential scores, as per the data, tend to have high unemployment rates, high numbers of slum populations, high illiteracy rates, low GDP's per capita, low levels of governance, etc. These also tend to be developing countries where social and economic marginalization are widespread. These are countries of potential management concern being that their populations are at considerable earthquake risk (revisit Figure 1.1), yet also have populations that may not have the ability to prepare for, respond to, and recover from damaging events when they occur. On the other hand, predominantly developed countries such as the United States and Canada, Australia and some European countries such as United Kingdom, Germany, Norway, Sweden and Finland show low human impact vulnerability from earthquake hazards. These countries will likely demonstrate a higher degree of earthquake resilience than the developing nations mentioned above.

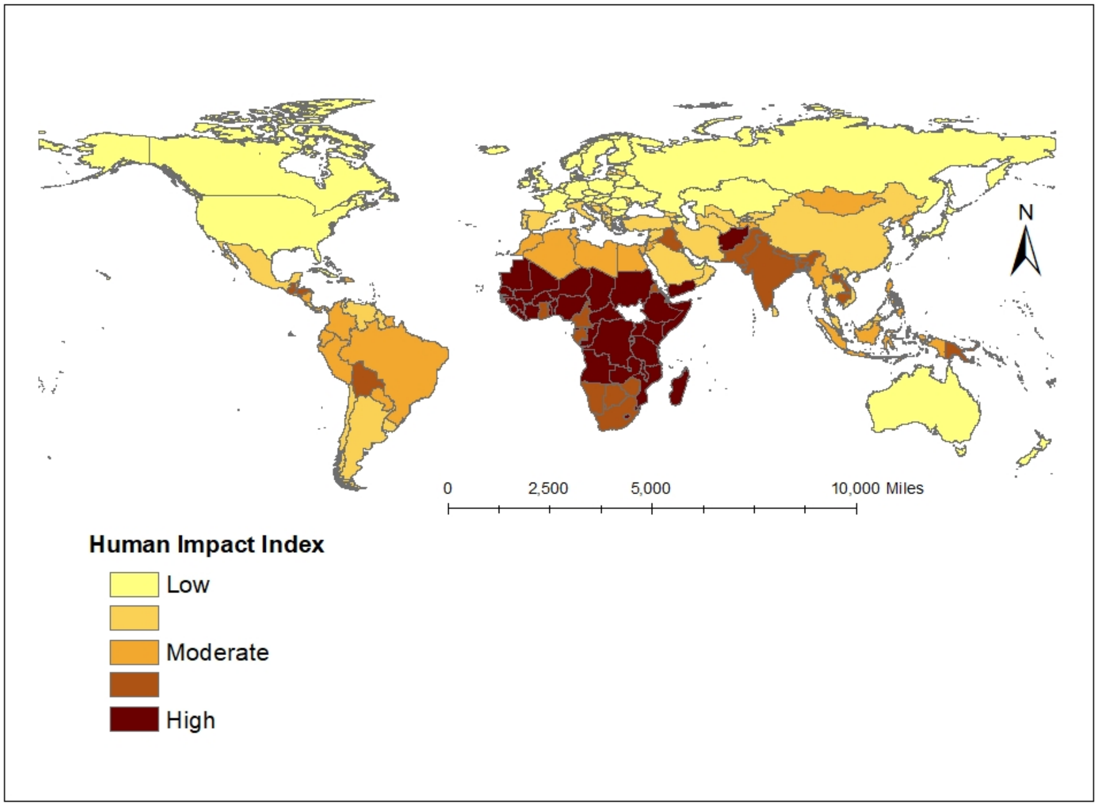

Figure 4. 1: Global human impact of earthquake

4.2.2 Global Economic Impact

The economic impact theme is designed to measure the exposure of a country's economy to exogenous shocks (Briguglio et al. 2009), and in this case, environmental shocks from earthquakes. The economic impacts theme represents the conditions which affect the overall economy of a country following an earthquake impact, such as per capita income, GDP per capita, inflation rate, etc. It should be noted here, that economic vulnerability can also be policy-induced and therefore not inherent or permanent. Understanding the spatial distribution of economic vulnerability is important as it could help organizations working on disaster management as well as to develop policy or good practices to reduce vulnerabilities within specific sectors of the economy.

Figure 4.2 demonstrates the worldwide potential for economic impacts from seismic hazards. The results show that most of the African countries including Mauritania, Democratic Republic of Congo, Namibia, Mozambique, Somalia and South Africa have high potential to suffer damages to their economies which, in turn, affects lives and livelihoods. Kyrgyzstan, India and

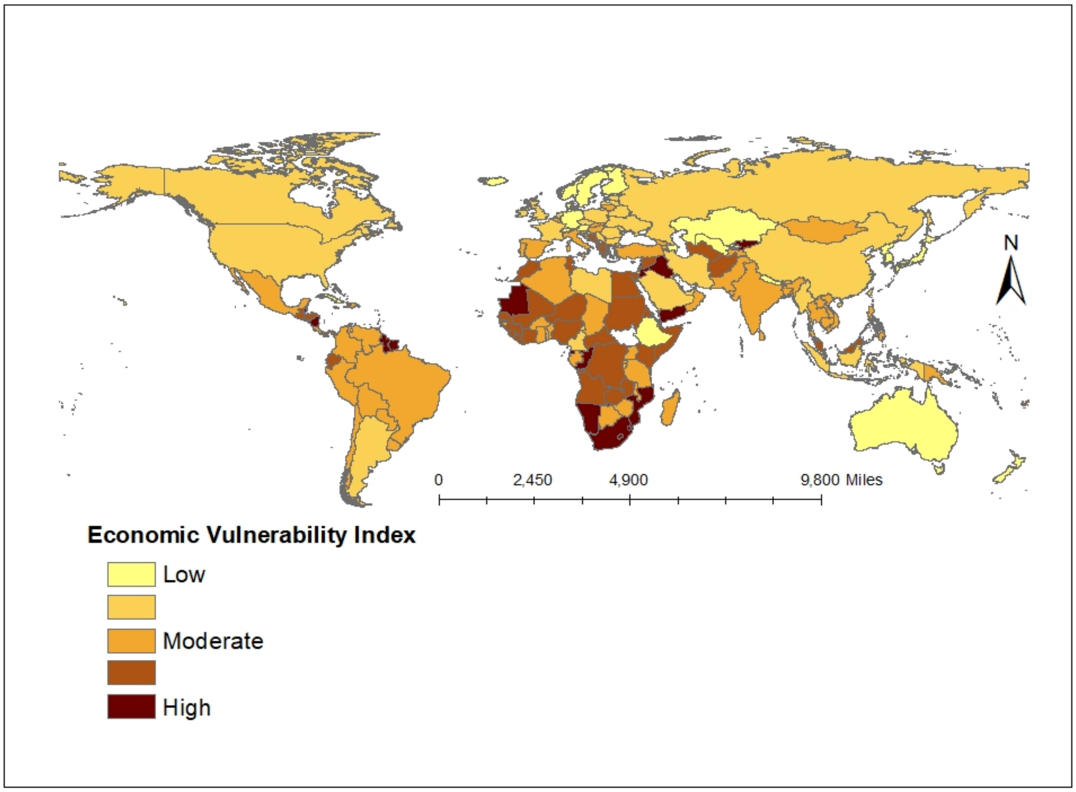

Figure 4. 2: Global economic impact of earthquake

some Middle Eastern countries such as Iraq, Syria and Yemen also share a high economic vulnerability to earthquake hazards. From the data, it can be argued that the countries that score high on economic impact potential have higher unemployment rates, low GDP's per capita, and high government debt. Here, the potential damage to a country's economy and the loss of employment will contribute to a slower recovery following a disaster (Cutter et al. 2003). On the other hand, developed countries including Australia, Canada, and some European countries including Norway, Sweden, Finland, Germany and Poland have a low economic impact potential

4.2.3 Global Recovery and Reconstruction Impact

The recovery and reconstruction potential theme represent the ability to reconstruct and restore communities after an earthquake impact. Understanding the geographic distribution of the recovery potential of countries is essential to identify which countries might have a differential ability to prepare for and withstand damaging events.

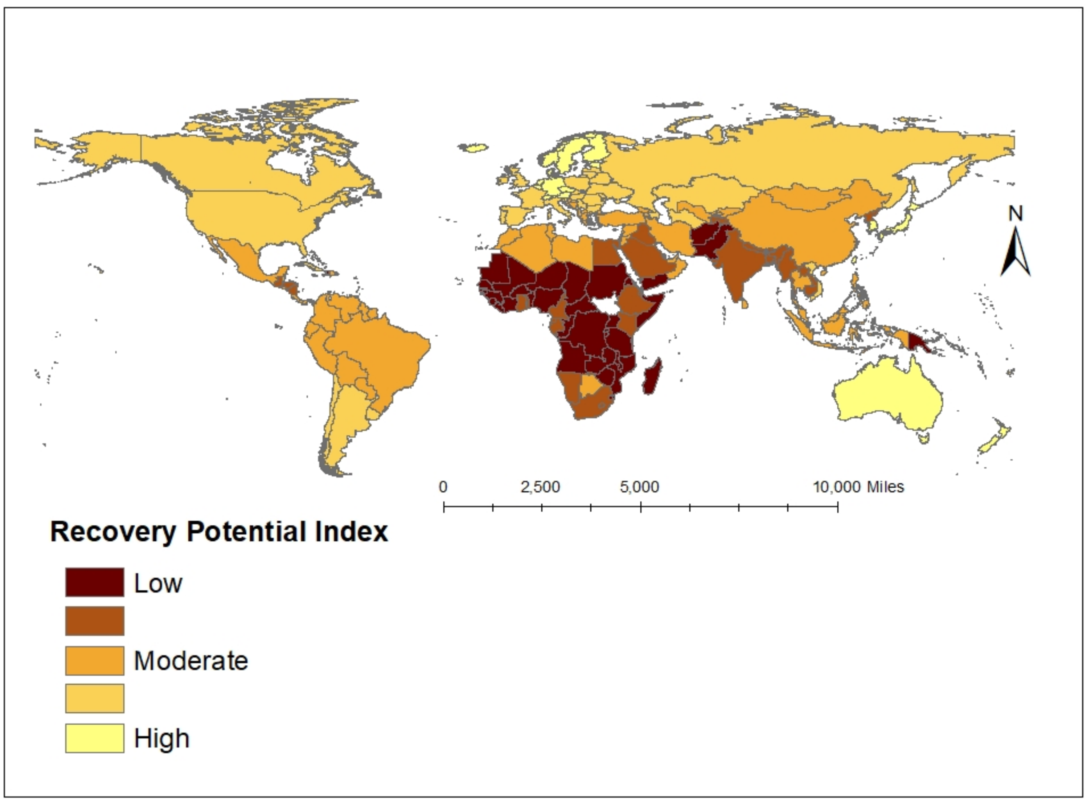

Figure 4. 3: Impact on global recovery for earthquakes

Figure 4.3 shows the recovery potential of the different countries for earthquakes. The results demonstrate that Australia and some European countries such as Norway, Sweden, Finland and Germany have the highest potential to recover from earthquake hazards. Most African countries and Pakistan and Afghanistan show the lowest potential for recovery. From the data it shows that the countries which have highest potential to recovery also has low unemployment rates, higher level of governance, higher number of hospital beds per capita, higher GDP per capita, higher gross national savings, lower government debt, etc. These variables measure the potential of recovery and reconstruction (shown in table 4.8).

4.3 Geographically Weighted Regression (GWR) Results:

GWR was used in this thesis to show the spatial variability of different indicators as it pertains to their association with earthquake impacts. For the GWR model, only those indicators which were statistically significant in the OLS regression model were used as input variables. After conducting the GWR model calibrations, the spatial variability of the indicators and their association with adverse earthquake impacts was demonstrated by mapping the beta coefficients for each country that were derived from the GWR. The maps show how the predictability of the indicators varies over space. It should be noted that not all variables statistically associated with at least one type of earthquake impact are mapped here due to the large number of individual geographically weighted regressions conducted. Maps of all indicators are presented in Appendix C. Only a selection of the results is demonstrated here.

4.3.1 GWR Results for Total Earthquake Losses

The regression results originally depicted in table 4.1 show that % population with no access to electricity (INFEWSACE) is a strong predictor of total damage for earthquakes. Figure 4.4 shows the spatial variability of the prediction power of earthquake damage associated with population with access to electricity. The figure shows that access to electricity is a strong predictor of earthquake damage for the East Asia and Pacific region, but it has very low predictability for North America and South America. The results show this pattern because many communities in East Asia and the Pacific are deprived of access to electricity, signifying lower levels of economic development. Because electricity is one of the basic services provided to people, there is a strong chance that there is also a lack of other services within these countries (e.g., water supply and sewerage system, healthcare, etc.) which could make earthquake impacts more severe. Critical infrastructure (CI), which includes electricity and water supply, also plays a key role here in shaping a society's vulnerability towards natural hazards and the resulting risk of disasters (Garschangen and Sandholz 2018). Conversely, some developed countries like Australia and Japan have a high impact predictability level considering access to electricity. This may be partially the result of the regional influence of surrounding countries when conducting the GWR.

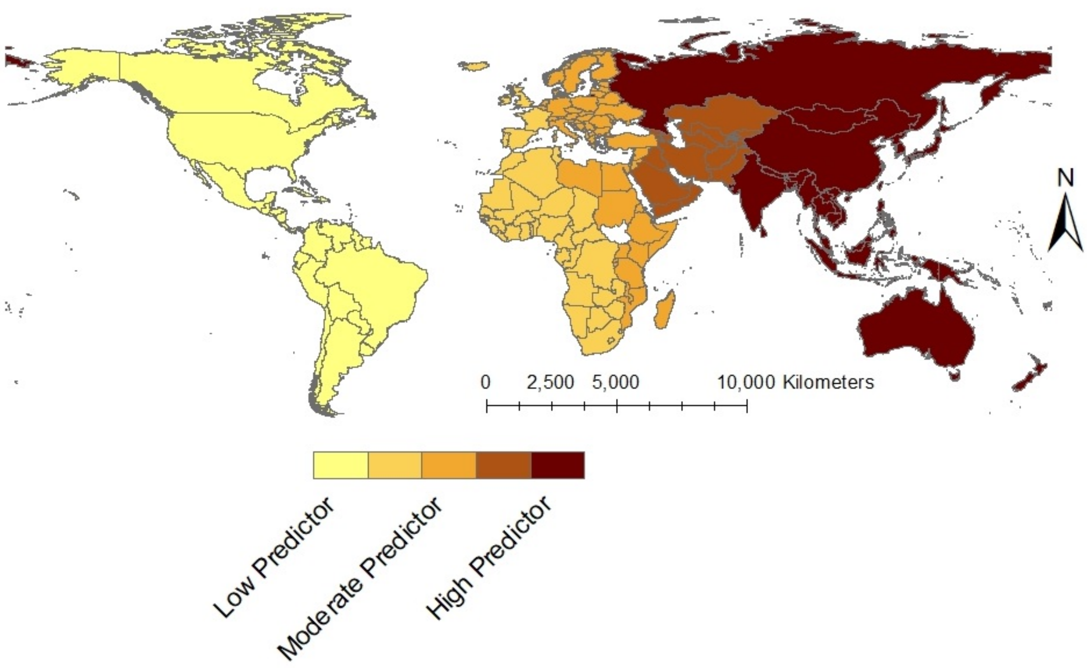

Figure 4. 4: % population with no access to electricity (INFEWSACE) predicting total damage for earthquake (From year 2000 to 2018)

The GWR results for age dependency (POPPPSADP) are demonstrated in Figure 4.5. Here, the spatial variability of the predictive power of age dependency related to earthquake damage shows that age dependency (the young and the old) is a strong predictor for the East Asia and Pacific region but a relatively weak predictor for North America and South America. Age dependency is likely a strong predictor because “extremes of the age spectrum affect the movement out of harm’s way” (Cutter 2003). Parents lose time and money caring for children when daycare facilities are affected for any reason and the elderly people sometimes have mobility constraints, which increases the lack of resilience (Cutter 2003).

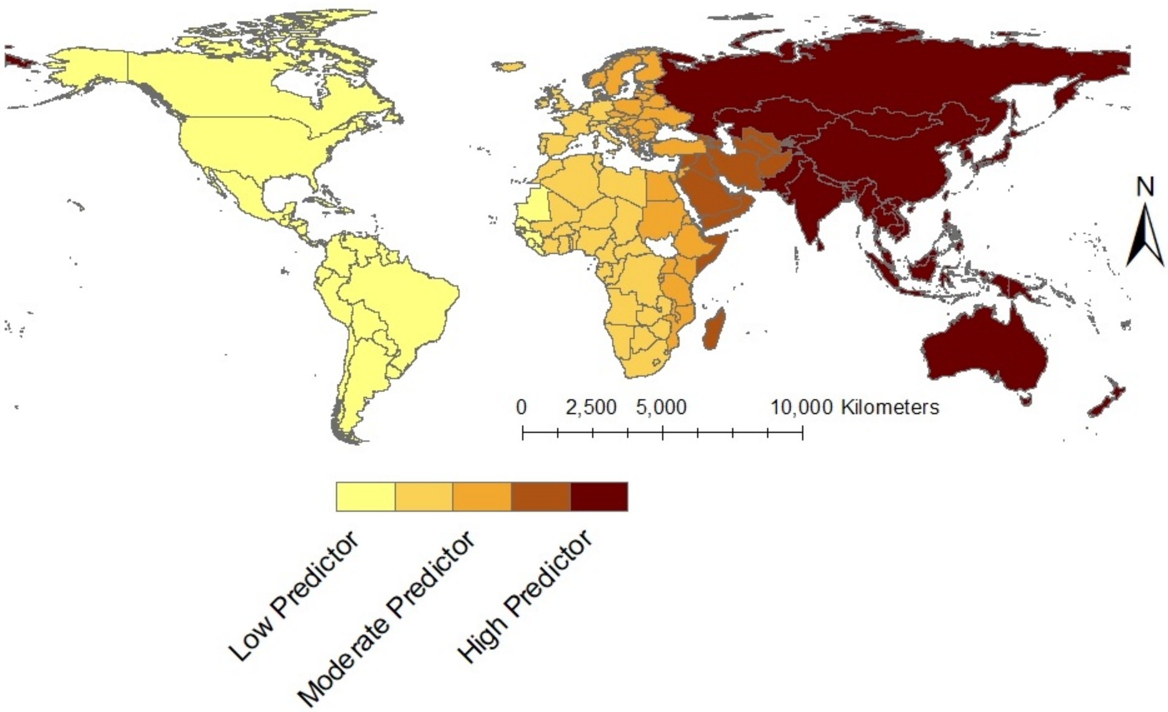

Figure 4. 5: Age dependency ratio (POPPPSADP) predicting total damage for earthquakes (From year 2000 to 2018)

4.3.2 GWR Results for Total Deaths

The OLS regression results originally depicted in table 4.2 show that Under 5 years mortality rate (HEAHSTMUF) is a good predictor of total deaths from earthquakes. Figure 4.6 shows the spatial variability of the predictive power of under 5 years child mortality (HEAHSTMUF) indicator associated with total deaths. The results show that HEAHSTMUF is a strong predictor of earthquake deaths in North and South America but a weak predictor for some African countries. This is a noteworthy pattern because developed countries such as the U.S. and Canada tend to have low child mortality rates, whereas countries in Africa (where the predictive power of the variable is low) tend to have higher under 5 mortality rates. These contradictory results are potentially a statistical anomaly that occurred by chance given that the frequency of damaging earthquakes in Africa is low.

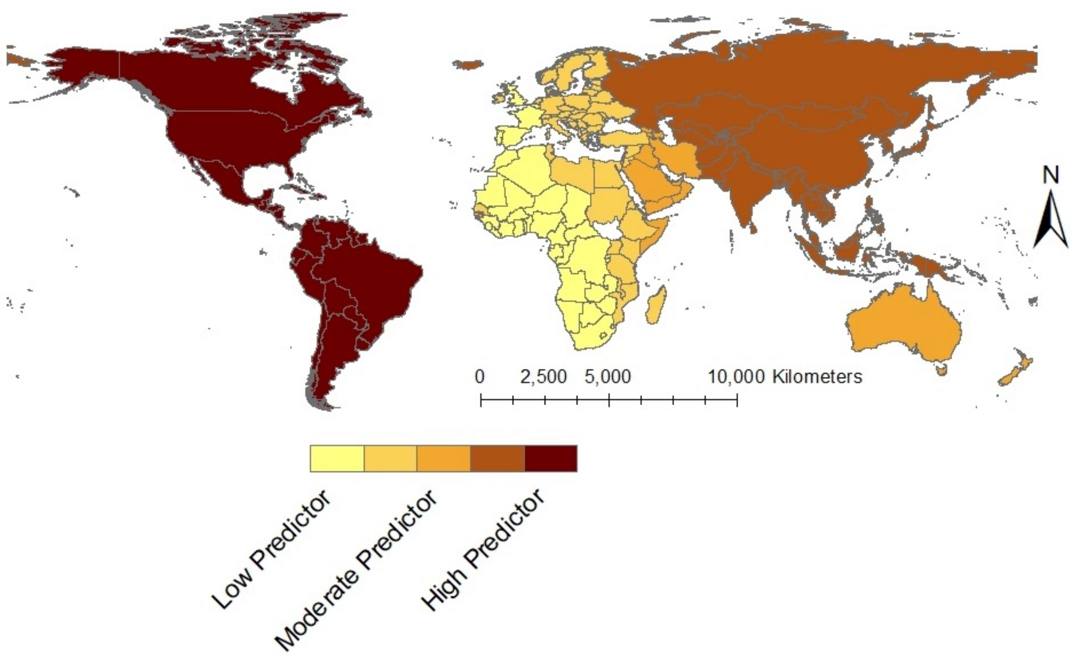

Figure 4. 6: Under 5 years child mortality rate (HEAHSTMUF) predicting earthquake deaths (From year 2000 to 2018)

The prevalence of undernourishment (HEAHSTPUP) is also a significant predictor of total deaths from earthquakes (see Table 4.2). Figure 4.7 shows the spatial variability of the prediction power of the undernourishment variable. The results show that undernourishment is a strong predictor of earthquake deaths for North and Central American countries and a few South American countries but weak predictor for countries in the East Asia and Pacific Region.

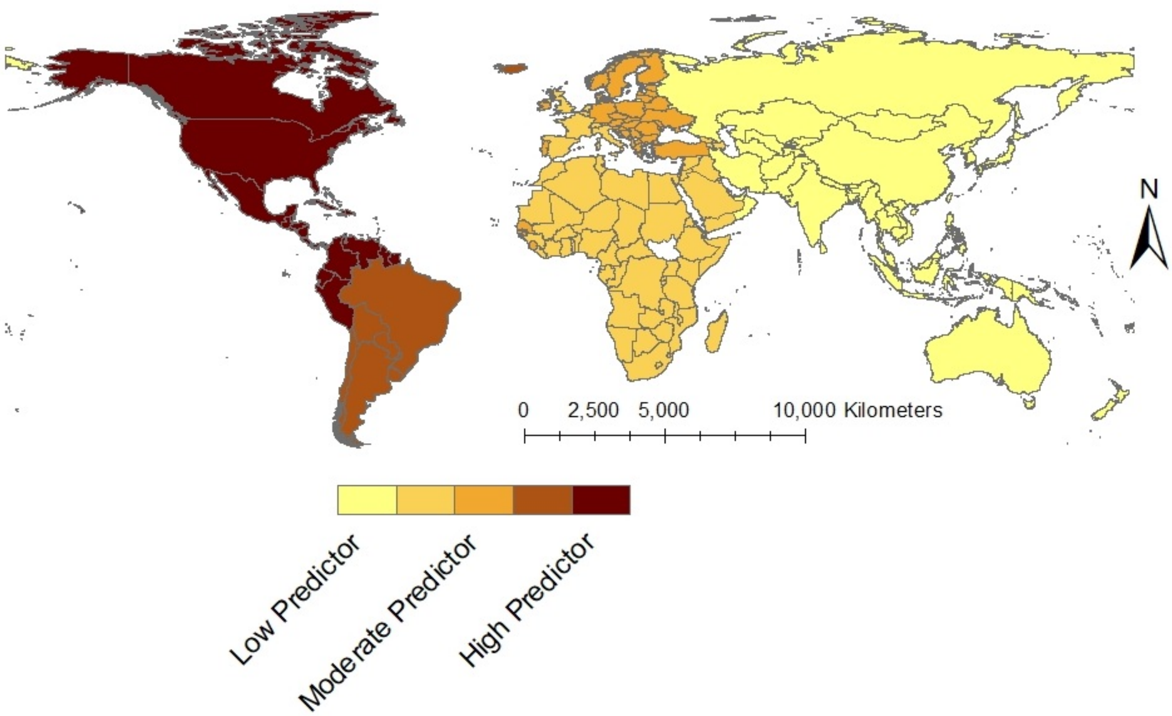

Figure 4. 7: Prevalence of undernourishment (HEAHSTPUP) predicting death from earthquakes (From year 2000 to 2018)

4.3.3 GWR Results for Total Homeless

The commercial building density (INFEXPDEN) within a country is the only significant predictor of total homelessness from earthquakes (see Table: 4.3). Figure 4.8 shows the spatial variability of the prediction power of the commercial building density (INFEXPDEN) for total homelessness due to earthquakes. The spatial distribution of the results shows that INFEXPDEN is a strong predictor of homelessness within some European and North African countries such as France, Germany, Italy, Norway, Sweden, Algeria, Libya, Niger, Chad and Central African Republic but a weak predictor for North American and South American countries.

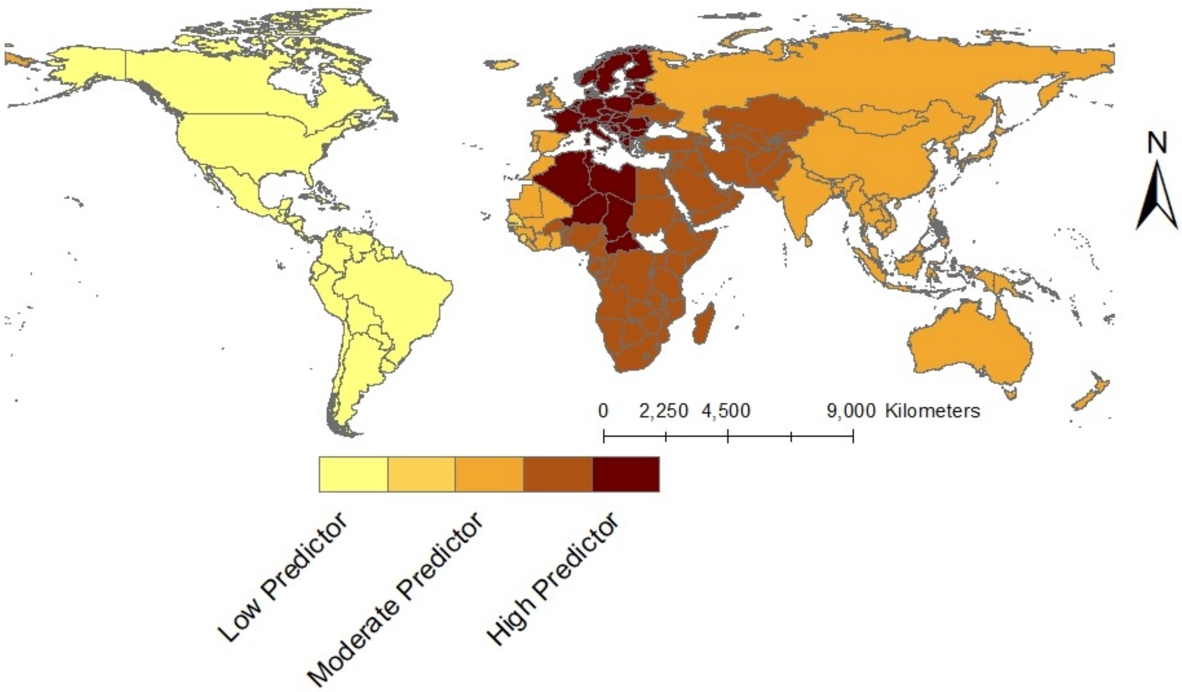

Figure 4. 8: Commercial building density (INFEXPDEN)) predicting homelessness for earthquakes (From year 2000 to 2018)

4.3.4 GWR Results for Total Population Affected

The commercial building density (INFEXPDEN) is also a significant predictor of total population affected by earthquakes (refer to Table 4.4). Figure 4.9 shows the spatial variability of the prediction power of the INFEXPDEN variable regressed against the total affected people by earthquakes. This metric is a strong predictor in Asian and Middle Eastern countries including Turkmenistan, Oman, Iran, Russia, China and Mongolia but a weak predictor for some South American countries including Colombia and Venezuela. Commercial development, which is often very high-density development in Asian countries, provides the backbone of country's economic and social systems, so it is not surprising that commercial development density is highly related to the number of people that have been affected by earthquake impacts.

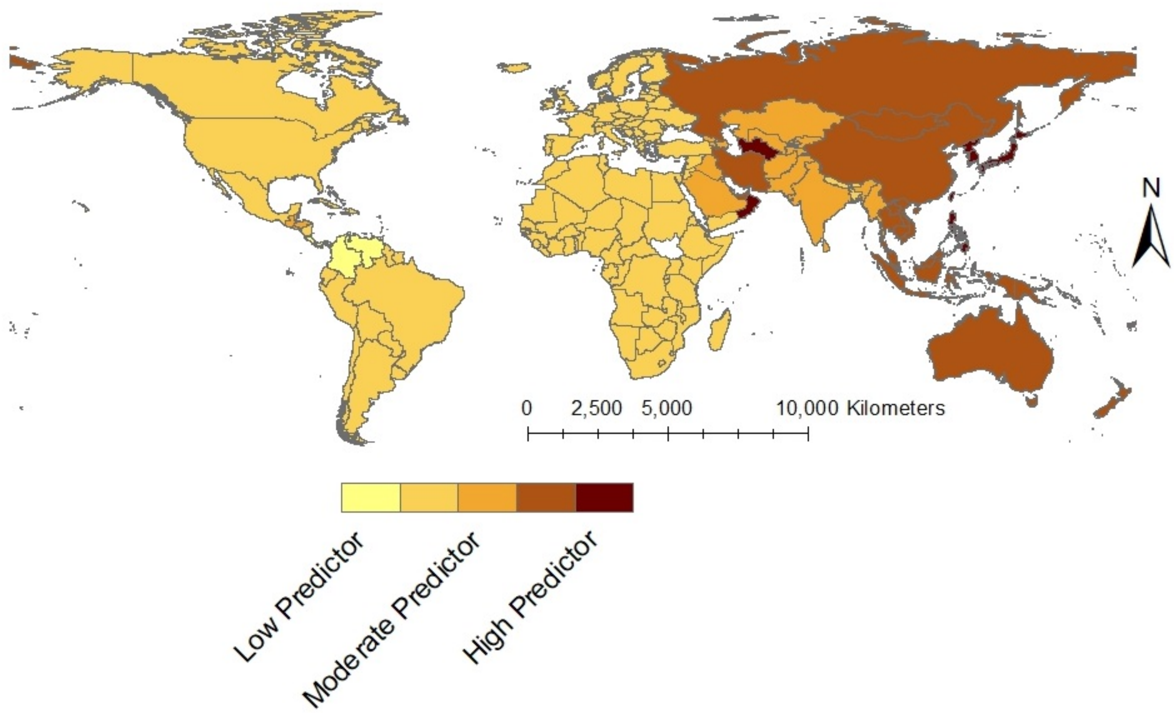

Figure 4. 9: Commercial building density (INFEXPDEN) predicting total affected for earthquake (From year 2000 to 2018)

Gross fixed capital formation (ECOEACGFC) is also a significant predictor for total affected population due to earthquakes. Figure 4.10 shows the spatial variability of the worldwide association between the percentage of gross fixed capital formation for total affected people for earthquakes. These results show that ECOEACGFC is a strong predictor of total affected people for earthquakes in the East Asian countries but weak predictor for the Mid-Asian countries (Pakistan, Afghanistan, Kazakhstan, and Uzbekistan).

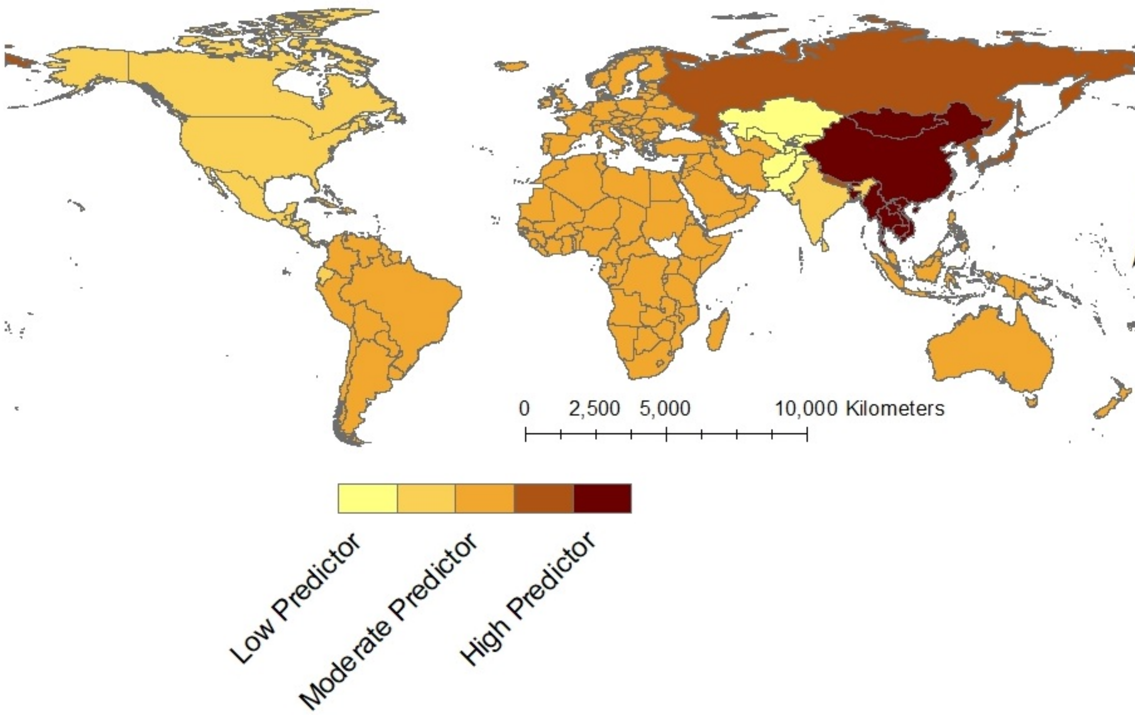

Figure 4. 10: Gross fixed capital formation (ECOEACGFC) predicting total affected for earthquakes (From year 2000 to 2018)

4.4 Discussion

The concept of social vulnerability helps to explain the reason behind differential consequences experienced by populations subjected to an earthquake even when people are exposed to same level of ground shaking (Burton and Silva 2015). The development of global metrics of social vulnerability to earthquakes considering human impact potential, economic vulnerabilities, and recovery and reconstruction potential is still in the nascent stage. Nonetheless, there is considerable interest in these measures. Indicators such as those described in this research might provide a broad first assessment of the social vulnerability of countries that lends to more detailed analysis at the sub-country level and for an increased understanding of place-specific factors affecting the social vulnerability of populations to earthquakes. Academic research on social vulnerability is largely bifurcated, however. In one group there are post-disaster case studies that collect empirical data to provide detailed and place-specific understandings of social vulnerability processes, interactions, and outcomes (Rufat et al. 2015). In the second group there are geospatial modeling studies, similar to this one, which tend to focus on the construction and mapping indicators that demonstrate only broad-brushed results (Rufat et al. 2015). As shown in the results section above, these metrics are used to rank and compare the social vulnerability of different places, yet these studies often lack hazard context, and rarely there are attempts to validate the findings.

For social vulnerability to earthquakes, few studies have integrated case studies using real-world hazard outcome data with indicators development (Fekete 2009; Finch et al. 2010; Oullahen et al. 2015; Burton 2015). Although the latter was accomplished here using a series of regression analyses, connections between case study knowledge of social vulnerability to earthquakes and choices made in the modelling process are tenous (Rufat et al. 2015). The methods applied as well as the results of this study highlight several gaps in knowledge regarding the construction of composite indicators of social vulnerability to earthquakes. Among these research needs are accounting for missing and incomplete data, the effects of scale on model results, and the effects of model sensitivities and uncertainties on the results.

4.4.1 Missing or Incomplete Data

Collecting data for a large number of variables, and for almost all the countries in the world, was a tedious task. One of the challenges was that data was not reported by all countries equally. Imputation of missing data was therefore important because it is a necessary step for conducting some of the statistical operations (e.g. correlation and regression analysis) which were essential to obtaining the results for this thesis. To impute missing values, it was important to come up with a justified methodology for imputing socio-economic variables by not considering all the countries of the world. It was not justifiable to consider the average value of the socioeconomic data of all the countries, for instance, or for a specific geographic region, because the results could be biased due to the influence of values for highly developed countries skewing the results for developing countries, and vice-versa. It is within this context that a number of methods for dealing with missing data exist. These include case deletion, single imputation, and multiple imputation (see Section 3.2.3). Each method of imputation will result in different data values being imputed, and will likely result in divergent country ranks when indices are calculated. More research is needed to discover optimal methods for data imputation and to determine the effects of imputation on final model results.

4.4.2 Issues of Scale

It is important to consider to what extent changes in scale and aggregation might lead to different, possibly contradicting results. The modelling framework developed for this thesis considered country comparisons, but to influence public policy for earthquake disaster risk reduction, social vulnerability assessments need to be conducted at the subnational level of geography (Burton and Silva 2016). At minimum, research should be conducted to better understand the association between potential social vulnerability indicators and earthquake impacts at various scales; for example, region, district, county, tract, neighborhood, and individual levels. Such work will help researchers to better understand the scale at which important social vulnerability processes operate and interact.

4.2.3 Model Sensitivity and Uncertainty

The outcomes of this thesis depend largely on the variables selected and the construction approaches applied for the development of the composite indicators. Here, the variable selection was based on the use of regression analyses in which only variables found statistically associated with earthquake impacts were included in the final models. Each decision, such as which variables to include and changes to steps in the modelling process could lead to different and contradictory results (Tate 2012). The use of Monte Carlo-based Sensitivity Analysis (SA) and Uncertainty Analysis (UA) provides a viable means to guage the robustness of decisions made during the modelling process, and should be applied in further research to assure optimal variable selections, weighting, and aggregation procedures in which modeling sensitivities and uncertainties are minimized. Here, uncertainty can be measured by using the range and median of the output distribution of social vulnerability scores when modelling parameters such as the variables chosen for the model used are changed. The uncertainty analysis may then be followed by a sensitivity analysis which quantifies the proportional contribution of each modeling choice to the overall uncertainty of the model (Tate 2012).

4.5 Summary

This chapter began by delineating the results of all OLS regression analyses where earthquake impact outcomes were used as dependent variables and proxy data for the social vulnerability of populations were used as dependent variables. Tables 4.1 to 4.4 shows the regression results for total damages, total deaths, total homelessness, and total population affected by earthquakes for different time periods. The maps (4.1 to 4.3) show the human impact vulnerability, economic vulnerability and recovery potentials. Only statistically significant variables of the year 2000 to 2018 was chosen for final list of variables as most of the social indicators are statistically significant between that time period (probably because it covers most earthquake hazard events).The regression beta coefficient indicates the degree of contribution of different indicators to the earthquake outcomes. Following the OLS regression, results of a series of GWR calibrations were revealed. GWR was used to show the spatial variability of different indicators in their association with earthquake impacts vary spatially. The regression beta coefficient indicates the degree of contribution of different indicators to the earthquake outcomes.

Chapter 5: Summary and Conclusions

5.1 Major Findings

Although earthquakes are one of the most devastating natural hazards which affect humanity, there are few studies which objectively measure social characteristics of earthquake risk considering validated metrics of social vulnerability. Also, there is no agreed-upon framework and established sets of data to measure social vulnerability to earthquakes. The purpose of this study was to produce composite indices representing the social vulnerability of countries to earthquakes within three topical areas (human impact potential, economic vulnerability, recovery and reconstruction potential). For this, more than three hundred pieces of literature were reviewed to find potential proxy indicators that could be used to model social vulnerability to earthquakes. As a first step, a wish list of potential indicators was developed, and data was collected for indicators that met three inclusion criteria. Upon the collection and preprocessing of the data, a correlation analysis was conducted to address measurement redundancy and to reduce the data to a parsimonious set of metrics suitable for regression analysis. Loss data for earthquakes were also collected for all the countries of the world, and for different time periods. OLS regression models were then calibrated to validate the data and to further reduce the selection of variables to those only statistically associated with earthquake impacts. Finally, a series of GWR analyses were performed to better understand how the association between the social vulnerability and impact variables vary by region.

The research objectives of this thesis were fulfilled by answering the research questions reiterated below:

RQ1: What metrics may provide the best comparative assessment of vulnerability to earthquakes from a societal perspective?

To find the best collection of indicators for assessing social vulnerability to earthquakes globally, a five-tiered workflow was followed. Thirty-eight total indicators were selected due to their statistically significant associations with earthquake-induced losses, fatalities, homelessness, and number of populations affected following a series of regression analyses. Among these, 21 indicators were allocated to measuring human impact potential, 19 indicators were allocated to measure economic impact potential, and 23 indicators were used to measure recovery and reconstruction potential (there are some overlaps). Examples of these variables include population density as well as percent of population living in slums-squatter neighborhoods (used exclusively in the human impacts sub-index), commercial building density and percent industrial development (utilized exclusively in the economic vulnerability sub-index), as well as share of budget spent on research and development and percent of the electorate voting in local elections (used exclusively in the recovery and reconstruction potential sub-index).

RQ2: To what extent do these metrics predict measurable outcomes from earthquakes including property losses, casualties, and displacement?

The strength and of the association between the independent and dependent variables were identified using the beta coefficients resulting from the regression analyses. The larger the beta coefficient between an independent and a dependent variable, the larger the association between the two variables. Variables with the highest association with earthquake losses, fatalities, homelessness, and population impacted include commercial buildings density, age dependency, under 5 years child mortality rate, gross fixed capital formation, population with no access to electricity, and percent of the population with no access to the potable water source. Variables that have a statistically significant relationship but have a weaker association with the earthquake outcome indicators, include crime rate (Losses due to Theft, robbery, vandalism), net migration rate, international tourism arrivals, and primary school completion rate.

RQ3: How does the predictability of metrics for measuring social vulnerability to earthquakes vary by region?

Geographically Weighted Regression (GWR) was conducted to understand how the association between the earthquake impact and variables chosen as proxy measures of social vulnerability vary across space. The results show where indicators may be good predictors of earthquake impacts as well as where they may be weak predictors. For example, population with access to electricity is a strong predictor of earthquake damage for the East Asia and Pacific region, but it has very low predictability for North America and South America. Additionally, the prevalence of undernourishment is a strong predictor of earthquake deaths for North and Middle American countries and South American countries yet a relatively weak predictor for countries in East Asia and the Pacific region.

5.2 Significance of the Study:

The impacts from damaging earthquakes will be expressed differentially across space, and to be effective, disaster managers, researchers, governments, and the general public must not only understand the physical components of earthquake risk, but also the social characteristics of the communities people live, work in, and protect. It is here that an increased understanding the social characteristics of populations at risk from earthquakes leads to a perspective on earthquake risk that allows stakeholders to:

- mainstream social vulnerability into policy discussions on reducing earthquake losses and damage;

- utilize social vulnerability assessments for benchmarking exercises to evaluate changes in social vulnerability over time;
- use social vulnerability to identify areas with populations that are least likely to be able to prepare for, respond to, and recover from damaging earthquake events; and
- recognise that the causes and solutions for reducing earthquake impacts are found in human-environmental interactions.

Although there have been a multitude of studies to quantify physical risk and vulnerability from earthquake hazards, very few attempts have been made to integrate economic aspects, human impact potential, and recovery and reconstruction potential. This study has attempted to address these aspects to quantify earthquake vulnerability at a global scale using a thematic composite index-based modelling approach. To enhance disaster-risk reduction before a disaster occurs, and also during the reconstruction process following a damaging event, it is vital to have enhanced knowledge regarding the most vulnerable groups within society, the areas at risk and the driving forces that influence and generate vulnerability and risk (Bogardi and Birkmann 2004). This study is a positive step forward in the identification of the most socially vulnerable regions and the drivers of social vulnerability to earthquake hazards within those regions.

Governments, disaster planners, and organizations working in disaster management and risk deduction need to understand that considering only physical components of earthquakes and their impacts are not enough to quantify and manage earthquake risk. Addressing the socio-economic aspects, economic vulnerabilities, and recovery potential are also crucial. Addressing these issues helps to explain how people exposed to the same level of earthquake shaking can have different outcomes in terms of loss of lives, property, and livelihoods as well as a differential ability to recover when damaging impacts occur.

5.3 Future Research Opportunities

The research reported here will be built upon by the Global Earthquake Model, so it is very likely that the methods and the results of this study will evolve. Because the indicator selection was subjective, for instance, an area of opportunity to improve upon the models would be to consult with stakeholders in various regions throughout the world. This would be to gain confirmation and confidence that the variables which were chosen, reflect the reality within the respective stakeholder's countries. Moreover, the work conducted for this research was at the country scale, yet the vulnerability of populations and the drivers of the vulnerability of populations, will likely vary considerably within a country. Thus, sub-country level analyses utilizing the framework developed for this research is essential, especially since decisions taken to reduce risk are often at the sub-country level. Finally, each step in the modeling process carries a certain level of sensitivity and uncertainty. In other words, changing variables, weighting, and aggregation schemes will likely render different results in terms of country rankings. Thus, to increase transparency, sensitivity and uncertainty analysis can be conducted to demonstrate the extent to which the composite models are affected by changes in variables and construction methodologies.

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Appendix A: Wishlist of Indicators from Literature

This appendix constitutes the wish list of approximately 440 indicators that were derived from the literature and that were considered for the work conducted for this thesis. The starting point of selecting the indicators was an exhaustive review of the social vulnerability literature. For this, more than three hundred papers were collected and compiled into a digital library. These papers were then reviewed to identify characteristics identified in the literature as either contributing to or reducing the social vulnerability of populations to natural hazard events, earthquakes in particular. Table A shows the wish list of indicators.

Table A: Indicator wish list from literature

Indicator Names	Themes Justification		
	Human Impact Theme	***Economic Impact Theme***	***Reconstruction and Recovery Theme***
% electorate voting in a local election			Holand et al. 2011 Geis 2001 Cutter et al. 2010
% employed in health care and social services	Holand et al. 2011	Holand et al. 2011	
% employed in the low-skill service sector	Holand et al. 2011	Holand et al. 2011	Kates et al. 2006
% employed in the primary sector	Holand et al. 2011	Holand et al. 2011	
% first generation Western immigrants	Holand et al 2011		
% first or second generation non-Western immigrants	Holand et al. 2011		
% of households earning less than 150,000	Holand et al. 2011		
% of households earning more than 500,000	Holand et al. 2011		

% of land use for Agriculture	Boruff & Cutter 2007 Cardona 2005	Boruff & Cutter 2007 Cardona 2005	
% of the municipality's expenditure on debt service		Holand et al. 2011	
% of the population five years or younger	Holand et al. 2011 Van Vandt 2012		Ebru et al. 2017
% of population 67 years or older Seniors (aged 75 and older)	Jones and Andrey Holand et al. 2011		Ebru et al. 2017
% of protected areas			Fukultat et al. 2009 Geis 2001, Godschalk 2003
% out-migration	Holand et al. 2011		Kates et al. 2006
% population living in nursing homes	Holand et al. 2011		Kates et al. 2006
% receiving invalidity pension	Holand et al. 2011		
% of residential buildings stock build after 1980		Holand et al. 2011	Godschalk 2003
% single-parent household Number of female-headed single parent households	Holand et al. 2011 Van Vandt 2012 Wood et al. 2007		Van Vandt 2012
% with four years of more of tertiary education			Holand et al. 2011 Ebru et al. 2017
% with only lower secondary education	Holand et al. 2011		Cutter et al. 2010 Burton 2012, 2015 Depotaki et al. 2018
Absence of educational opportunities	Cardona 2003	Cardona 2003	
Acceptance of uncertainty and change			Bahadur et al. 2010
Access to financial services		Shaw 2009	Shaw 2009
Access to healthcare	Rufat et al. 2015		Cutter et al. 2010 Burton 2012, 2015 Depotaki et al. 2018

Activity rate	Guillard-Goncalves et al. 2014	Guillard-Goncalves et al. 2014	
Adaption of a cross-scalar perspective			Bahadur et al. 2010
Adult literacy	Pelling & Uitto 2001		Pelling & Uitto 2001
Affected vulnerable infrastructure and facilities	Tang et al. 2008		
Affected vulnerable population	Tang et al. 2008		
Age	Cutter et al. 2003 Alexander et al. 2011 (Kienberger) Alexander et Al 2011(Torsten Welle et Al) Cutter and Finch 2007 Baum et al. 2008 Birkman & Fernando, 2007 Borden et al.2007 Boruff & Cutter 2007 Boruff et al. 2005 Buckle et al. 2001 Buckle et al. 2000 Burton 2008, 2009 Chakraborty et al. 2005 Chang 2001 Cutter et al. 2000 Eakin &Tapia 2008 ECLAC 2011 study Zoppou et al. 2004 Eidsvig et al. 2011 Rufat et al. 2015 Bara 2010 Van Vandt 2012 Birkmann et al. 2013	Buckle et al. 2001 Cardona 2005 Eakin &Tapia 2008	Cutter et al. 2003 Cutter and Finch 2007 Birkman & fernando, 2007 Zoppou et al. 2004 Eidsvig et al. 2011 Rufat et al. 2015 Van Vandt 2012 Birkmann et al. 2013 Morrow 2008 Kates et al. 2006 Ebru et al. 2017 Cutter et al. 2010 Burton 2012, 2015 Depotaki et al. 2018

	Yeletaysi et al. 2009 Peacock et al. 2012		
Agricultural production	Giupponi et al 2012		
Alarm system			Kumpulainen 2006
Availability of emergency planning, response and recovery resources in the community			Arbon et al. 2012 Sungay el al 2012 Beccari 2016
The average age of sewer lines		Holand et al. 2011	
The average age of water pipelines		Holand et al. 2011	
Average monthly amount paid for renting a conventional dwelling	Guillard-Goncalves et al. 2014	Guillard-Goncalves et al. 2014	
Average mortgage charge resulting from dwelling purchase	Guillard-Goncalves et al. 2014	Guillard-Goncalves et al. 2014	
The average number of people per bedroom	Baum et al. 2008		
The average number of people per household	Guillard-Goncalves et al. 2014	Guillard-Goncalves et al. 2014	
Awareness			Rufat et al. 2015
Bank deposits per capita	Mendes 2009		
Basin morphology	Giupponi et al. 2012		
Biology and Genetic Endowment	Lindsay 2003		Lindsay 2003
Birth rate	Boruff et al. 2005 Mendes 2009		
Budget and subsidy		Shaw 2009	Shaw 2009
Building code			Schiller et al. 2001 Geis 2001
Building code controls			Tang et al. 2008 Godschalk 2003

Building types (damage by an earthquake)	Kappos et al. 1998		
caloric intake	Brooks et al. 2005		
capital stock	Cardona 2005	Cardona 2005	Cutter et al. 2008 Cutter et al. 2008b
Casualties	Zahran et al. 2008		
Change in the proportion of the resident population with a foreign nationality between 1991 and 2001	Guillard-Goncalves et al. 2014	Guillard-Goncalves et al. 2014	
Change in the resident population	Guillard-Goncalves et al. 2014	Guillard-Goncalves et al. 2014	Gilbert 2010
Civil liberties	Brooks et al. 2005		
Community hospitals per capita	Burton 2009		Green et al. 2007 Kates et al. 2006
Community integration "Closer Knit" (As oppose of household isolation)	Anderson-Berry 2003		Anderson-Berry 2003 Geis 2001
Community involvement and inclusion of local knowledge			Bahadur et al. 2010
Conflict density(km2)	Hagenlocher et al 2016		
Connected among the members of the community			Arbon et al. 2012 Gilbert 2010
Construction concluded per 1000 inhabitants	Mendes 2009		
Cooperation			Schiller et al. 2001
Coordinate with neighboring/state/federal agencies			Tang et al. 2008
Cost for remediation and emergency measures		Hiete and Merz 2009	
Crime rate	Kotter and Friesecke 2009		

Critical infrastructure		Serre 2018	Serre 2018 Beccari 2016
Critical response facilities and support systems			national academy 2012
Culturally significant sites	Kumpulainen 2006		
Culture	Lindsay 2003		
Damage to the company's image			Hiete and Merz 2009
Dams			Zahran et al. 2008
Day-care centers for per 1000 inhabitants			Mendes 2009
Debt service ratio		Pelling & Uitto 2001	
Debt servicing	Cardona 2005	Cardona 2005	
Decreased competitiveness	Hiete and Merz 2009		Gilbert 2010
Delineation of tsunami risk areas			Tang et al. 2008
Demographic attributes	Fatemi et al 2017		
Age dependency ratio	Brenkert 2005 Kumpulainen 2006 Hagenlocher et al. 2016	Brenkert 2005	
development level (building density)	Cardona 2005		
Development patterns (Urban Sprawal)	Van Vandt 2012		Van Vandt 2012
Disability and special needs	Fatemi et al. 2017 Adeger et Al. 2004 Flanagan et al. 2011 Baum et al. 2008 Boruff & Cutter 2007 Buckle et al. 2001 Chang 2001 Clark et Al. 1998 Zoppou et al. 2004		Buckle et al. 2001 Chang 2001 Zoppou et al. 2004 Morrow 2008 Ebru et al. 2017

	Bara 2010 Buckle 2001 Eisenmam et al. 2007		
Disaster mitigatio plan	Van Vandt 2012		Schiller et al. 2001 Van Vandt 2012 Geis 2001 Godschalk 2003
Disaster proneness		Briguglio 1995	
Disaster Risk Index (DRI)	Fussel 2009, Gal 2007		Fussel 2009, Gal 2007
disruption costs for occupancy			Martinelli et al. 2013
Distance to hospitals/health centers (cost path) Distance to the nearest hospital (km)	Hagenlocher et al. 2016 Holand et al. 2011		
Disease	Rufat et al. 2015		
Distance to schools (cost path)	Hagenlocher et al. 2016		
Doctors per 1000 inhabitants	Mendes 2009		
Dominating land use			Fukultat et al. 2009
Duration (of a flood, dichotomously)	Zahran et al. 2008		
Early warning system			Schiller et al. 2001
Economic disruptions Personal disruptions		Helies et al. 2010	
Economically active population		Serre 2018	Serre 2018 Gilbert 2010
Education attendance	Boruff & Cutter 2007 Clark et Al. 1998 Cutter 2003 Eakin &Tapia 2008 ECLAC 2011 study Caldwell 1990	Eakin &Tapia 2008	Cutter 2003 Gall 2013
Education expenditure	Adeger et Al. 2004		Gall 2013

Education rate	Kumpulainen 2006 Van Vandt 2012		Van Vandt 2012 Ebru et al. 2017
Effective governance/institutions/control mechanism		Shaw 2009	Bahadur et al. 2010
Emergency evacuation system			Tang et al. 2008
Emergency housing systems			national academis 2012
Employment by sectors Employment	Boruff et al. 2005 Giupponi et al. 2012 Cutter 2003	Alexander et Al 2011 (Kienberger) Sherrieb et al. 2010	Cutter et. 2008
Energy production			Giupponi et al. 2012
Environmental sustainability	Cardona 2005	Cardona 2005	
ethnic and political discrimination	Cardona 2003	Cardona 2003	
Evacuation plan			Schiller et al. 2001
Extra labor for process recovery			Hiete and Merz 2009
family structure and social networks Family status	Chang 2001 Cutter 2003		Chang 2001 Cutter 2003 Rufat et al. 2015
Fatalities	Noriga and Ludwing 2012		
FEEMA rating	Zahran et al. 2008		
Female activity rate	Guillard-Goncalves et al. 2014	Guillard-Goncalves et al 2014	
Female fertility	Patt et al 2010		
Female labor force participation rate	Baum et al 2008 Boruff et al. 2005 Burton 2008, 2009 Cutter et al. 2000 Wood et al. 2007		Burton 2012, 2015 Cutter et al. 2010

Female population Number of females	Boruff et al. 2005 Burton 2008, 2009 Cutter et al. 2000 Eakin &Tapia 2008 Wood et al. 2007		Serre 2018 Burton 2012, 2015 Cutter et al. 2010
Firemen corporations per 1000 inhabitants			Mendes 2009
Foreign economic conditions		Briguglio 1995	
Forest management			Giupponi et al. 2012
Fragmented natural areas	Kumpulainen 2006		
Functional needs	Rufat et al. 2015		Rufat et al. 2015
GDP growth rate (%)		Gall 2004	Gall 2004
GDP per capita	Boruff et al. 2005 Brenkert 2005 Burton 2008, 2009 Bohle et al. 1994	Fukultat et al. 2009 Alcomo et al. 2001 Adeger et Al. 2004 Burton 2008, 2009 Pelling & Uitto 2001 Kumpulainen 2006 Gall 2004	Fukultat et al 2009
Gender	Fatemi et al. 2017 Birkman & fernando, 2007 Borden et al.2007 Buckle et al. 2001 Burton 2008 Cutter 2003 Ebert et al. 2003 Zoppou et al 2004 Enarson & Scanlon 1999 Rufat et al. 2015 Van Vandt 2012 Denton 2002		Cutter 2003 Enarson & Scanlon 1999 Rufat et al. 2015 Van Vandt 2012 Denton 2002 Ebru et al. 2017
Gender equality index	Holand et al 2011		Cutter et al. 2010

GINI index	Alcomo et al. 2001 Adeger et Al. 2004 Brenkert 2005 Birkmann et al. 2013	Alcomo et al. 2001 Adeger et Al. 2004	Birkmann et al. 2013
Good governance		Briguglio 2008	
Governance & Socio Ecological Systems	Adeger 2006		
Government debt	Boruff et al. 2005	Boruff et al. 2005	Boruff et al. 2005
Government effectiveness	Brooks et al. 2005		Geis 2001
Graduates with only elementary education Educational level Education	Alexander et Al 2011 (Kienberger) Rufat et al. 2015	Mayunga 2007	Fekete 2009
Growth in per capita real wealth	Choi and Fisher 2003	Choi and Fisher 2003	
hazard evaluation, emergency response, EWS	Eidsvig et al. 2011		Eidsvig et al. 2011
health expenditure	Adeger et Al. 2004		Gall 2013
Health human resources	Alexander et al. 2011(Carreño) Brenkert 2005 ECLAC 2011 study Zoppou et al. 2004 Cannon at al 2001		Alexander et al. 2011(Carreño) Gall 2013 Green et al. 2007
Health services	Lindsay 2003		Ebru et al. 2017
Healthcare system	Alexander et al. 2011(Miniati et al.) Burton 2008 Chambers 1989 Eisenmam et al 2007		Chambers 1989 Tobin & Whiteford, 2002 Gall 2013 Green et al. 2007
High degree of equity			Bahadur et al. 2010
High Diversity			Bahadur et al. 2010
Hispanic populations	Van Vandt 2012		Van Vandt 2012
hospital beds per 1000 people	Cardona 2005	Cardona 2005	Ebru et al. 2017

Household capacity	Rufat et al. 2015		Rufat et al. 2015
Household composition	Flanagan et al 2011		wein et al 2012
Household has no access to safe water (%)	Hagenlocher et al 2016		
Household has no car/truck (%)	Hagenlocher et al 2016 Van Vandt 2012		Van Vandt 2012 Cutter et al. 2008 Cutter et al 2008b Cutter et al 2010
Household has no radio/TV (%)	Hagenlocher et al 2016 Van Vandt 2012		Cutter et al. 2008 Cutter et al 2008b Cutter et al 2010
Household size/Average number of people per household	Baum et al 2008 Boruff et al. 2005 Van Vandt 2012		
Household uses firewood for cooking (%)	Hagenlocher et al 2016		
Households need major repair	Jones and Andrey 2007		
Housing	Rufat et al. 2015	Mayunga 2007	
Housing Age	Van Vandt 2012		
Housing characteristics	Helies et al 2010		
Housing construction density		Holand et al 2011	
Housing disruptions	Helies et al 2010		
Housing quality	Flanagan et al 2011		Green et al. 2007
Housing units with electricity	Boruff & Cutter 2007		wein et al. 2012 Kates et al. 2006
Housing units with Gas or kerosene	Boruff & Cutter 2007		Kates et al. 2006
human and social capital			Morrow 2008 Gilbert 2010
Human Development index (HDI)	Fussel 2009, Gal 2007 Cardona 2005 Gall 2004	Cardona 2005 Gall 2004 Fussel 2009, Gall 2007	Fussel 2009, Gal 2007 Pelling & Uitto 2001

	Pelling & Uitto 2001		
Human Vulnerability Component of the 2005 Environmental Sustainability Index (ESI)	Fussel 2009, Gal 2007		Fussel 2009, Gal 2007
Human Wellbeing index (HWI)	Fussel 2009, Gal 2007		Fussel 2009, Gal 2007, Geis 2001
Illeteracy:no/low education (%)	Hagenlocher et al 2016		
Illiteracy rate	Guillard-Goncalves et al. 2014	Guillard-Goncalves et al. 2014	
import and exports	Cardona 2005	Cardona 2005	
Income	Cannon et al. 2001		
Income and material resources	Chang 2001		Chang 2001
income per day per square foot for occupancy			Martinelli et al. 2013
Index of Social Vulnerability to Climate Change for Africa (SVA)	Fussel 2009, Gal 2007		Fussel 2009, Gal 2007
Indigenous population	Buckle et al. 2000		
Indirect cost for rertofit (planning,permitting etc)		Kappos et al 1998	
Individual capacity	Rufat et al. 2015		Rufat et al. 2015
Infant mortality rate	Mendes 2009		
inflation			
inflation rate (%)	Cardona 2005 Choi and Fisher 2003	Gall 2004 Cardona 2005 Choi and Fisher 2003	
Infrastructure pressures	Giupponi et al 2012		
Injuries required emergency department visit	Noriga and Ludwing 2012		

Institutional prepardness			Kumpulainen 2006
Institutionalized population (prison, hospitals, old-age homes)	Bara 2010		Bara 2010
insurance of infrastructure and housing	Cardona 2005 Birkmann et al 2013	Cardona 2005 Birkmann et al 2013	Van Vandt 2012 Birkmann et al 2013 Gilbert 2010 Green et al. 2007 Kates et al. 2006
Internal conflicts	Cannon et al 2001		
Knowledge of flood protection measures			Rufat et al. 2015
Labor force % employed in labor force		Baum et al 2008 Burton 2008, 2009 Holand et al 2011	
Labor force population	Boruff et al. 2005	Boruff et al. 2005	
lack of access to property and credit	Cardona 2003	Cardona 2003	
Land owners	Rufat et al. 2015		
Landuse permit			Tang et al. 2008 Godschalk 2003
Language Proficiency Population with no knowledge of english	Flanagan et al 2011 Buckle et al. 2000 Zoppou et al 2004 Eidsvig et al 2011 Rufat et al. 2015 Bara 2010		Eidsvig et al 2011 Rufat et al. 2015 Van Vandt 2012
Large families	Buckle et al 2001		Buckle et al 2001
Learning			Bahadur et al. 2010
Length of municipal roads (km per ccapita)			Holand et al 2011
Level of risk and vulnerability			Arbon et al. 2012
life expectancy	Brooks et al 2005		
lifelines	Clark et Al. 1998		

Limited financial means at the same time located in hazardous places	Bara 2010		
literacy rate	Adeger et Al. 2004 Brenkert 2005 Brooks et al 2005 Ebert et al 2003 Cannon at al 2001	Brenkert 2005	
literacy ratio male to female	Brooks et al 2005		
living in disaster prone areas	ECLAC 2011 study	ECLAC 2011 study	
Living space per person	Fekete 2009		
Loss of production due to direct damages	Hiete and Merz 2009		
Loss of production due to infrastructure disruption	Hiete and Merz 2009		
Loss of production due to supply chain disruption	Hiete and Merz 2009		
Loss of water, electricity, transportation services		Rose et al.2011 Rose andKrausmann 2013	Rose et al.2011 Kates et al. 2006
Low income (Poverty)	Alexander et Al 2011(Carreño) Zoppou et al 2004 Van Vandt 2012	Alexander et Al 2011(Carreño)	Zoppou et al 2004 Van Vandt 2012
Low rise (1-3 stories),medium rise (4-7 stories) and highrise (more than 8 stories) bulidings	Kappos et al 1998		
Macroeconomy stability		Briguglio 2008	
Market disturbance	Hiete and Merz 2009		
Maternal mortality	Brooks et al 2005		
Mean age (Years) of resident population	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	

Mean income of private households Income inequality Income	Bolin et al 2000	Fukultat et al 2009 Adger. 1998 Baum et al 2008 Rufat et al. 2015 Mayunga 2007 Shaw 2009	
Median house value	Hebb and Mortsch 2007 Wood et al. 2007	Hebb and Mortsch 2007 Wood et al. 2007	
Median household income	Helies et al 2010	Fukultat et al 2009 Adger. 1998 Baum et al 2008 Rufat et al. 2015 Mayunga 2007 Shaw 2009	Sherrieb et al 2010
Median per capita assets	Holand et al 2011	Holand et al 2011	Holand et al 2011
Median rent	Meyers et al 2008		
mental health	Cannon et al 2001		
Microeconomy market efficiency		Briguglio 2008	
Mortality Rate	Rufat et al. 2015 Cardona 2005		
Municipal building inspection			Groven et al 2006
Municipality's financial capacity		Groven et al 2006	
Municipallities disposable income per inhabitant (median=100)			Holand et al 2011
Net debt as percentage of gross revenue			Holand et al 2011
No access to potable water	Adeger et Al. 2004 Brenkert 2005 Ebert et al 2003	Brenkert 2005	
No access to sanitation	Adeger et Al. 2004 Brooks et al 2005		

	Ebert et al 2003 Birkmann et al 2013		
No. of exit routs per 1000 inhabitants			Holand et al 2011
Non-equlibrium system dynamics			Bahadur et al. 2010
Number of boarding houses per 1000 inhabitants	Mendes 2009		
Number of children (age<15 years)	Hagenlocher et al 2016		
Number of employees in sectors vulnerable to climate change	Groven et al 2006		
Number of female-headed single parent household	Hebb and Mortsch 2007		Van Vandt 2012
Number of hotels per 1000 inhabitants	Mendes 2009		
Number of housing units per square km	Boruff et al. 2005 Clark et Al. 1998	Boruff et al. 2005	
Number of non-white resiednts	Hebb and Mortsch 2007		
number of people in household who migrated	Eakin &Tapia 2008	Eakin &Tapia 2008	
Number of people under 18			
Number of people under 60			
Number of pharmacies for 1000 inhabitants (in 2002)	Guillard-Goncalves et al 2014 Mendes 2009	Guillard-Goncalves et al 2014	
Number of renter-occupied housing units	Hebb and Mortsch 2007 Van Vandt 2012		Van Vandt 2012
Nutritional status	Cannon et al 2001		
Nymber of non-white residents			
Occupation		Rufat et al. 2015	

Occupation in primary sector (%)	Hagenlocher et al 2016		Cutter 2003
One and two family homes	Fekete 2009		
Other hospitalized injuries	Noriga and Ludwing 2012		
People widowed	Baum et al 2008		
people with limited resources to meet essential dayly needs	Buckle et al 2001		Buckle et al 2001
Per capita greenhouse gas emission from transportation	Groven et al 2006		
Per capita income (median) Per capita income	Holand et al 2011		Gall 2013
Per capita length of drainage pipes	Groven et al 2006		
Per capita length of water pipes	Groven et al 2006		
Per capita power consumption	Groven et al 2006		
Per capita social security recipient	Meyers et al 2008		
Per capita social security recipients	Boruff et al. 2005 Burton 2008, 2009	Boruff et al. 2005	
Percent female headed households	Boruff et al. 2005 Burton 2008, 2009 ECLAC 2011 study Van Vandt 2012 Cannon at al 2001	Boruff et al. 2005	Van Vandt 2012
Percent impervious surface	Zahran et al. 2008		
Percent of employed in service occupations	Burton 2009		Cutter et al. 2008 Burton 2012 Burton 2015 Cutter et al. 2010
Percent of employed in transportation industries	Burton 2009		
Percent of housing units that are mobile homes	Burton 2009 Chakraborty et al 2005		

	Cutter et al 2000 Van Vandt 2012		
Percent of population 25 years or older with no high school diploma	Boruff et al. 2005	Boruff et al. 2005	Cutter et al. 2008 Burton 2012 Burton 2015 Cutter et al. 2010
Percent of population living in urban areas	Burton 2009		
Percent of rural farm population	Burton 2009		
Percent without health insurance	Meyers et al 2008		
Percentage females participating in labor force	Boruff et al. 2005	Boruff et al. 2005	Cutter et al. 2008 Burton 2012 Burton 2015 Cutter et al. 2010
Percentage of armed forces in the working population	Mendes 2009		
Percentage of children under 18 living in poverty	Helies et al 2010		
Percentage of income from farm activities	Eakin &Tapia 2008	Eakin &Tapia 2008	
Percentage of overcrowded households	Mendes 2009		
Percentage of popole over 65 in poverty	Helies et al 2010		
Percentage of population killed and affected as a proxy for risk	Brooks & Adger 2003		
Percentage of population with access to potable water	Milman & Short, 2008		Milman & Short, 2008
Percentage of precarious lodging	Mendes 2009		
Percentage of rented lodging	Mendes 2009		
Percentage of secondary or seasonal housing	Mendes 2009		

Percentage of vacant lodging	Mendes 2009		
Percentage of working population in primary sector	Mendes 2009		
Percentage of working population in secondarysector	Mendes 2009	Mendes 2009	
Percentage of working population in tertiary sector	Mendes 2009		
Personal health practices and coping skills	Lindsay 2003		Lindsay 2003
Physical damage to control installation	Hiete and Merz 2009		
Physical damage to production instruments	Hiete and Merz 2009		
Physical damage to products in stock	Hiete and Merz 2009		
Physical damage to raw materials	Hiete and Merz 2009		
Physical damage to service installations	Hiete and Merz 2009		
Physical damege to semi-finished products	Hiete and Merz 2009		
Physical damage to buildings	Hiete and Merz 2009		Green et al. 2007
Physicians per 100,000 population	Burton 2009		Burton 2012, 2015 Cutter et al 2008 Cuter et al. 2008b
Police stations per 1000 inhabitants			Mendes 2009
Political rights	Brooks et al 2005		
polluted air and water resources	Cardona 2003	Cardona 2003	
Population change	Burton 2008	Burton 2008	
Population change	Jones and Andrey 2007		Geis 2001 Gilbert 2010

Population density	Alexander et Al 2011(Carreño) Boruff & Cutter 2007 Cardona 2005 Cova & Church 1997 Cutter et al 1996 Holand et al 2011 Jones and Andrey 2007 Kumpulainen 2006	Birkmann 2007 Cardona 2005	
Population density	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Population dynamics	Giupponi et al 2012		
Population growth	Borden et al.2007 Choi and Fisher 2003 Cutter 2003 Anderson-Berry 2003	Choi and Fisher 2003	Cutter 2003
Population growth, avg anual growth	Cardona 2005	Cardona 2005	
Population in group quarters	Van Vandt 2012		Van Vandt 2012
Population numbers (people per grid square)	Hagenlocher et al 2016		
Population per settlement area Density (Urban) Proportion urban population	Fekete 2009 Cutter and Finch 2007 Borden et al 2007 Chakraborty et al 2005 Patt et al 2010 Mennis 2002 Rufat et al. 2015 Zahran et al. 2008 Cross 2001	Cross 2001	Cutter and Finch 2007 Cross 2001 Geos 2001
Population undernourished/food unsecurity	Birkmann et al 2013 Bohle et al 1994		

Population with no telephone	Van Vandt 2012		Van Vandt 2012
Population with no vehicle access	Van Vandt 2012 Eisenman 2007		Van Vandt 2012
Possessing of TV/radio sets	Boruff & Cutter 2007 Cross 2001		Cross 2001
Power outage, non-delicered electric power	Groven et al 2006		
Precipitation (day bafore flood)	Zahran et al. 2008		
Precipitation (day of flood)	Zahran et al. 2008		
Predictive Indicator of Vulnerability (PIV)	Fussel 2009, Gal 2007		Fussel 2009, Gal 2007
Prepardness, planning and readiness			Bahadur et al. 2010
preparedness/emergency planning	Cardona 2005		Beccari 2016
Presence of Wetlands			Van Vandt 2012
Prevalent Vulnerability Index (PVI)	Fussel 2009, Gal 2007		Fussel 2009, Gal 2007
Prior experience			Rufat et al. 2015
probability of occupancy Being in structural damage state			Martinelli et al 2013, Green et al. 2007, Green et al. 2007
Procedures to support community disaster planning, response and recovery			Arbon et al. 2012
Propeerty damage (log)	Zahran et al. 2008	Zahran et al. 2008	Green et al. 2007
Proportion of housing units without bath or shower installation	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of persons that are disabled and unemployed or without economic activity	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	

Proportion of resident population that, 5 years before, inhabited outside municipality	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of disabled persons (auditory, visual, motor or mental disability, or cerebral paralysis)	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	Ebru et al. 2017
Proportion of female populaton	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	Ebru et al. 2017
Proportion of housing units without at least one basic infrastructure (electricity, sanitary installation,piped water,bath, or shower facilities)	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of housing units without sewerage installation	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of labor force permanently disabled for work	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of over crowded living quarters	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of person with a disability degree above 60% (the disability degree have been attributed by a health authority constuted for this purpose)	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of persons that are disabled and are under 4 or above 65 years old	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of population born abroad	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	

Proportion of population born in Africa	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of population employed in tourism	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	Cutter et al 2008
Proportion of population whose portuguese is not first language	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of population with an African nationality	Guillard-Goncalves et al 2014 Van Vandt 2012	Guillard-Goncalves et al 2014	Van Vandt 2012
Proportion of population with foreign nationality	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of private households in housing units without electrical installation	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of professionals socially more valued	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of rented or sub-rented conventional dwellings	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of resident population aged 15-19	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of resident population aged 5 and below	Guillard-Goncalves et al 2014 Van Vandt 2012	Guillard-Goncalves et al 2014	
Proportion of resident population aged 5-14	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of resident population aged 65 and over	Guillard-Goncalves et al 2014 Van Vandt 2012	Guillard-Goncalves et al 2014	Van Vandt 2012

Proportion of resident population in housing units without flush toiler installation	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of resident population in housing units without private toilet installation	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of resident population in housing units without toilet installation in the building (Shared toilet)	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of school leavers (resident population aged between 10 and 15 years old who left school without attaining lower secondary education)	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of single-parent family nuclei	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proportion of university students	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Proporton of sole agricultural holders	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Public expenditure on health as percent of GDP		Pelling & Uitto 2001	
Public resources			Fatemi et al 2017
Quality of transportation network	Kotter and Friesecke 2009		
Race & Class	Elliot&Pais 2006 Van Vandt 2012 Colten 2006		Elliot&Pais 2006 Van Vandt 2012

Race/Ethnicity Minotrity	Cutter and Finch 2007 Alexander et Al 2011(Torsten Welle et Al) Flanagan et al 2011 Baum et al 2008 Borden et al.2007 Boruff et al. 2005 Burton 2008 Chang 2001 Clark et Al. 1998 Cutter et al 1996 Cutter et al 2000 Cutter 2003 Elliot&Pais 2006 Fothergill 1999 Rivera & Miler 2007 Rufat et al. 2015 Van Vandt 2012 Bolin et al 2000 Downey 2006 Yeletaysi et al. 2009		Alexander et Al 2011(Miniati et Al) Chang 2001 Cutter 2003 Elliot&Pais 2006 Rufat et al. 2015 Van Vandt 2012 Ebru et al. 2017
Rate of people with unhealthy living conditions			Kotter and Friesecke 2009
Ratio of employed population Employment rate([Employed population/Resident population with 15 and more years old]*100)	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Ratio of unemployed population and labor force	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Records of historical tsunami experiences	Tang et al. 2008		
recovery time for the damage state			Martinelli et al 2013, Green et al. 2007,
Regional/local geologic and seismic settings	Tang et al. 2008		

Regulatory impacts			Helies et al 2010
Religion			Van Vandt 2012
Relocation cost		Kappos et al 1998	
Remoteness and insularity		Briguglio 1995	
rental cost for occupancy			Martinelli et al 2013
Renters	Boruff et al. 2005 Burton 2008 Burton 2008, 2009; Van Vandt 2012		Cutter 2003
Renters Number of renter occupied housing units	Rufat et al. 2015 Van Vandt 2012 Wood et al. 2007 Peacock et al 2012		Rufat et al. 2015 Van Vandt 2012
Replacement cost for buildings		Kappos et al 1998	
rescue and firemen manpower	Cardona 2005		
Residents age 65 and older	Fekete 2009		
Residents from age 30 to 50	Fekete 2009		
Resource dependency	Rufat et al. 2015		
Risk denial/acceptance			Rufat et al. 2015
Risk perception	Anderson-Berry 2003		Kumpulainen 2006 Anderson-Berry 2003
Rural extent/areas (yes/no)	Hagenlocher et al 2016		
Rural population	Fekete 2009 Boruff et al. 2005 Eidsvig et al 2011		Eidsvig et al 2011
Salary expenditures in physical planning and environmental management		Groven et al 2006	Groven et al 2006
Sanitation	Rufat et al. 2015		

Savings and Insurance		Shaw 2009	Shaw 2009 Gilbert 2010 Green et al. 2007
Seawalls in coastal areas			Van Vandt 2012
Secondary hazards and damage (e.g. due to explosions)	Hiete and Merz 2009		
Seismic/coastal zoning and subdivision			Tang et al. 2008
Sex ratio (male population)	Hagenlocher et al 2016		
Share of budget spent on research and development			Kumpulainen 2006 Cutter et al. 2010 Burton 2012 Burton 2015
Share of budget spent on civil defence			Kumpulainen 2006
Significant natural areas	Kumpulainen 2006		
Single parent families	Baum et al 2008 Buckle et al 2001 Peacock et al 2012		Buckle et al 2001
Slums-squatter neighborhoods	Cardona 2005		Ebru et al. 2017
Small apartments	Fekete 2009		
Social capacity	Rufat et al. 2015		Rufat et al. 2015
Social class and minorities			Morrow 2008 Kates et al. 2006
Social development (Education, Health)		Briguglio 2008	
Social disparity	Alexander et Al 2011(Carreño) Cardona 2005	Alexander et Al 2011(Carreño) Cardona 2005	Geis 2001
Social expenditure on health, pension, education	Cardona 2005	Cardona 2005	
Social inequality		Kuhlicke and Steinfuhrer, 2010	Ebru et al. 2017

Social isolation			Van Vandt 2012
Social networks for coping capacities		Mayunga 2007	Birkman & fernando, 2007 Kuhlicke and Steinfuhrer, 2010
Social polarization rate	Kotter and Friesecke 2009		
Social values and structures			Bahadur et al. 2010
Social vulnerability (index of standard variables)	Zahran et al. 2008		
Socio-economic status (Poverty) Poverty Poverty Level	Cutter et al. 2003; Burton & Silva 2015; Adger. 1998 Fatemi et al 2017 Cutter and Finch 2007 Flanagan et al 2011 Boruff et al. 2005 Buckle et al. 2000 Burton 2008, 2009 Cardona 2005 Chakraborty et al 2005 Clark et Al. 1998 Cutter et al 1996 ECLAC 2011 study Fothergill & Peak 2004 Adger & Kelly 1999; Van Vandt 2012 Cannon at al 2001 Chambers 1989 Downey 2006 Yeletaysi et al. 2009	Cutter et al. 2003; Burton & Silva 2015; Adger. 1998 Fothergill & Peak 2004 Yeletaysi et al. 2009 Morrow 2008	Cutter et al. 2003; Burton & Silva 2015; Cutter and Finch 2007 Chakraborty et al 2005 Fothergill & Peak 2004; Van Vandt 2012 Chambers 1989 Morrow 2008 Kates et al. 2006 Ebru et al. 2017
Sports and leisure equipments per 1000 inhabitants			Mendes 2009
Squatters	Rufat et al. 2015		

Status of local plan for crises management			Groven et al 2006
Stress	Rufat et al. 2015		
Technical infrastructure			Kumpulainen 2006
television sets per 1000 people	Cardona 2005	Cardona 2005	
The seriously ill	Buckle et al 2001 Buckle et al. 2000		Buckle et al 2001
The socially isolated	Buckle et al 2001		Buckle et al 2001
Total dependency ratio	Guillard-Goncalves et al 2014	Guillard-Goncalves et al 2014	
Total Housing units	Wood et al. 2007		Wood et al. 2007
Total livestock	Hebb and Mortsch 2007		
Total percent of land with agricultural chemical applied	Hebb and Mortsch 2007		
Total percentage of deeded land with irrigation	Hebb and Mortsch 2007		
Total Population	Jones and Andrey 2007 Wood et al. 2007		
Tourism (e.g. number of tourists/number of hotel beds)			Kumpulainen 2006
Transportation	Flanagan et al 2011		
Transportation	Rufat et al. 2015		
trasnportation network	Adeger et Al. 2004	Alexander et Al 2011 (Kienberger) Adeger et Al. 2004	
Trauma injuries	Noriga and Ludwing 2012		

Travel time to the closest urban centre (mins)	Hagenlocher et al 2016		
Trust in officials			Rufat et al. 2015
Tsunami indication map			Tang et al. 2008
Tsunami monitoring and warning system			Tang et al. 2008
Tsunami risk identification and probability estimation			Tang et al. 2008
Underclass (welfare, not in labor force, no formal education)	Ricketts & Mincy 1990		
Unemployment rate district Unemployment % Unemployed Unemployment rate	Fukultat et al 2009 Fekete 2009 Alexander et Al 2011(Torsten Welle et Al) Baum et al 2008 Borden et al 2007 Boruff & Cutter 2007 Cardona 2005 Zoppou et al 2004 Holand et al 2011 Mendes 2009 Van Vandt 2012 Eisenman 2007	Fukultat et al 2009 Alexander et Al 2011 (Kienberger) Baum et al 2008 Cardona 2005 Shaw 2009	Van Vandt 2012 Cross 2001
Update status of development plan population growth prognosos emplyment rate			Groven et al 2006
Update status of risk and vulnerability analysis			Groven et al 2006
urban growth	Cardona 2005	Cardona 2005	
Urban networks		Serre 2018	Serre 2018
Voice and aacountability	Brooks et al 2005		
Volunteer/community groups for tsunamis			Tang et al. 2008

Water shortage		Alcomo et al 2001	Alcomo et al 2001 wein et al 2012
Wealth		Rufat et al. 2015	Van Vandt 2012
Wealth index:poorest,poor (%)	Hagenlocher et al 2016		Kates et al. 2006
Zoning			Schiller et al. 2001 Geis 2001
Population Decline			Gilbert 2010
Economic Decline	Kates et al. 2006	Kates et al. 2006	Kates et al. 2006
Nunber of schools per capita (or km2)			Kates et al. 2006
Food stores per capita (or km2)			Kates et al. 2006
Education, Research, Awaereness and knowledge			Beccari 2016
Information and Communication			Beccari 2016
Culture and Diversity			Beccari 2016
Exposure, Experience and Impact Severity			Beccari 2016

Appendix B: OLS Regression Results

Appendix B shows the complete results of OLS regression analysis for earthquake losses. A series of regression models were generated for four different time periods (years 2000 to 2018, 2000 to 2009, 2005 to 2014, and 2009 to 2018) to capture the effect of temporal variability in the model. For the models, earthquake loss data were taken as dependent variable and the social vulnerability indicators were taken as independent variables.

Regression Results:

A1: Total damage as dependent variable:

- A1.1 Year 2000 to 2018
- A1.2 Year 2000-2009
- A1.3 Year 2005- 2014
- A1.4 Year 2009-2018

A2: Total homeless as dependent variable:

- A2.1 Year 2000 to 2018
- A2.2 Year 2000-2009
- A2.3 Year 2005- 2014
- A2.4 Year 2009-2018

A3: Total homeless as dependent variable:

- A3.1 Year 2000 to 2018
- A3.2 Year 2000-2009
- A3.3 Year 2005- 2014
- A3.4 Year 2009-2018

A4: Total affected as dependent variable:

A4.1 Year 2000 to 2018

A4.2 Year 2000-2009

A4.3 Year 2005- 2014

A4.4 Year 2009-2018

A1: Total damage as dependent variable:

Table A1.1: Year 2000 to 2018

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.695[a]	.483	.481	.71886769

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-8.452E-16	.007		.000	1.000		
	Zscore(ECOEREIRP)	-.138	.009	-.138	-14.533	.000	.589	1.699
	Zscore(ECOERERDE)	.111	.014	.111	8.147	.000	.285	3.508
	Zscore(ECOEREGGD)	.173	.009	.173	18.613	.000	.612	1.634
	Zscore(ECOIDPGIN)	.112	.011	.112	10.225	.000	.437	2.291
	Zscore(INXXXXESI)	-.067	.011	-.067	-6.271	.000	.458	2.184
	Zscore(INFEWSACE)	.237	.021	.237	11.150	.000	.117	8.557
	Zscore(POPPPSADP)	.230	.019	.230	12.090	.000	.146	6.835
	Zscore(POPPPSIMP)	-.068	.014	-.068	-5.026	.000	.285	3.514
	Zscore(ECOLAMLAF)	.091	.014	.091	6.477	.000	.270	3.710
	Zscore(ECOEACFDP)	.015	.038	.015	.385	.700	.037	27.300
	Zscore(ECOEACGFC)	.138	.010	.138	13.749	.000	.525	1.904
	Zscore(GICAVTLCP)	-.037	.010	-.037	-3.672	.000	.524	1.907

	Zscore(GICLRVVTE)	-.186	.009	-.186	-19.860	.000	.599	1.669
	Zscore(INFEWSIWP)	-.092	.015	-.092	-5.939	.000	.222	4.499
	Zscore(POPVNPPIP)	-.154	.019	-.154	-7.957	.000	.141	7.073
	Zscore(HEAHCRHBE)	.290	.014	.290	21.505	.000	.289	3.456
	Zscore(HEAHCRPHY)	-.162	.016	-.162	-10.437	.000	.219	4.560
	Zscore(POPPPSNMR)	-.030	.010	-.030	-2.923	.003	.517	1.932
	Zscore(POPPPSPDE)	-.124	.029	-.124	-4.220	.000	.061	16.488
	Zscore(POPVNPSLP)	.094	.017	.094	5.396	.000	.175	5.727
	Zscore(ECOLAMUEP)	-.016	.010	-.016	-1.624	.104	.566	1.767
	Zscore(ECOEACGRW)	.008	.010	.008	.796	.426	.549	1.822
	Zscore(INFTCORDE)	.092	.030	.092	3.110	.002	.060	16.619
	Zscore(POPPPSLPF)	.162	.013	.162	12.100	.000	.296	3.376
	Zscore(GICGEFGVA)	-.249	.017	-.249	-14.579	.000	.182	5.509
	Zscore(INFEXPCOM)	.422	.009	.422	45.556	.000	.616	1.623
	Zscore(INFEXPIND)	-.021	.009	.021	-2.456	.014	.713	1.403
	Zscore(POPPPSPPH)	-.006	.011	-.006	-.501	.616	.427	2.341
	Zscore(POPVNPFHH)	-.011	.010	-.011	-1.075	.282	.521	1.920
	Zscore(ECOEACGDP)	.035	.018	.035	1.927	.054	.157	6.374
	Zscore(EDUEOCLTP)	-.029	.021	-.029	-1.390	.165	.123	8.135
	Zscore(ECOEACIPD)	.008	.039	.008	.210	.834	.035	28.436
	Zscore(ECOEACPEE)	-.056	.011	-.056	-5.210	.000	.464	2.157
	Zscore(ECOTREEEE)	-.223	.017	-.223	-12.867	.000	.176	5.679
	Zscore(ECOTREMIC)	.069	.015	.069	4.539	.000	.229	4.375
	Zscore(ECOLAMEIT)	.035	.013	.035	2.671	.008	.305	3.275
	Zscore(ECOLAMEST)	.053	.018	.053	2.923	.003	.162	6.156
	Zscore(ECOEREGNS)	.114	.011	.114	10.820	.000	.476	2.102
	Zscore(EDUEOCSAM)	-.116	.027	-.116	-4.311	.000	.073	13.651
	Zscore(HEAHSTMUF)	.033	.028	.033	1.182	.237	.068	14.769
	Zscore(ECOECPIND)	-.125	.018	-.125	-6.887	.000	.161	6.202
	Zscore(INFTCOMCC)	-.061	.013	-.061	-4.861	.000	.332	3.012
	Zscore(ECOEACGRB)	.011	.012	.011	.964	.335	.385	2.597
	Zscore(ECOEACTRE)	-.155	.012	-.155	-13.264	.000	.384	2.602
	Zscore(EDUEOCLFM)	-.134	.012	-.134	-10.896	.000	.349	2.867
	Zscore(EDUEACEEG)	-.081	.011	-.081	-7.662	.000	.469	2.132

	Zscore(EDUEOCSAF)	.134	.031	.134	4.343	.000	.055	18.067
	Zscore(EDUEEOCCT)	.041	.015	.041	2.701	.007	.233	4.286
	Zscore(ECOECPSER)	-.035	.019	-.035	-1.875	.061	.154	6.504
	Zscore(HEAHSTDRC)	.005	.015	.005	.312	.755	.221	4.515
	Zscore(HEAHSTPUP)	-.130	.014	-.130	-9.316	.000	.272	3.673
	Zscore(POPVNPTPP)	-.028	.009	-.028	-3.045	.002	.638	1.568
	Zscore(POPVNPITA)	.096	.011	.096	9.012	.000	.463	2.160
	Zscore(POPPPSRPP)	.064	.014	.064	4.641	.000	.277	3.612

a. Dependent Variable: Zscore(TOT_DAM000)

Table A1.2: Year 2000-2009

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.721[a]	.519	.331	.81779645	1.997

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-6.945E-16	.059		.000	1.000		
	Zscore(ECOEREIRP)	-.107	.077	-.107	-1.395	.165	.589	1.699
	Zscore(ECOERERDE)	.159	.111	.159	1.440	.152	.285	3.508
	Zscore(ECOEREGGD)	.136	.075	.136	1.801	.074	.612	1.634
	Zscore(ECOIDPGIN)	.138	.089	.138	1.549	.124	.437	2.291
	Zscore(INXXXXESI)	-.055	.087	-.055	-.629	.531	.458	2.184
	Zscore(INFEWSACE)	.220	.173	.220	1.272	.206	.117	8.557
	Zscore(POPPPSADP)	.220	.154	.220	1.423	.157	.146	6.835
	Zscore(POPPPSIMP)	-.078	.111	-.078	-.703	.483	.285	3.514
	Zscore(ECOLAMLAF)	.093	.114	.093	.819	.414	.270	3.710
	Zscore(ECOEACFDP)	-.015	.308	-.015	-.048	.962	.037	27.300

	Zscore(ECOEACGFC)	.143	.081	.143	1.751	.082	.525	1.904
	Zscore(GICAVTLCP)	-.030	.082	-.030	-.367	.715	.524	1.907
	Zscore(GICLRVVTE)	-.199	.076	-.199	-2.611	.010	.599	1.669
	Zscore(INFEWSIWP)	-.073	.125	-.073	-.585	.560	.222	4.499
	Zscore(POPVNPPIP)	-.190	.157	-.190	-1.210	.228	.141	7.073
	Zscore(HEAHCRHBE)	.231	.110	.231	2.103	.037	.289	3.456
	Zscore(HEAHCRPHY)	-.141	.126	-.141	-1.118	.265	.219	4.560
	Zscore(POPPPSNMR)	-.018	.082	-.018	-.224	.823	.517	1.932
	Zscore(POPPPSPDE)	-.125	.240	-.125	-.520	.604	.061	16.488
	Zscore(POPVNPSLP)	.113	.141	.113	.802	.424	.175	5.727
	Zscore(ECOLAMUEP)	-.021	.078	-.021	-.271	.787	.566	1.767
	Zscore(ECOEACGRW)	.024	.080	.024	.303	.763	.549	1.822
	Zscore(INFTCORDE)	.122	.241	.122	.507	.613	.060	16.619
	Zscore(POPPPSLPF)	.161	.108	.161	1.481	.141	.296	3.376
	Zscore(GICGEFGVA)	-.297	.139	-.297	-2.147	.034	.182	5.509
	Zscore(INFEXPCOM)	.475	.075	.475	6.312	.000	.616	1.623
	Zscore(INFEXPIND)	-.016	.070	-.016	-.233	.816	.713	1.403
	Zscore(POPPPSPPH)	.010	.090	.010	.110	.912	.427	2.341
	Zscore(POPVNPFHH)	-.060	.082	-.060	-.734	.464	.521	1.920
	Zscore(ECOEACGDP)	-4.164E-5	.149	.000	.000	1.000	.157	6.374
	Zscore(EDUEOCLTP)	-.049	.168	-.049	-.290	.772	.123	8.135
	Zscore(ECOEACIPD)	.058	.315	.058	.183	.855	.035	28.436
	Zscore(ECOEACPEE)	-.073	.087	-.073	-.847	.398	.464	2.157
	Zscore(ECOTREEEE)	-.229	.141	-.229	-1.630	.105	.176	5.679
	Zscore(ECOTREMIC)	.116	.123	.116	.938	.350	.229	4.375
	Zscore(ECOLAMEIT)	.014	.107	.014	.127	.899	.305	3.275
	Zscore(ECOLAMEST)	.055	.146	.055	.372	.710	.162	6.156
	Zscore(ECOEREGNS)	.127	.086	.127	1.487	.139	.476	2.102
	Zscore(EDUEOCSAM)	-.055	.218	-.055	-.253	.800	.073	13.651
	Zscore(HEAHSTMUF)	-.073	.227	-.073	-.320	.749	.068	14.769
	Zscore(ECOECPIND)	-.132	.147	-.132	-.901	.369	.161	6.202
	Zscore(INFTCOMCC)	-.079	.102	-.079	-.768	.444	.332	3.012
	Zscore(ECOEACGRB)	.030	.095	.030	.318	.751	.385	2.597

	Zscore(ECOEACTRE)	-.112	.095	-.112	-1.172	.243	.384	2.602
	Zscore(EDUEOCLFM)	-.106	.100	-.106	-1.056	.293	.349	2.867
	Zscore(EDUEACEEG)	-.080	.086	-.080	-.927	.356	.469	2.132
	Zscore(EDUEOCSAF)	.037	.251	.037	.149	.882	.055	18.067
	Zscore(EDUEEOCCT)	-.004	.122	-.004	-.032	.975	.233	4.286
	Zscore(ECOECPSER)	-.085	.151	-.085	-.562	.575	.154	6.504
	Zscore(HEAHSTDRC)	.058	.125	.058	.466	.642	.221	4.515
	Zscore(HEAHSTPUP)	-.126	.113	-.126	-1.110	.269	.272	3.673
	Zscore(POPVNPTPP)	-.017	.074	-.017	-.236	.814	.638	1.568
	Zscore(POPVNPITA)	.107	.087	.107	1.235	.219	.463	2.160
	Zscore(POPPPSRPP)	.097	.112	.097	.863	.389	.277	3.612

a. Dependent Variable: Zscore(TOT_DAM000)

Table A1.3: Year 2005- 2014

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.661[a]	.437	.216	.88526571	1.913

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-8.262E-16	.064		.000	1.000
	Zscore(ECOEREIRP)	-.090	.083	-.090	-1.082	.281
	Zscore(ECOERERDE)	.073	.120	.073	.612	.541
	Zscore(ECOEREGGD)	-.014	.082	-.014	-.176	.861
	Zscore(ECOIDPGIN)	.102	.097	.102	1.054	.294
	Zscore(INXXXXESI)	-.117	.094	-.117	-1.235	.219
	Zscore(INFEWSACE)	.223	.187	.223	1.194	.234
	Zscore(POPPPSADP)	.153	.167	.153	.913	.363
	Zscore(POPPPSIMP)	-.052	.120	-.052	-.435	.664
	Zscore(ECOLAMLAF)	.111	.123	.111	.903	.368

	Zscore(ECOEACFDP)	-.108	.334	-.108	-.322	.748
	Zscore(ECOEACGFC)	.183	.088	.183	2.073	.040
	Zscore(GICAVTLCP)	-.049	.088	-.049	-.560	.577
	Zscore(GICLRVVTE)	-.199	.083	-.199	-2.412	.017
	Zscore(INFEWSIWP)	-.074	.136	-.074	-.548	.585
	Zscore(POPVNPPIP)	-.221	.170	-.221	-1.299	.196
	Zscore(HEAHCRHBE)	.089	.119	.089	.747	.457
	Zscore(HEAHCRPHY)	-.016	.136	-.016	-.116	.908
	Zscore(POPPPSNMR)	-.014	.089	-.014	-.153	.879
	Zscore(POPPPSPDE)	.027	.259	.027	.105	.917
	Zscore(POPVNPSLP)	.120	.153	.120	.784	.434
	Zscore(ECOLAMUEP)	.015	.085	.015	.177	.860
	Zscore(ECOEACGRW)	.050	.086	.050	.580	.563
	Zscore(INFTCORDE)	-.065	.260	-.065	-.249	.804
	Zscore(POPPPSLPF)	.162	.117	.162	1.381	.169
	Zscore(GICGEFGVA)	-.157	.150	-.157	-1.049	.296
	Zscore(INFEXPCOM)	.487	.081	.487	5.979	.000
	Zscore(INFEXPIND)	-.010	.076	-.010	-.132	.895
	Zscore(POPPPSPPH)	-.016	.098	-.016	-.165	.869
	Zscore(POPVNPFHH)	.021	.089	.021	.237	.813
	Zscore(ECOEACGDP)	.053	.161	.053	.331	.741
	Zscore(EDUEOCLTP)	-.071	.182	-.071	-.391	.696
	Zscore(ECOEACIPD)	.134	.341	.134	.392	.695
	Zscore(ECOEACPEE)	-.051	.094	-.051	-.543	.588
	Zscore(ECOTREEEE)	-.201	.152	-.201	-1.323	.188
	Zscore(ECOTREMIC)	.077	.134	.077	.576	.566
	Zscore(ECOLAMEIT)	.038	.116	.038	.332	.741
	Zscore(ECOLAMEST)	-.005	.159	-.005	-.029	.977
	Zscore(ECOEREGNS)	.066	.093	.066	.717	.475
	Zscore(EDUEOCSAM)	-.145	.236	-.145	-.616	.539
	Zscore(HEAHSTMUF)	-.024	.246	-.024	-.098	.922
	Zscore(ECOECPIND)	-.159	.159	-.159	-1.001	.319
	Zscore(INFTCOMCC)	-.067	.111	-.067	-.607	.545
	Zscore(ECOEACGRB)	.092	.103	.092	.895	.372
	Zscore(ECOEACTRE)	-.050	.103	-.050	-.482	.630
	Zscore(EDUEOCLFM)	-.106	.108	-.106	-.977	.330
	Zscore(EDUEACEEG)	-.058	.093	-.058	-.619	.537
	Zscore(EDUEOCSAF)	.149	.272	.149	.549	.584
	Zscore(EDUEEOCCT)	-.081	.132	-.081	-.612	.542

	Zscore(ECOECPSER)	-.112	.163	-.112	-.688	.493
	Zscore(HEAHSTDRC)	.028	.136	.028	.207	.836
	Zscore(HEAHSTPUP)	-.038	.122	-.038	-.312	.756
	Zscore(POPVNPTPP)	-.009	.080	-.009	-.115	.909
	Zscore(POPVNPITA)	.086	.094	.086	.917	.361
	Zscore(POPPPSRPP)	.037	.121	.037	.309	.758

a. Dependent Variable: Zscore(TOT_DAM000)

Tabel A1.4: Year 2009-2018

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.520[a]	.270	-.015	1.00745075	1.952

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.352E-15	.073		.000	1.000
	Zscore(ECOEREIRP)	-.170	.095	-.170	-1.793	.075
	Zscore(ECOERERDE)	-.039	.136	-.039	-.286	.775
	Zscore(ECOEREGGD)	.206	.093	.206	2.214	.028
	Zscore(ECOIDPGIN)	.004	.110	.004	.040	.968
	Zscore(INXXXXESI)	-.079	.107	-.079	-.731	.466
	Zscore(INFEWSACE)	.177	.213	.177	.833	.406
	Zscore(POPPPSADP)	.175	.190	.175	.919	.360
	Zscore(POPPPSIMP)	-.032	.136	-.032	-.234	.815
	Zscore(ECOLAMLAF)	.060	.140	.060	.427	.670
	Zscore(ECOEACFDP)	.075	.380	.075	.197	.844
	Zscore(ECOEACGFC)	.083	.100	.083	.828	.409
	Zscore(GICAVTLCP)	-.045	.100	-.045	-.449	.654
	Zscore(GICLRVVTE)	-.092	.094	-.092	-.978	.330
	Zscore(INFEWSIWP)	-.106	.154	-.106	-.689	.492
	Zscore(POPVNPPIP)	-.020	.193	-.020	-.102	.919

	Zscore(HEAHCRHBE)	.301	.135	.301	2.225	.028
	Zscore(HEAHCRPHY)	-.154	.155	-.154	-.994	.322
	Zscore(POPPPSNMR)	-.045	.101	-.045	-.448	.655
	Zscore(POPPPSPDE)	-.076	.295	-.076	-.256	.798
	Zscore(POPVNPSLP)	.013	.174	.013	.076	.940
	Zscore(ECOLAMUEP)	.004	.097	.004	.045	.964
	Zscore(ECOEACGRW)	-.035	.098	-.035	-.352	.725
	Zscore(INFTCORDE)	-.011	.296	-.011	-.037	.971
	Zscore(POPPPSLPF)	.101	.134	.101	.757	.450
	Zscore(GICGEFGVA)	-.048	.171	-.048	-.280	.780
	Zscore(INFEXPCOM)	.173	.093	.173	1.870	.064
	Zscore(INFEXPIND)	-.017	.086	-.017	-.203	.839
	Zscore(POPPPSPPH)	-.043	.111	-.043	-.384	.702
	Zscore(POPVNPFHH)	.104	.101	.104	1.029	.305
	Zscore(ECOEACGDP)	.095	.184	.095	.518	.605
	Zscore(EDUEOCLTP)	-.001	.207	-.001	-.006	.995
	Zscore(ECOEACIPD)	-.101	.388	-.101	-.261	.794
	Zscore(ECOEACPEE)	-.004	.107	-.004	-.035	.972
	Zscore(ECOTREEEE)	-.137	.173	-.137	-.791	.430
	Zscore(ECOTREMIC)	-.062	.152	-.062	-.409	.683
	Zscore(ECOLAMEIT)	.073	.132	.073	.552	.582
	Zscore(ECOLAMEST)	.028	.180	.028	.152	.879
	Zscore(ECOEREGNS)	.051	.105	.051	.482	.631
	Zscore(EDUEOCSAM)	-.217	.269	-.217	-.809	.420
	Zscore(HEAHSTMUF)	.256	.279	.256	.916	.361
	Zscore(ECOECPIND)	-.065	.181	-.065	-.356	.722
	Zscore(INFTCOMCC)	.005	.126	.005	.039	.969
	Zscore(ECOEACGRB)	-.035	.117	-.035	-.300	.765
	Zscore(ECOEACTRE)	-.205	.117	-.205	-1.748	.083
	Zscore(EDUEOCLFM)	-.152	.123	-.152	-1.235	.219
	Zscore(EDUEACEEG)	-.059	.106	-.059	-.555	.580
	Zscore(EDUEOCSAF)	.322	.309	.322	1.043	.299
	Zscore(EDUEEOCCT)	.131	.151	.131	.870	.386
	Zscore(ECOECPSER)	.081	.185	.081	.437	.663
	Zscore(HEAHSTDRC)	-.111	.154	-.111	-.717	.474
	Zscore(HEAHSTPUP)	-.097	.139	-.097	-.693	.489
	Zscore(POPVNPTPP)	-.046	.091	-.046	-.505	.614
	Zscore(POPVNPITA)	.035	.107	.035	.332	.740
	Zscore(POPPPSRPP)	-.037	.138	-.037	-.268	.789

a. Dependent Variable: Zscore(TOT_DAM000)

A.2: Total death as dependent variable:

Table A.2.1: Year 200-2009

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.680[a]	.462	.251	.86528382	1.998

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-2.011E-16	.062		.000	1.000		
	Zscore(ECOEREIRP)	.069	.081	.069	.844	.400	.589	1.699
	Zscore(ECOERERDE)	.122	.117	.122	1.043	.299	.285	3.508
	Zscore(ECOEREGGD)	-.102	.080	-.102	-1.283	.202	.612	1.634
	Zscore(ECOIDPGIN)	.003	.095	.003	.037	.971	.437	2.291
	Zscore(INXXXXESI)	-.078	.092	-.078	-.848	.398	.458	2.184
	Zscore(INFEWSACE)	.081	.183	.081	.442	.659	.117	8.557
	Zscore(POPPPSADP)	-.027	.163	-.027	-.165	.869	.146	6.835
	Zscore(POPPPSIMP)	-.108	.117	-.108	-.922	.358	.285	3.514
	Zscore(ECOLAMLAF)	.033	.120	.033	.275	.783	.270	3.710
	Zscore(ECOEACFDP)	-.096	.326	-.096	-.296	.768	.037	27.300
	Zscore(ECOEACGFC)	.043	.086	.043	.498	.619	.525	1.904
	Zscore(GICAVTLCP)	-.063	.086	-.063	-.731	.466	.524	1.907
	Zscore(GICLRVVTE)	-.217	.081	-.217	-2.694	.008	.599	1.669
	Zscore(INFEWSIWP)	.168	.132	.168	1.270	.206	.222	4.499
	Zscore(POPVNPPIP)	-.185	.166	-.185	-1.113	.268	.141	7.073
	Zscore(HEAHCRHBE)	-.059	.116	-.059	-.504	.615	.289	3.456

	Zscore(HEAHCRPHY)	.042	.133	.042	.318	.751	.219	4.560
	Zscore(POPPPSNMR)	-.001	.087	-.001	-.013	.990	.517	1.932
	Zscore(POPPPSPDE)	.167	.254	.167	.658	.512	.061	16.488
	Zscore(POPVNPSLP)	.125	.149	.125	.833	.406	.175	5.727
	Zscore(ECOLAMUEP)	.028	.083	.028	.341	.734	.566	1.767
	Zscore(ECOEACGRW)	.078	.084	.078	.925	.356	.549	1.822
	Zscore(INFTCORDE)	-.127	.255	-.127	-.497	.620	.060	16.619
	Zscore(POPPPSLPF)	-.009	.115	-.009	-.082	.935	.296	3.376
	Zscore(GICGEFGVA)	-.045	.147	-.045	-.308	.759	.182	5.509
	Zscore(INFEXPCOM)	.465	.080	.465	5.850	.000	.616	1.623
	Zscore(INFEXPIND)	-.004	.074	-.004	-.057	.955	.713	1.403
	Zscore(POPPPSPPH)	.097	.096	.097	1.018	.311	.427	2.341
	Zscore(POPVNPFHH)	-.025	.087	-.025	-.291	.771	.521	1.920
	Zscore(ECOEACGDP)	-.019	.158	-.019	-.122	.903	.157	6.374
	Zscore(EDUEOCLTP)	-.054	.178	-.054	-.304	.762	.123	8.135
	Zscore(ECOEACIPD)	.145	.333	.145	.437	.663	.035	28.436
	Zscore(ECOEACPEE)	-.079	.092	-.079	-.864	.389	.464	2.157
	Zscore(ECOTREEEE)	-.093	.149	-.093	-.623	.534	.176	5.679
	Zscore(ECOTREMIC)	.020	.131	.020	.151	.880	.229	4.375
	Zscore(ECOLAMEIT)	.093	.113	.093	.819	.414	.305	3.275
	Zscore(ECOLAMEST)	-.016	.155	-.016	-.104	.917	.162	6.156
	Zscore(ECOEREGNS)	.037	.091	.037	.411	.682	.476	2.102
	Zscore(EDUEOCSAM)	-.283	.231	-.283	-1.226	.222	.073	13.651
	Zscore(HEAHSTMUF)	.044	.240	.044	.184	.854	.068	14.769
	Zscore(ECOECPIND)	-.062	.156	-.062	-.401	.689	.161	6.202
	Zscore(INFTCOMCC)	-.105	.108	-.105	-.972	.333	.332	3.012
	Zscore(ECOEACGRB)	.058	.101	.058	.580	.563	.385	2.597
	Zscore(ECOEACTRE)	.027	.101	.027	.264	.792	.384	2.602
	Zscore(EDUEOCLFM)	.021	.106	.021	.195	.845	.349	2.867
	Zscore(EDUEACEEG)	-.052	.091	-.052	-.568	.571	.469	2.132
	Zscore(EDUEOCSAF)	.271	.265	.271	1.022	.309	.055	18.067
	Zscore(EDUEEOCCT)	-.098	.129	-.098	-.757	.450	.233	4.286
	Zscore(ECOECPSER)	-.044	.159	-.044	-.276	.783	.154	6.504
	Zscore(HEAHSTDRC)	-.018	.133	-.018	-.137	.892	.221	4.515
	Zscore(HEAHSTPUP)	.086	.120	.086	.715	.476	.272	3.673
	Zscore(POPVNPTPP)	.000	.078	.000	.006	.995	.638	1.568
	Zscore(POPVNPITA)	.055	.092	.055	.601	.549	.463	2.160
	Zscore(POPPPSRPP)	.075	.119	.075	.630	.530	.277	3.612

a. Dependent Variable: Zscore(TOT_DEATHS)

Table A2.2: Year 2005-2014

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.665[a]	.442	.224	.88097426	1.959

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2.837E-15	.063		.000	1.000
	Zscore(ECOEREIRP)	-.107	.083	-.107	-1.293	.198
	Zscore(ECOERERDE)	.125	.119	.125	1.049	.296
	Zscore(ECOEREGGD)	-.124	.081	-.124	-1.525	.130
	Zscore(ECOIDPGIN)	.045	.096	.045	.463	.644
	Zscore(INXXXXESI)	-.148	.094	-.148	-1.580	.116
	Zscore(INFEWSACE)	.206	.186	.206	1.110	.269
	Zscore(POPPPSADP)	-.360	.166	-.360	-2.165	.032
	Zscore(POPPPSIMP)	-.120	.119	-.120	-1.007	.316
	Zscore(ECOLAMLAF)	-.036	.122	-.036	-.297	.767
	Zscore(ECOEACFDP)	.060	.332	.060	.180	.858
	Zscore(ECOEACGFC)	.027	.088	.027	.311	.756
	Zscore(GICAVTLCP)	-.042	.088	-.042	-.475	.636
	Zscore(GICLRVVTE)	-.251	.082	-.251	-3.060	.003
	Zscore(INFEWSIWP)	.030	.135	.030	.223	.824
	Zscore(POPVNPPIP)	-.243	.169	-.243	-1.438	.153
	Zscore(HEAHCRHBE)	.067	.118	.067	.563	.574
	Zscore(HEAHCRPHY)	.172	.136	.172	1.270	.206
	Zscore(POPPPSNMR)	-.117	.088	-.117	-1.327	.187
	Zscore(POPPPSPDE)	.078	.258	.078	.302	.763
	Zscore(POPVNPSLP)	.152	.152	.152	1.002	.318
	Zscore(ECOLAMUEP)	.061	.085	.061	.721	.472

	Zscore(ECOEACGRW)	.031	.086	.031	.365	.715
	Zscore(INFTCORDE)	-.034	.259	-.034	-.132	.895
	Zscore(POPPPSLPF)	.089	.117	.089	.763	.447
	Zscore(GICGEFGVA)	.203	.149	.203	1.360	.176
	Zscore(INFEXPCOM)	.141	.081	.141	1.737	.085
	Zscore(INFEXPIND)	.012	.075	.012	.155	.877
	Zscore(POPPPSPPH)	.063	.097	.063	.650	.517
	Zscore(POPVNPFHH)	.072	.088	.072	.820	.413
	Zscore(ECOEACGDP)	.075	.161	.075	.470	.639
	Zscore(EDUEOCLTP)	.133	.181	.133	.732	.465
	Zscore(ECOEACIPD)	-.064	.339	-.064	-.189	.850
	Zscore(ECOEACPEE)	.157	.093	.157	1.682	.095
	Zscore(ECOTREEEE)	-.031	.152	-.031	-.203	.839
	Zscore(ECOTREMIC)	-.018	.133	-.018	-.137	.892
	Zscore(ECOLAMEIT)	.054	.115	.054	.470	.639
	Zscore(ECOLAMEST)	.009	.158	.009	.057	.955
	Zscore(ECOEREGNS)	.015	.092	.015	.165	.869
	Zscore(EDUEOCSAM)	-.355	.235	-.355	-1.511	.133
	Zscore(HEAHSTMUF)	.947	.244	.947	3.875	.000
	Zscore(ECOECPIND)	.018	.158	.018	.115	.909
	Zscore(INFTCOMCC)	-.076	.110	-.076	-.685	.495
	Zscore(ECOEACGRB)	.150	.102	.150	1.468	.144
	Zscore(ECOEACTRE)	.016	.103	.016	.154	.878
	Zscore(EDUEOCLFM)	-.267	.108	-.267	-2.480	.014
	Zscore(EDUEACEEG)	-.161	.093	-.161	-1.729	.086
	Zscore(EDUEOCSAF)	.438	.270	.438	1.621	.107
	Zscore(EDUEEOCCT)	.047	.132	.047	.354	.724
	Zscore(ECOECPSER)	.194	.162	.194	1.199	.233
	Zscore(HEAHSTDRC)	-.282	.135	-.282	-2.086	.039
	Zscore(HEAHSTPUP)	.394	.122	.394	3.233	.002
	Zscore(POPVNPTPP)	-.057	.080	-.057	-.711	.478
	Zscore(POPVNPITA)	.030	.093	.030	.324	.746
	Zscore(POPPPSRPP)	-.003	.121	-.003	-.022	.982

a. Dependent Variable: Zscore(TOT_DEATHS)

Table A2.3: Year 2009-2018

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.655[a]	.429	.205	.89158078	1.830

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-3.292E-15	.064		.000	1.000
	Zscore(ECOEREIRP)	-.143	.084	-.143	-1.711	.089
	Zscore(ECOERERDE)	.082	.121	.082	.681	.497
	Zscore(ECOEREGGD)	-.098	.082	-.098	-1.189	.236
	Zscore(ECOIDPGIN)	.032	.097	.032	.330	.742
	Zscore(INXXXXESI)	-.117	.095	-.117	-1.225	.223
	Zscore(INFEWSACE)	.194	.188	.194	1.029	.305
	Zscore(POPPPSADP)	-.404	.168	-.404	-2.403	.018
	Zscore(POPPPSIMP)	-.088	.121	-.088	-.729	.467
	Zscore(ECOLAMLAF)	-.068	.124	-.068	-.547	.585
	Zscore(ECOEACFDP)	.136	.336	.136	.404	.686
	Zscore(ECOEACGFC)	-.005	.089	-.005	-.060	.952
	Zscore(GICAVTLCP)	-.021	.089	-.021	-.239	.812
	Zscore(GICLRVVTE)	-.169	.083	-.169	-2.029	.044
	Zscore(INFEWSIWP)	-.046	.136	-.046	-.338	.736
	Zscore(POPVNPPIP)	-.146	.171	-.146	-.850	.397
	Zscore(HEAHCRHBE)	.108	.120	.108	.901	.369
	Zscore(HEAHCRPHY)	.162	.137	.162	1.177	.241
	Zscore(POPPPSNMR)	-.125	.089	-.125	-1.397	.165
	Zscore(POPPPSPDE)	.009	.261	.009	.034	.973
	Zscore(POPVNPSLP)	.071	.154	.071	.461	.646
	Zscore(ECOLAMUEP)	.076	.086	.076	.894	.373
	Zscore(ECOEACGRW)	.003	.087	.003	.036	.972
	Zscore(INFTCORDE)	.029	.262	.029	.112	.911
	Zscore(POPPPSLPF)	.081	.118	.081	.687	.493
	Zscore(GICGEFGVA)	.272	.151	.272	1.800	.074

	Zscore(INFEXPCOM)	-.041	.082	-.041	-.502	.617
	Zscore(INFEXPIND)	.018	.076	.018	.236	.814
	Zscore(POPPPSPPH)	.012	.098	.012	.126	.900
	Zscore(POPVNPFHH)	.101	.089	.101	1.136	.258
	Zscore(ECOEACGDP)	.092	.162	.092	.566	.572
	Zscore(EDUEOCLTP)	.214	.184	.214	1.168	.245
	Zscore(ECOEACIPD)	-.166	.343	-.166	-.484	.629
	Zscore(ECOEACPEE)	.230	.094	.230	2.433	.016
	Zscore(ECOTREEEE)	.025	.153	.025	.161	.872
	Zscore(ECOTREMIC)	-.049	.135	-.049	-.365	.716
	Zscore(ECOLAMEIT)	.033	.116	.033	.287	.775
	Zscore(ECOLAMEST)	.008	.160	.008	.050	.960
	Zscore(ECOEREGNS)	.017	.093	.017	.180	.858
	Zscore(EDUEOCSAM)	-.304	.238	-.304	-1.279	.203
	Zscore(HEAHSTMUF)	1.059	.247	1.059	4.284	.000
	Zscore(ECOECPIND)	.059	.160	.059	.371	.711
	Zscore(INFTCOMCC)	-.036	.112	-.036	-.324	.746
	Zscore(ECOEACGRB)	.129	.104	.129	1.244	.216
	Zscore(ECOEACTRE)	.011	.104	.011	.108	.914
	Zscore(EDUEOCLFM)	-.314	.109	-.314	-2.883	.005
	Zscore(EDUEACEEG)	-.150	.094	-.150	-1.597	.113
	Zscore(EDUEOCSAF)	.430	.273	.430	1.570	.119
	Zscore(EDUEEOCCT)	.125	.133	.125	.936	.351
	Zscore(ECOECPSER)	.239	.164	.239	1.454	.148
	Zscore(HEAHSTDRC)	-.316	.137	-.316	-2.308	.022
	Zscore(HEAHSTPUP)	.400	.123	.400	3.246	.001
	Zscore(POPVNPTPP)	-.072	.081	-.072	-.892	.374
	Zscore(POPVNPITA)	.003	.095	.003	.032	.975
	Zscore(POPPPSRPP)	-.050	.122	-.050	-.410	.683

a. Dependent Variable: Zscore(TOT_DEATHS)

Table A2.4: Year 2000-2018

Model Summary[b]				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.613[a]	.376	.132	.93178026

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.619E-16	.067		.000	1.000
	Zscore(ECOEREIRP)	.118	.088	.118	1.347	.180
	Zscore(ECOERERDE)	.015	.126	.015	.123	.902
	Zscore(ECOEREGGD)	-.077	.086	-.077	-.891	.374
	Zscore(ECOIDPGIN)	-.099	.102	-.099	-.977	.331
	Zscore(INXXXXESI)	.013	.099	.013	.134	.894
	Zscore(INFEWSACE)	-.042	.197	-.042	-.214	.831
	Zscore(POPPPSADP)	-.136	.176	-.136	-.771	.442
	Zscore(POPPPSIMP)	-.039	.126	-.039	-.312	.755
	Zscore(ECOLAMLAF)	-.035	.130	-.035	-.271	.787
	Zscore(ECOEACFDP)	-.086	.351	-.086	-.245	.807
	Zscore(ECOEACGFC)	-.092	.093	-.092	-.997	.321
	Zscore(GICAVTLCP)	-.054	.093	-.054	-.583	.561
	Zscore(GICLRVVTE)	-.102	.087	-.102	-1.176	.242
	Zscore(INFEWSIWP)	.279	.143	.279	1.958	.052
	Zscore(POPVNPPIP)	-.053	.179	-.053	-.295	.768
	Zscore(HEAHCRHBE)	-.040	.125	-.040	-.324	.747
	Zscore(HEAHCRPHY)	.081	.144	.081	.563	.574
	Zscore(POPPPSNMR)	-.006	.093	-.006	-.064	.949
	Zscore(POPPPSPDE)	.188	.273	.188	.688	.493
	Zscore(POPVNPSLP)	.109	.161	.109	.678	.499
	Zscore(ECOLAMUEP)	.005	.089	.005	.059	.953
	Zscore(ECOEACGRW)	.049	.091	.049	.538	.591
	Zscore(INFTCORDE)	-.124	.274	-.124	-.451	.653
	Zscore(POPPPSLPF)	-.113	.124	-.113	-.918	.360
	Zscore(GICGEFGVA)	.174	.158	.174	1.100	.273
	Zscore(INFEXPCOM)	.432	.086	.432	5.046	.000
	Zscore(INFEXPIND)	.010	.080	.010	.122	.903
	Zscore(POPPPSPPH)	.170	.103	.170	1.648	.102
	Zscore(POPVNPFHH)	-.046	.093	-.046	-.493	.623
	Zscore(ECOEACGDP)	-.089	.170	-.089	-.527	.599
	Zscore(EDUEOCLTP)	-.079	.192	-.079	-.411	.682
	Zscore(ECOEACIPD)	.114	.359	.114	.317	.752
	Zscore(ECOEACPEE)	-.048	.099	-.048	-.490	.625

	Zscore(ECOTREEEE)	.034	.160	.034	.211	.833
	Zscore(ECOTREMIC)	-.039	.141	-.039	-.278	.782
	Zscore(ECOLAMEIT)	.079	.122	.079	.648	.518
	Zscore(ECOLAMEST)	.016	.167	.016	.097	.923
	Zscore(ECOEREGNS)	-.043	.097	-.043	-.438	.662
	Zscore(EDUEOCSAM)	-.239	.248	-.239	-.963	.337
	Zscore(HEAHSTMUF)	.221	.258	.221	.857	.393
	Zscore(ECOECPIND)	.095	.167	.095	.566	.572
	Zscore(INFTCOMCC)	-.046	.117	-.046	-.395	.693
	Zscore(ECOEACGRB)	-.001	.108	-.001	-.007	.994
	Zscore(ECOEACTRE)	.046	.108	.046	.420	.675
	Zscore(EDUEOCLFM)	.094	.114	.094	.828	.409
	Zscore(EDUEACEEG)	-.041	.098	-.041	-.420	.675
	Zscore(EDUEOCSAF)	.271	.286	.271	.949	.344
	Zscore(EDUEEOCCT)	-.093	.139	-.093	-.671	.503
	Zscore(ECOECPSER)	.101	.172	.101	.587	.558
	Zscore(HEAHSTDRC)	-.118	.143	-.118	-.826	.410
	Zscore(HEAHSTPUP)	.175	.129	.175	1.354	.178
	Zscore(POPVNPTPP)	.020	.084	.020	.242	.809
	Zscore(POPVNPITA)	-.019	.099	-.019	-.192	.848
	Zscore(POPPPSRPP)	.093	.128	.093	.731	.466

a. Dependent Variable: Zscore(HOMELESS)

A3: Total homeless as dependent variable:

Table A3.1: Year 2000-2009

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.603[a]	.364	.114	.94103631	2.021

Coefficients[a]					
Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.	Collinearity Statistics

		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	5.330E-16	.068		.000	1.000		
	Zscore(ECOEREIRP)	.122	.089	.122	1.378	.170	.589	1.699
	Zscore(ECOERERDE)	.012	.127	.012	.097	.923	.285	3.508
	Zscore(ECOEREGGD)	-.076	.087	-.076	-.878	.381	.612	1.634
	Zscore(ECOIDPGIN)	-.102	.103	-.102	-.988	.325	.437	2.291
	Zscore(INXXXXESI)	.016	.100	.016	.162	.872	.458	2.184
	Zscore(INFEWSACE)	-.045	.199	-.045	-.227	.821	.117	8.557
	Zscore(POPPPSADP)	-.143	.178	-.143	-.808	.421	.146	6.835
	Zscore(POPPPSIMP)	-.036	.127	-.036	-.280	.780	.285	3.514
	Zscore(ECOLAMLAF)	-.041	.131	-.041	-.317	.752	.270	3.710
	Zscore(ECOEACFDP)	-.080	.355	-.080	-.226	.821	.037	27.300
	Zscore(ECOEACGFC)	-.098	.094	-.098	-1.048	.297	.525	1.904
	Zscore(GICAVTLCP)	-.052	.094	-.052	-.557	.579	.524	1.907
	Zscore(GICLRVVTE)	-.098	.088	-.098	-1.112	.268	.599	1.669
	Zscore(INFEWSIWP)	.285	.144	.285	1.975	.050	.222	4.499
	Zscore(POPVNPPIP)	-.047	.181	-.047	-.259	.796	.141	7.073
	Zscore(HEAHCRHBE)	-.040	.126	-.040	-.321	.749	.289	3.456
	Zscore(HEAHCRPHY)	.083	.145	.083	.571	.569	.219	4.560
	Zscore(POPPPSNMR)	-.007	.094	-.007	-.070	.944	.517	1.932
	Zscore(POPPPSPDE)	.189	.276	.189	.686	.494	.061	16.488
	Zscore(POPVNPSLP)	.109	.163	.109	.669	.505	.175	5.727
	Zscore(ECOLAMUEP)	.004	.090	.004	.043	.966	.566	1.767
	Zscore(ECOEACGRW)	.047	.092	.047	.514	.608	.549	1.822
	Zscore(INFTCORDE)	-.124	.277	-.124	-.446	.656	.060	16.619
	Zscore(POPPPSLPF)	-.117	.125	-.117	-.936	.351	.296	3.376
	Zscore(GICGEFGVA)	.181	.159	.181	1.137	.258	.182	5.509
	Zscore(INFEXPCOM)	.419	.087	.419	4.842	.000	.616	1.623
	Zscore(INFEXPIND)	.009	.080	.009	.108	.914	.713	1.403
	Zscore(POPPPSPPH)	.171	.104	.171	1.645	.102	.427	2.341
	Zscore(POPVNPFHH)	-.045	.094	-.045	-.480	.632	.521	1.920
	Zscore(ECOEACGDP)	-.089	.171	-.089	-.521	.603	.157	6.374
	Zscore(EDUEOCLTP)	-.074	.194	-.074	-.384	.702	.123	8.135
	Zscore(ECOEACIPD)	.107	.362	.107	.294	.769	.035	28.436
	Zscore(ECOEACPEE)	-.046	.100	-.046	-.458	.648	.464	2.157
	Zscore(ECOTREEEE)	.044	.162	.044	.270	.787	.176	5.679

	Zscore(ECOTREMIC)	-.044	.142	-.044	-.311	.757	.229	4.375
	Zscore(ECOLAMEIT)	.077	.123	.077	.630	.529	.305	3.275
	Zscore(ECOLAMEST)	.015	.169	.015	.089	.929	.162	6.156
	Zscore(ECOEREGNS)	-.048	.098	-.048	-.486	.628	.476	2.102
	Zscore(EDUEOCSAM)	-.234	.251	-.234	-.934	.352	.073	13.651
	Zscore(HEAHSTMUF)	.226	.261	.226	.865	.389	.068	14.769
	Zscore(ECOECPIND)	.099	.169	.099	.586	.559	.161	6.202
	Zscore(INFTCOMCC)	-.044	.118	-.044	-.377	.707	.332	3.012
	Zscore(ECOEACGRB)	-.003	.109	-.003	-.030	.976	.385	2.597
	Zscore(ECOEACTRE)	.047	.110	.047	.432	.666	.384	2.602
	Zscore(EDUEOCLFM)	.099	.115	.099	.861	.391	.349	2.867
	Zscore(EDUEACEEG)	-.038	.099	-.038	-.387	.699	.469	2.132
	Zscore(EDUEOCSAF)	.264	.289	.264	.915	.362	.055	18.067
	Zscore(EDUEEOCCT)	-.092	.141	-.092	-.654	.514	.233	4.286
	Zscore(ECOECPSER)	.105	.173	.105	.606	.546	.154	6.504
	Zscore(HEAHSTDRC)	-.122	.144	-.122	-.845	.400	.221	4.515
	Zscore(HEAHSTPUP)	.178	.130	.178	1.371	.173	.272	3.673
	Zscore(POPVNPTPP)	.021	.085	.021	.245	.807	.638	1.568
	Zscore(POPVNPITA)	-.021	.100	-.021	-.214	.831	.463	2.160
	Zscore(POPPPSRPP)	.094	.129	.094	.727	.469	.277	3.612

a. Dependent Variable: Zscore(HOMELESS)

Table A3.2: Year 2005-2014

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.429[a]	.184	-.135	1.06536209	2.052

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.084E-16	.077		.000	1.000
	Zscore(ECOEREIRP)	.120	.100	.120	1.199	.233

	Zscore(ECOERERDE)	.040	.144	.040	.281	.779
	Zscore(ECOEREGGD)	-.051	.098	-.051	-.516	.606
	Zscore(ECOIDPGIN)	-.120	.116	-.120	-1.032	.304
	Zscore(INXXXXESI)	-.024	.114	-.024	-.212	.832
	Zscore(INFEWSACE)	-.062	.225	-.062	-.277	.782
	Zscore(POPPPSADP)	-.156	.201	-.156	-.775	.440
	Zscore(POPPPSIMP)	-.072	.144	-.072	-.501	.617
	Zscore(ECOLAMLAF)	-.028	.148	-.028	-.187	.852
	Zscore(ECOEACFDP)	-.068	.402	-.068	-.168	.866
	Zscore(ECOEACGFC)	-.095	.106	-.095	-.891	.374
	Zscore(GICAVTLCP)	-.049	.106	-.049	-.462	.645
	Zscore(GICLRVVTE)	-.129	.099	-.129	-1.297	.197
	Zscore(INFEWSIWP)	.297	.163	.297	1.823	.070
	Zscore(POPVNPPIP)	-.078	.204	-.078	-.382	.703
	Zscore(HEAHCRHBE)	-.064	.143	-.064	-.451	.653
	Zscore(HEAHCRPHY)	.040	.164	.040	.242	.809
	Zscore(POPPPSNMR)	-.015	.107	-.015	-.139	.890
	Zscore(POPPPSPDE)	.224	.312	.224	.719	.473
	Zscore(POPVNPSLP)	.182	.184	.182	.989	.324
	Zscore(ECOLAMUEP)	-.021	.102	-.021	-.209	.835
	Zscore(ECOEACGRW)	.034	.104	.034	.326	.745
	Zscore(INFTCORDE)	-.173	.313	-.173	-.552	.582
	Zscore(POPPPSLPF)	-.114	.141	-.114	-.809	.420
	Zscore(GICGEFGVA)	.145	.180	.145	.801	.424
	Zscore(INFEXPCOM)	.103	.098	.103	1.055	.293
	Zscore(INFEXPIND)	.023	.091	.023	.250	.803
	Zscore(POPPPSPPH)	.189	.118	.189	1.603	.111
	Zscore(POPVNPFHH)	-.032	.107	-.032	-.296	.768
	Zscore(ECOEACGDP)	-.069	.194	-.069	-.353	.724
	Zscore(EDUEOCLTP)	-.111	.219	-.111	-.504	.615
	Zscore(ECOEACIPD)	.093	.410	.093	.227	.821
	Zscore(ECOEACPEE)	-.060	.113	-.060	-.529	.598
	Zscore(ECOTREEEE)	.024	.183	.024	.129	.898
	Zscore(ECOTREMIC)	-.070	.161	-.070	-.435	.664
	Zscore(ECOLAMEIT)	.062	.139	.062	.442	.659
	Zscore(ECOLAMEST)	.026	.191	.026	.134	.893
	Zscore(ECOEREGNS)	-.065	.111	-.065	-.585	.560
	Zscore(EDUEOCSAM)	-.239	.284	-.239	-.840	.403
	Zscore(HEAHSTMUF)	.166	.295	.166	.563	.574

	Zscore(ECOECPIND)	.090	.191	.090	.471	.639
	Zscore(INFTCOMCC)	-.060	.133	-.060	-.447	.656
	Zscore(ECOEACGRB)	-.018	.124	-.018	-.149	.882
	Zscore(ECOEACTRE)	.017	.124	.017	.135	.893
	Zscore(EDUEOCLFM)	.108	.130	.108	.827	.410
	Zscore(EDUEACEEG)	-.043	.112	-.043	-.385	.701
	Zscore(EDUEOCSAF)	.241	.327	.241	.737	.462
	Zscore(EDUEEOCCT)	-.067	.159	-.067	-.418	.677
	Zscore(ECOECPSER)	.121	.196	.121	.615	.539
	Zscore(HEAHSTDRC)	-.098	.163	-.098	-.601	.549
	Zscore(HEAHSTPUP)	.167	.147	.167	1.133	.259
	Zscore(POPVNPTPP)	.014	.096	.014	.143	.886
	Zscore(POPVNPITA)	-.018	.113	-.018	-.158	.875
	Zscore(POPPPSRPP)	.073	.146	.073	.501	.617

a. Dependent Variable: Zscore(HOMELESS)

Table A3.3: Year 2009 – 2018

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.749[a]	.561	.389	.78168789	2.043

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-4.085E-16	.056		.000	1.000
	Zscore(ECOEREIRP)	-.017	.074	-.017	-.225	.823
	Zscore(ECOERERDE)	.077	.106	.077	.724	.470
	Zscore(ECOEREGGD)	-.032	.072	-.032	-.440	.660
	Zscore(ECOIDPGIN)	-.023	.085	-.023	-.264	.793
	Zscore(INXXXXESI)	-.077	.083	-.077	-.920	.359
	Zscore(INFEWSACE)	.029	.165	.029	.175	.861
	Zscore(POPPPSADP)	.080	.147	.080	.544	.587

	Zscore(POPPPSIMP)	-.105	.106	-.105	-.996	.321
	Zscore(ECOLAMLAF)	.107	.109	.107	.985	.326
	Zscore(ECOEACFDP)	-.207	.295	-.207	-.704	.483
	Zscore(ECOEACGFC)	.076	.078	.076	.974	.332
	Zscore(GICAVTLCP)	-.054	.078	-.054	-.698	.486
	Zscore(GICLRVVTE)	-.164	.073	-.164	-2.247	.026
	Zscore(INFEWSIWP)	.099	.120	.099	.831	.408
	Zscore(POPVNPPIP)	-.142	.150	-.142	-.944	.347
	Zscore(HEAHCRHBE)	-.067	.105	-.067	-.643	.522
	Zscore(HEAHCRPHY)	.039	.120	.039	.322	.748
	Zscore(POPPPSNMR)	.004	.078	.004	.046	.964
	Zscore(POPPPSPDE)	.096	.229	.096	.421	.674
	Zscore(POPVNPSLP)	.096	.135	.096	.713	.477
	Zscore(ECOLAMUEP)	.034	.075	.034	.455	.650
	Zscore(ECOEACGRW)	.059	.076	.059	.776	.439
	Zscore(INFTCORDE)	-.084	.230	-.084	-.365	.715
	Zscore(POPPPSLPF)	-.004	.104	-.004	-.036	.971
	Zscore(GICGEFGVA)	-.060	.132	-.060	-.455	.650
	Zscore(INFEXPCOM)	.582	.072	.582	8.096	.000
	Zscore(INFEXPIND)	.028	.067	.028	.414	.680
	Zscore(POPPPSPPH)	.080	.086	.080	.922	.358
	Zscore(POPVNPFHH)	-.036	.078	-.036	-.459	.647
	Zscore(ECOEACGDP)	-.059	.142	-.059	-.415	.679
	Zscore(EDUEOCLTP)	-.158	.161	-.158	-.980	.329
	Zscore(ECOEACIPD)	.256	.301	.256	.851	.396
	Zscore(ECOEACPEE)	-.111	.083	-.111	-1.344	.181
	Zscore(ECOTREEEE)	-.191	.134	-.191	-1.420	.158
	Zscore(ECOTREMIC)	.075	.118	.075	.632	.528
	Zscore(ECOLAMEIT)	.091	.102	.091	.893	.374
	Zscore(ECOLAMEST)	.025	.140	.025	.177	.860
	Zscore(ECOEREGNS)	.080	.082	.080	.979	.329
	Zscore(EDUEOCSAM)	-.295	.208	-.295	-1.417	.159
	Zscore(HEAHSTMUF)	.031	.217	.031	.142	.887
	Zscore(ECOECPIND)	-.046	.140	-.046	-.329	.743
	Zscore(INFTCOMCC)	-.060	.098	-.060	-.611	.542
	Zscore(ECOEACGRB)	.076	.091	.076	.839	.403
	Zscore(ECOEACTRE)	-.020	.091	-.020	-.220	.826
	Zscore(EDUEOCLFM)	-.032	.096	-.032	-.336	.738
	Zscore(EDUEACEEG)	-.103	.082	-.103	-1.251	.213

	Zscore(EDUEOCSAF)	.344	.240	.344	1.433	.154
	Zscore(EDUEEOCCT)	-.099	.117	-.099	-.846	.399
	Zscore(ECOECPSER)	-.024	.144	-.024	-.168	.867
	Zscore(HEAHSTDRC)	.012	.120	.012	.098	.922
	Zscore(HEAHSTPUP)	.031	.108	.031	.287	.775
	Zscore(POPVNPTPP)	-.002	.071	-.002	-.023	.982
	Zscore(POPVNPITA)	.039	.083	.039	.474	.636
	Zscore(POPPPSRPP)	.076	.107	.076	.705	.482

a. Dependent Variable: Zscore(HOMELESS)

Table A4: Total affected as dependent variable:

A4.1: Year 2000-2018

Model Summary[b]				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.742[a]	.550	.374	.79109151

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-7.195E-16	.057		.000	1.000
	Zscore(ECOEREIRP)	-.053	.074	-.053	-.716	.475
	Zscore(ECOERERDE)	.085	.107	.085	.798	.426
	Zscore(ECOEREGGD)	-.094	.073	-.094	-1.282	.202
	Zscore(ECOIDPGIN)	.091	.086	.091	1.054	.294
	Zscore(INXXXXESI)	-.111	.084	-.111	-1.311	.192
	Zscore(INFEWSACE)	.214	.167	.214	1.284	.201
	Zscore(POPPPSADP)	.106	.149	.106	.708	.480
	Zscore(POPPPSIMP)	-.081	.107	-.081	-.759	.449
	Zscore(ECOLAMLAF)	.116	.110	.116	1.055	.293
	Zscore(ECOEACFDP)	-.136	.298	-.136	-.455	.649
	Zscore(ECOEACGFC)	.158	.079	.158	2.011	.046

	Zscore(GICAVTLCP)	-.050	.079	-.050	-.637	.525
	Zscore(GICLRVVTE)	-.198	.074	-.198	-2.684	.008
	Zscore(INFEWSIWP)	-.019	.121	-.019	-.156	.876
	Zscore(POPVNPPIP)	-.185	.152	-.185	-1.219	.225
	Zscore(HEAHCRHBE)	.011	.106	.011	.101	.919
	Zscore(HEAHCRPHY)	.032	.122	.032	.262	.794
	Zscore(POPPPSNMR)	-.011	.079	-.011	-.133	.895
	Zscore(POPPPSPDE)	.069	.232	.069	.298	.766
	Zscore(POPVNPSLP)	.188	.137	.188	1.373	.172
	Zscore(ECOLAMUEP)	.001	.076	.001	.017	.986
	Zscore(ECOEACGRW)	.066	.077	.066	.852	.396
	Zscore(INFTCORDE)	-.063	.233	-.063	-.272	.786
	Zscore(POPPPSLPF)	.156	.105	.156	1.491	.138
	Zscore(GICGEFGVA)	-.101	.134	-.101	-.755	.451
	Zscore(INFEXPCOM)	.582	.073	.582	8.006	.000
	Zscore(INFEXPIND)	.026	.068	.026	.380	.705
	Zscore(POPPPSPPH)	.009	.087	.009	.098	.922
	Zscore(POPVNPFHH)	-.028	.079	-.028	-.349	.728
	Zscore(ECOEACGDP)	-.008	.144	-.008	-.052	.958
	Zscore(EDUEOCLTP)	-.012	.163	-.012	-.071	.944
	Zscore(ECOEACIPD)	.183	.304	.183	.601	.548
	Zscore(ECOEACPEE)	.000	.084	.000	.002	.999
	Zscore(ECOTREEEE)	-.176	.136	-.176	-1.296	.197
	Zscore(ECOTREMIC)	.085	.119	.085	.714	.476
	Zscore(ECOLAMEIT)	.023	.103	.023	.225	.823
	Zscore(ECOLAMEST)	.002	.142	.002	.014	.989
	Zscore(ECOEREGNS)	.073	.083	.073	.877	.382
	Zscore(EDUEOCSAM)	-.122	.211	-.122	-.578	.564
	Zscore(HEAHSTMUF)	-.150	.219	-.150	-.683	.496
	Zscore(ECOECPIND)	-.097	.142	-.097	-.681	.497
	Zscore(INFTCOMCC)	-.092	.099	-.092	-.926	.356
	Zscore(ECOEACGRB)	.093	.092	.093	1.016	.312
	Zscore(ECOEACTRE)	.013	.092	.013	.145	.885
	Zscore(EDUEOCLFM)	-.086	.097	-.086	-.889	.375
	Zscore(EDUEACEEG)	-.053	.083	-.053	-.630	.530
	Zscore(EDUEOCSAF)	.112	.243	.112	.461	.645
	Zscore(EDUEEOCCT)	-.110	.118	-.110	-.930	.354
	Zscore(ECOECPSER)	-.112	.146	-.112	-.770	.443
	Zscore(HEAHSTDRC)	.050	.121	.050	.412	.681

	Zscore(HEAHSTPUP)	-.001	.109	-.001	-.010	.992
	Zscore(POPVNPTPP)	.000	.071	.000	.002	.999
	Zscore(POPVNPITA)	.088	.084	.088	1.045	.298
	Zscore(POPPPSRPP)	.056	.109	.056	.519	.605

a. Dependent Variable: Zscore(TOT_AFFECTED)

Table A4.2: Year 2000-2009

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.739[a]	.545	.368	.79528704	2.014

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-6.447E-16	.057		.000	1.000		
	Zscore(ECOEREIRP)	-.047	.075	-.047	-.628	.531	.589	1.699
	Zscore(ECOERERDE)	.091	.108	.091	.848	.398	.285	3.508
	Zscore(ECOEREGGD)	-.082	.073	-.082	-1.116	.266	.612	1.634
	Zscore(ECOIDPGIN)	.092	.087	.092	1.059	.291	.437	2.291
	Zscore(INXXXXESI)	-.099	.085	-.099	-1.165	.246	.458	2.184
	Zscore(INFEWSACE)	.151	.168	.151	.900	.370	.117	8.557
	Zscore(POPPPSADP)	.114	.150	.114	.762	.447	.146	6.835
	Zscore(POPPPSIMP)	-.069	.108	-.069	-.637	.525	.285	3.514
	Zscore(ECOLAMLAF)	.109	.111	.109	.983	.327	.270	3.710
	Zscore(ECOEACFDP)	-.139	.300	-.139	-.465	.643	.037	27.300
	Zscore(ECOEACGFC)	.158	.079	.158	1.994	.048	.525	1.904
	Zscore(GICAVTLCP)	-.046	.079	-.046	-.582	.562	.524	1.907

	Zscore(GICLRVVTE)	-.189	.074	-.189	-2.550	.012	.599	1.669
	Zscore(INFEWSIWP)	-.023	.122	-.023	-.187	.852	.222	4.499
	Zscore(POPVNPPIP)	-.221	.153	-.221	-1.450	.149	.141	7.073
	Zscore(HEAHCRHBE)	-.023	.107	-.023	-.215	.830	.289	3.456
	Zscore(HEAHCRPHY)	.036	.123	.036	.292	.771	.219	4.560
	Zscore(POPPPSNMR)	-.009	.080	-.009	-.116	.908	.517	1.932
	Zscore(POPPPSPDE)	.052	.233	.052	.225	.823	.061	16.488
	Zscore(POPVNPSLP)	.130	.137	.130	.946	.346	.175	5.727
	Zscore(ECOLAMUEP)	.005	.076	.005	.065	.949	.566	1.767
	Zscore(ECOEACGRW)	.059	.077	.059	.758	.450	.549	1.822
	Zscore(INFTCORDE)	-.049	.234	-.049	-.211	.833	.060	16.619
	Zscore(POPPPSLPF)	.138	.105	.138	1.313	.191	.296	3.376
	Zscore(GICGEFGVA)	-.143	.135	-.143	-1.064	.289	.182	5.509
	Zscore(INFEXPCOM)	.602	.073	.602	8.232	.000	.616	1.623
	Zscore(INFEXPIND)	.008	.068	.008	.111	.912	.713	1.403
	Zscore(POPPPSPPH)	.003	.088	.003	.040	.968	.427	2.341
	Zscore(POPVNPFHH)	-.032	.080	-.032	-.404	.687	.521	1.920
	Zscore(ECOEACGDP)	-.004	.145	-.004	-.029	.977	.157	6.374
	Zscore(EDUEOCLTP)	-.072	.164	-.072	-.442	.659	.123	8.135
	Zscore(ECOEACIPD)	.190	.306	.190	.622	.535	.035	28.436
	Zscore(ECOEACPEE)	-.054	.084	-.054	-.640	.524	.464	2.157
	Zscore(ECOTREEEE)	-.179	.137	-.179	-1.309	.193	.176	5.679
	Zscore(ECOTREMIC)	.112	.120	.112	.934	.352	.229	4.375
	Zscore(ECOLAMEIT)	.032	.104	.032	.308	.759	.305	3.275
	Zscore(ECOLAMEST)	-.001	.142	-.001	-.010	.992	.162	6.156
	Zscore(ECOEREGNS)	.070	.083	.070	.840	.402	.476	2.102
	Zscore(EDUEOCSAM)	-.103	.212	-.103	-.487	.627	.073	13.651
	Zscore(HEAHSTMUF)	-.131	.221	-.131	-.593	.554	.068	14.769
	Zscore(ECOECPIND)	-.120	.143	-.120	-.842	.401	.161	6.202
	Zscore(INFTCOMCC)	-.081	.100	-.081	-.811	.419	.332	3.012
	Zscore(ECOEACGRB)	.094	.092	.094	1.020	.309	.385	2.597
	Zscore(ECOEACTRE)	.012	.093	.012	.125	.901	.384	2.602
	Zscore(EDUEOCLFM)	-.061	.097	-.061	-.624	.533	.349	2.867
	Zscore(EDUEACEEG)	-.045	.084	-.045	-.543	.588	.469	2.132
	Zscore(EDUEOCSAF)	.091	.244	.091	.373	.710	.055	18.067

	Zscore(EDUEEOCCT)	-.119	.119	-.119	-1.002	.318	.233	4.286
	Zscore(ECOECPSER)	-.137	.146	-.137	-.937	.350	.154	6.504
	Zscore(HEAHSTDRC)	.063	.122	.063	.515	.607	.221	4.515
	Zscore(HEAHSTPUP)	-.012	.110	-.012	-.113	.910	.272	3.673
	Zscore(POPVNPTPP)	.006	.072	.006	.081	.936	.638	1.568
	Zscore(POPVNPITA)	.083	.084	.083	.989	.324	.463	2.160
	Zscore(POPPPSRPP)	.059	.109	.059	.543	.588	.277	3.612

a. Dependent Variable: Zscore(TOT_AFFECTED)

Table A4.3: Year 2005-2014

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.695[a]	.482	.280	.84860721	2.017

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-9.626E-16	.061		.000	1.000
	Zscore(ECOEREIRP)	-.063	.080	-.063	-.794	.428
	Zscore(ECOERERDE)	.101	.115	.101	.877	.382
	Zscore(ECOEREGGD)	-.087	.078	-.087	-1.107	.270
	Zscore(ECOIDPGIN)	.104	.093	.104	1.126	.262
	Zscore(INXXXXESI)	-.131	.091	-.131	-1.443	.151
	Zscore(INFEWSACE)	.204	.179	.204	1.138	.257
	Zscore(POPPPSADP)	.111	.160	.111	.691	.491
	Zscore(POPPPSIMP)	-.093	.115	-.093	-.812	.418
	Zscore(ECOLAMLAF)	.111	.118	.111	.940	.349
	Zscore(ECOEACFDP)	-.133	.320	-.133	-.416	.678
	Zscore(ECOEACGFC)	.175	.085	.175	2.066	.041
	Zscore(GICAVTLCP)	-.046	.085	-.046	-.541	.590
	Zscore(GICLRVVTE)	-.213	.079	-.213	-2.695	.008

	Zscore(INFEWSIWP)	-.029	.130	-.029	-.225	.822
	Zscore(POPVNPPIP)	-.240	.163	-.240	-1.474	.143
	Zscore(HEAHCRHBE)	-.019	.114	-.019	-.170	.865
	Zscore(HEAHCRPHY)	.035	.131	.035	.267	.790
	Zscore(POPPPSNMR)	-.009	.085	-.009	-.106	.916
	Zscore(POPPPSPDE)	.074	.249	.074	.298	.766
	Zscore(POPVNPSLP)	.188	.147	.188	1.282	.202
	Zscore(ECOLAMUEP)	-.002	.081	-.002	-.024	.981
	Zscore(ECOEACGRW)	.068	.083	.068	.821	.413
	Zscore(INFTCORDE)	-.074	.250	-.074	-.295	.769
	Zscore(POPPPSLPF)	.158	.113	.158	1.408	.161
	Zscore(GICGEFGVA)	-.142	.144	-.142	-.986	.326
	Zscore(INFEXPCOM)	.519	.078	.519	6.645	.000
	Zscore(INFEXPIND)	.011	.073	.011	.155	.877
	Zscore(POPPPSPPH)	.007	.094	.007	.074	.941
	Zscore(POPVNPFHH)	-.026	.085	-.026	-.301	.764
	Zscore(ECOEACGDP)	.014	.155	.014	.092	.927
	Zscore(EDUEOCLTP)	-.072	.175	-.072	-.415	.679
	Zscore(ECOEACIPD)	.180	.327	.180	.551	.583
	Zscore(ECOEACPEE)	-.036	.090	-.036	-.400	.689
	Zscore(ECOTREEEE)	-.194	.146	-.194	-1.328	.186
	Zscore(ECOTREMIC)	.102	.128	.102	.792	.429
	Zscore(ECOLAMEIT)	.015	.111	.015	.138	.890
	Zscore(ECOLAMEST)	-.006	.152	-.006	-.040	.968
	Zscore(ECOEREGNS)	.074	.089	.074	.839	.403
	Zscore(EDUEOCSAM)	-.089	.226	-.089	-.395	.693
	Zscore(HEAHSTMUF)	-.126	.235	-.126	-.534	.594
	Zscore(ECOECPIND)	-.128	.153	-.128	-.840	.402
	Zscore(INFTCOMCC)	-.089	.106	-.089	-.836	.404
	Zscore(ECOEACGRB)	.106	.099	.106	1.074	.285
	Zscore(ECOEACTRE)	.008	.099	.008	.077	.939
	Zscore(EDUEOCLFM)	-.087	.104	-.087	-.841	.402
	Zscore(EDUEACEEG)	-.057	.089	-.057	-.639	.524
	Zscore(EDUEOCSAF)	.056	.260	.056	.217	.829
	Zscore(EDUEEOCCT)	-.119	.127	-.119	-.943	.348
	Zscore(ECOECPSER)	-.135	.156	-.135	-.867	.387
	Zscore(HEAHSTDRC)	.064	.130	.064	.491	.625
	Zscore(HEAHSTPUP)	.005	.117	.005	.040	.968
	Zscore(POPVNPTPP)	-.003	.077	-.003	-.043	.966

	Zscore(POPVNPITA)	.094	.090	.094	1.047	.297
	Zscore(POPPPSRPP)	.046	.116	.046	.392	.696

a. Dependent Variable: Zscore(TOT_AFFECTED)

Table A4.4: Year 2009-2018

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.693[a]	.481	.277	.85001138	2.096

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.978E-15	.061		.000	1.000
	Zscore(ECOEREIRP)	-.096	.080	-.096	-1.204	.231
	Zscore(ECOERERDE)	.003	.115	.003	.026	.980
	Zscore(ECOEREGGD)	-.116	.078	-.116	-1.479	.141
	Zscore(ECOIDPGIN)	-.002	.093	-.002	-.018	.986
	Zscore(INXXXXESI)	-.133	.091	-.133	-1.464	.145
	Zscore(INFEWSACE)	.405	.179	.405	2.256	.026
	Zscore(POPPPSADP)	.024	.160	.024	.152	.879
	Zscore(POPPPSIMP)	-.135	.115	-.135	-1.173	.243
	Zscore(ECOLAMLAF)	.126	.118	.126	1.063	.290
	Zscore(ECOEACFDP)	-.054	.321	-.054	-.170	.865
	Zscore(ECOEACGFC)	.106	.085	.106	1.248	.214
	Zscore(GICAVTLCP)	-.065	.085	-.065	-.767	.444
	Zscore(GICLRVVTE)	-.177	.079	-.177	-2.229	.027
	Zscore(INFEWSIWP)	-.018	.130	-.018	-.138	.890
	Zscore(POPVNPPIP)	.040	.163	.040	.248	.805
	Zscore(HEAHCRHBE)	.133	.114	.133	1.169	.244

	Zscore(HEAHCRPHY)	-.021	.131	-.021	-.163	.870
	Zscore(POPPPSNMR)	-.014	.085	-.014	-.167	.868
	Zscore(POPPPSPDE)	.165	.249	.165	.661	.509
	Zscore(POPVNPSLP)	.394	.147	.394	2.687	.008
	Zscore(ECOLAMUEP)	-.017	.082	-.017	-.206	.837
	Zscore(ECOEACGRW)	.073	.083	.073	.881	.380
	Zscore(INFTCORDE)	-.139	.250	-.139	-.554	.580
	Zscore(POPPPSLPF)	.182	.113	.182	1.615	.108
	Zscore(GICGEFGVA)	.197	.144	.197	1.368	.174
	Zscore(INFEXPCOM)	.361	.078	.361	4.617	.000
	Zscore(INFEXPIND)	.134	.073	.134	1.839	.068
	Zscore(POPPPSPPH)	.024	.094	.024	.259	.796
	Zscore(POPVNPFHH)	.001	.085	.001	.009	.993
	Zscore(ECOEACGDP)	-.044	.155	-.044	-.282	.779
	Zscore(EDUEOCLTP)	.201	.175	.201	1.149	.253
	Zscore(ECOEACIPD)	.075	.327	.075	.228	.820
	Zscore(ECOEACPEE)	.249	.090	.249	2.764	.006
	Zscore(ECOTREEEE)	-.125	.146	-.125	-.853	.395
	Zscore(ECOTREMIC)	-.076	.128	-.076	-.591	.555
	Zscore(ECOLAMEIT)	-.031	.111	-.031	-.282	.778
	Zscore(ECOLAMEST)	.020	.152	.020	.129	.897
	Zscore(ECOEREGNS)	.079	.089	.079	.887	.377
	Zscore(EDUEOCSAM)	-.146	.227	-.146	-.646	.519
	Zscore(HEAHSTMUF)	-.176	.236	-.176	-.748	.456
	Zscore(ECOECPIND)	.085	.153	.085	.557	.578
	Zscore(INFTCOMCC)	-.106	.106	-.106	-.998	.320
	Zscore(ECOEACGRB)	.021	.099	.021	.214	.831
	Zscore(ECOEACTRE)	.013	.099	.013	.129	.898
	Zscore(EDUEOCLFM)	-.192	.104	-.192	-1.850	.066
	Zscore(EDUEACEEG)	-.060	.090	-.060	-.668	.505
	Zscore(EDUEOCSAF)	.220	.261	.220	.845	.400
	Zscore(EDUEEOCCT)	-.008	.127	-.008	-.061	.952
	Zscore(ECOECPSER)	.029	.156	.029	.183	.855
	Zscore(HEAHSTDRC)	-.023	.130	-.023	-.177	.860
	Zscore(HEAHSTPUP)	.062	.118	.062	.524	.601
	Zscore(POPVNPTPP)	-.036	.077	-.036	-.467	.641
	Zscore(POPVNPITA)	.066	.090	.066	.734	.464
	Zscore(POPPPSRPP)	-.012	.117	-.012	-.101	.920

Appendix C: GWR Maps

This appendix shows the Geographically Weighted Regression (GWR) maps. GWR was used in this thesis to show the spatial variability of different indicators as it pertains to their association with earthquake impacts. For the GWR model, only those indicators which were statistically significant in the OLS regression model were used as input variables. After conducting the GWR model calibrations, the spatial variability of the indicators and their association with adverse earthquake impacts was demonstrated by mapping the beta coefficients for each country that were derived from the GWR. The maps show how the predictability of the indicators varies over space.

C1: Total damage as dependent variable

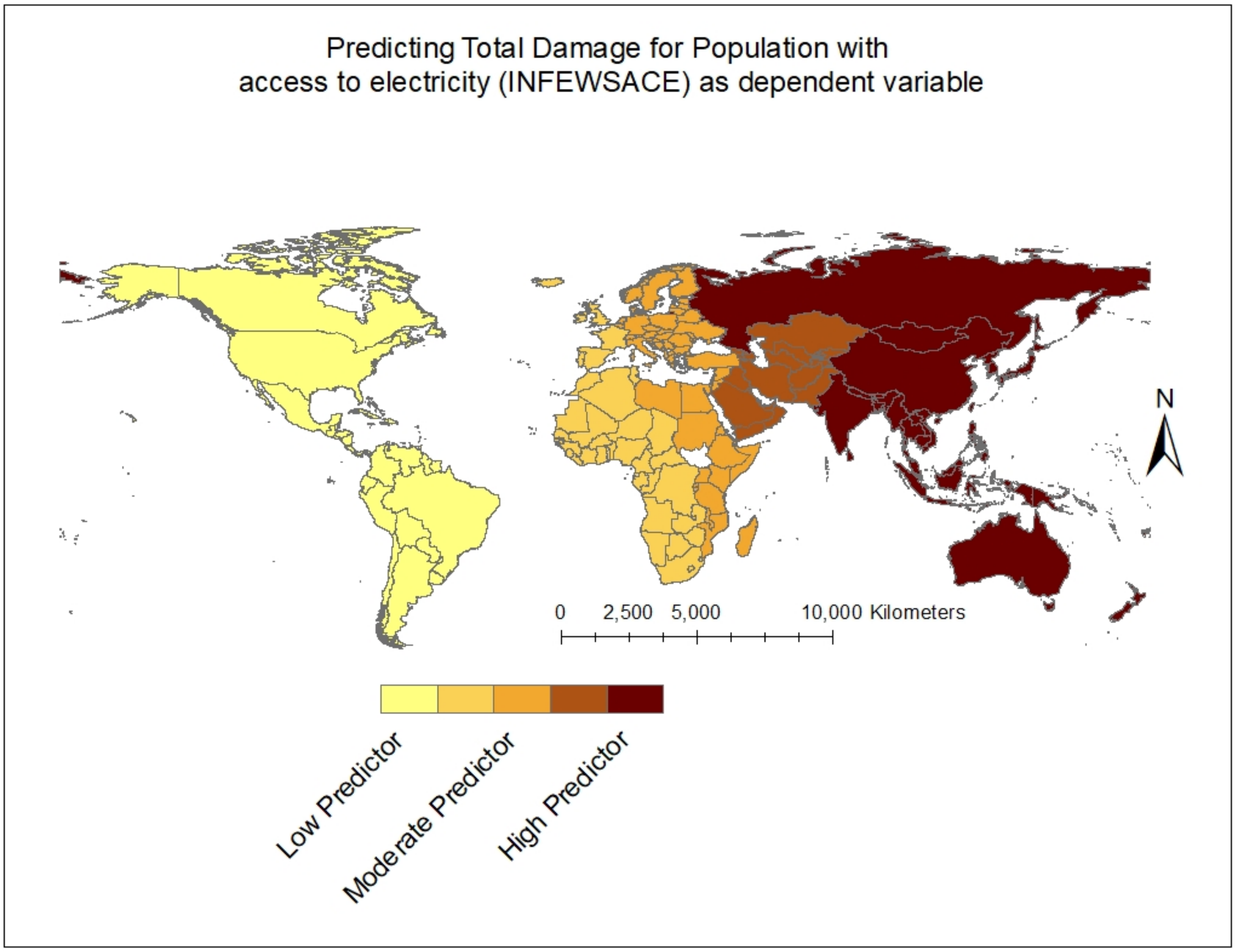
C2: Total Death as dependent variable

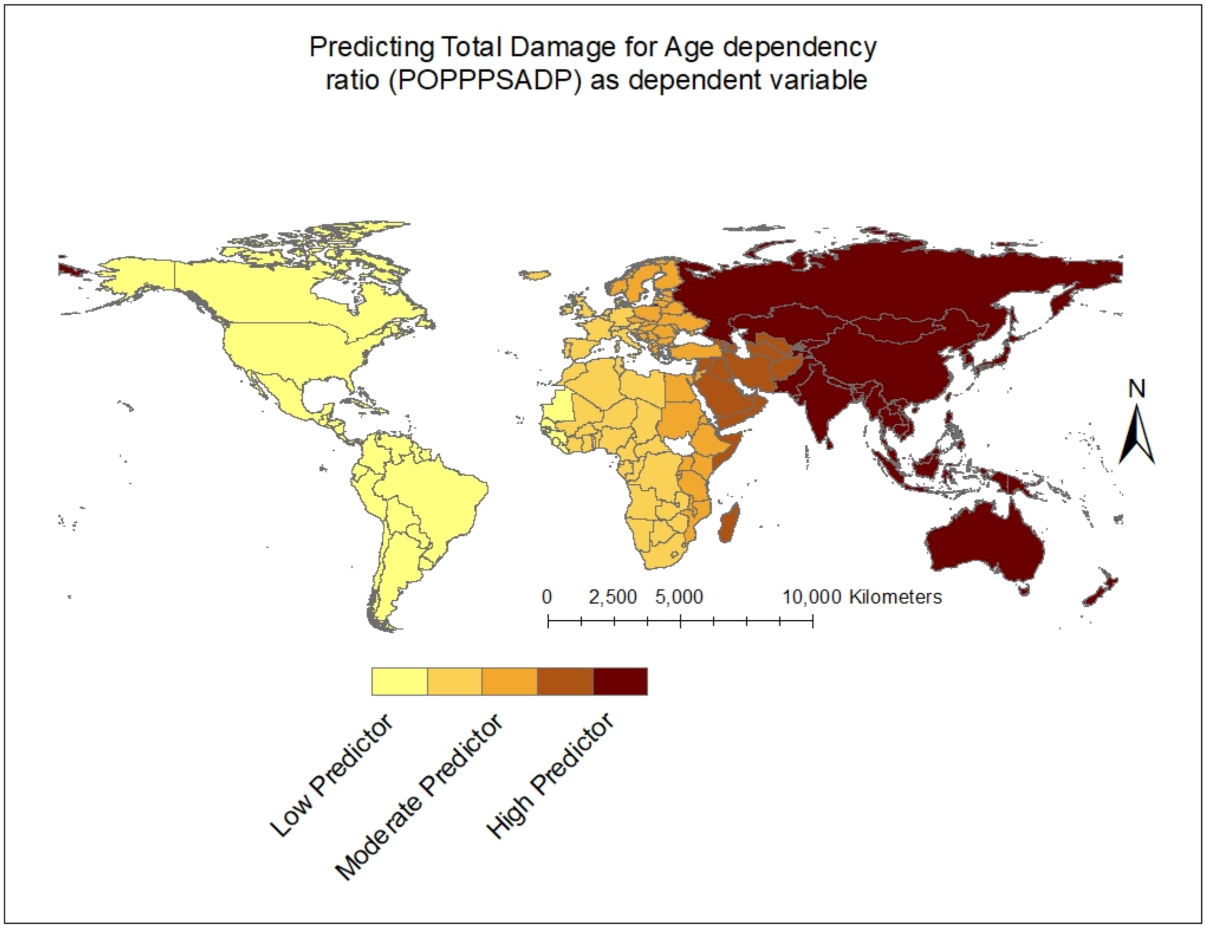
C3: Total Homeless as dependent variable

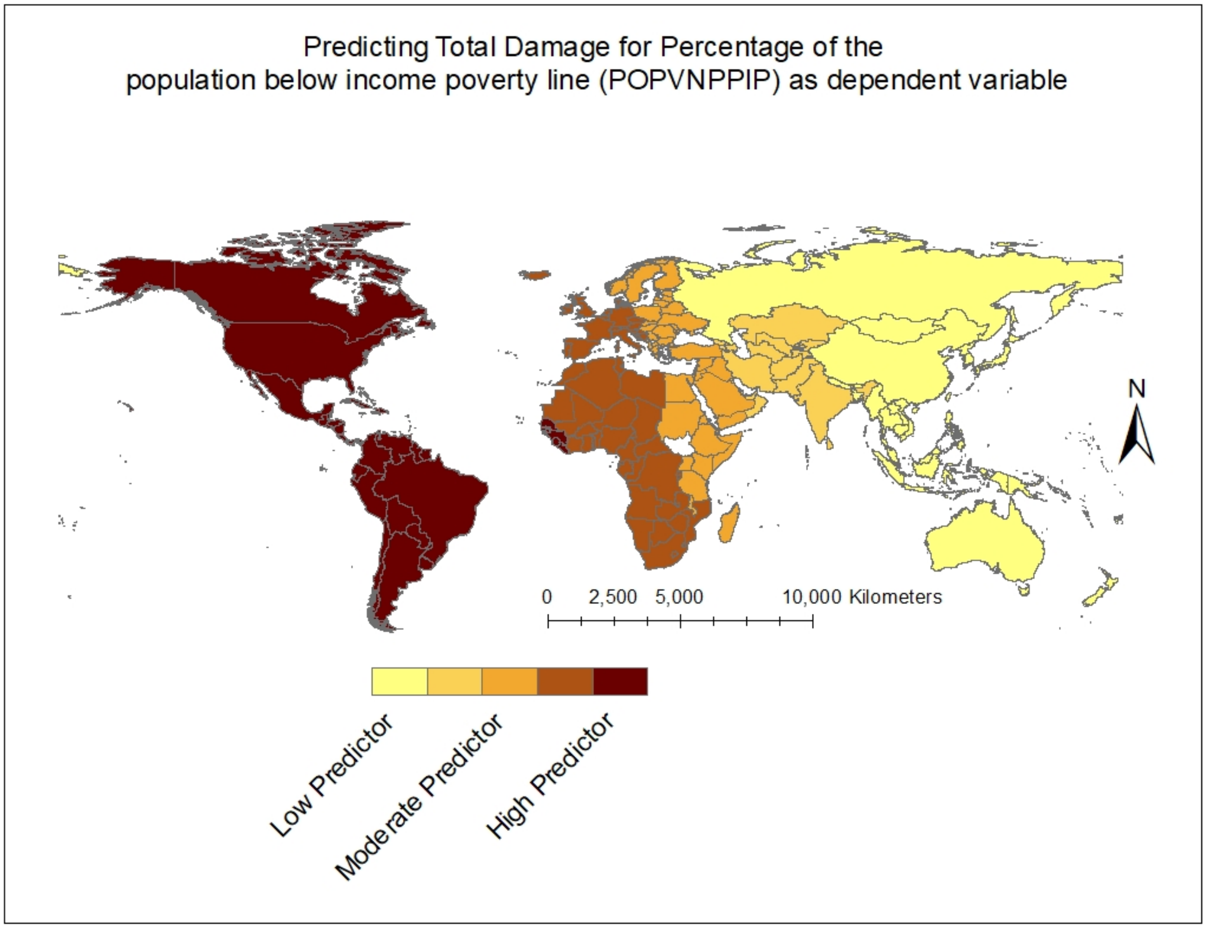
C4: Total affected as dependent variable

Geographically weighted regression result maps:

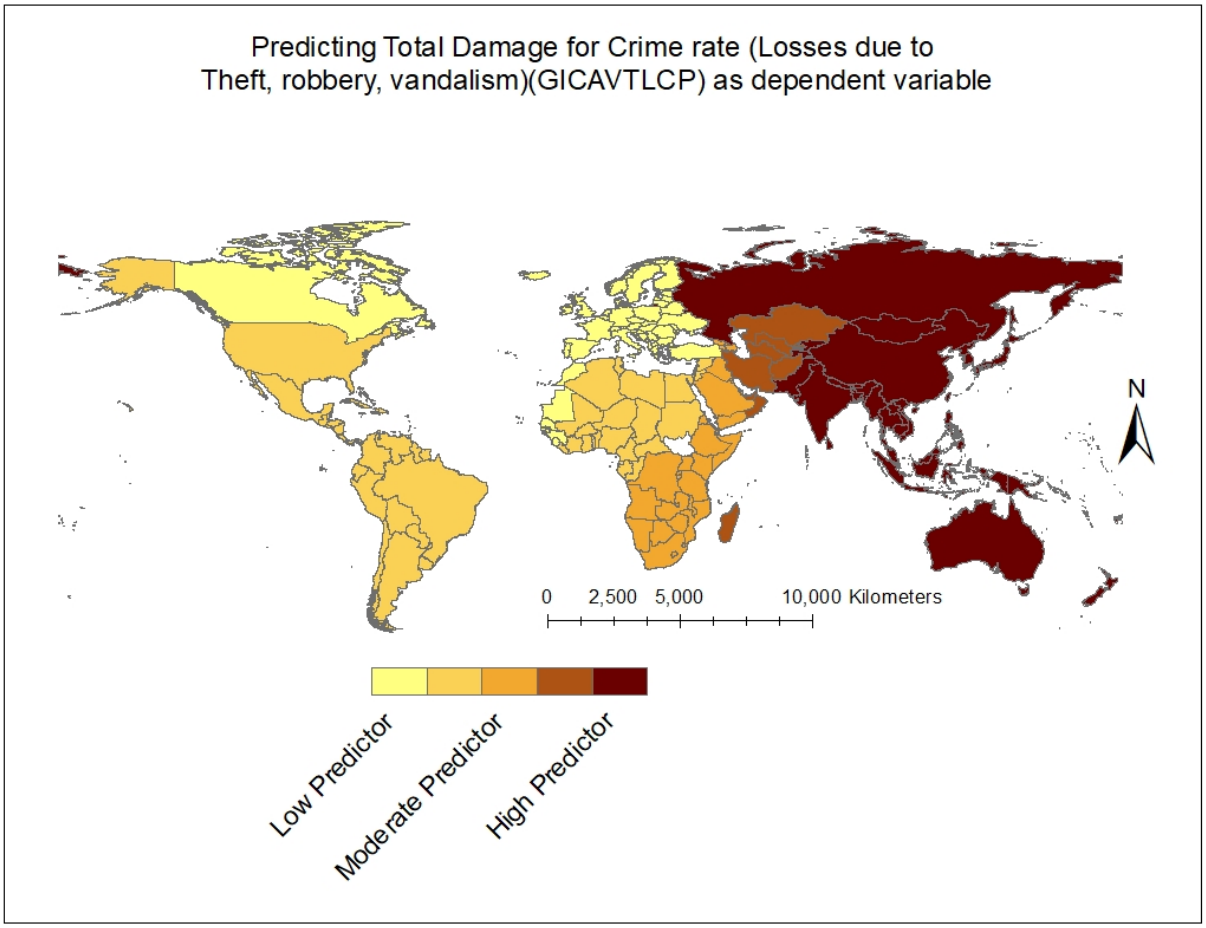
C1: Total damage as dependent

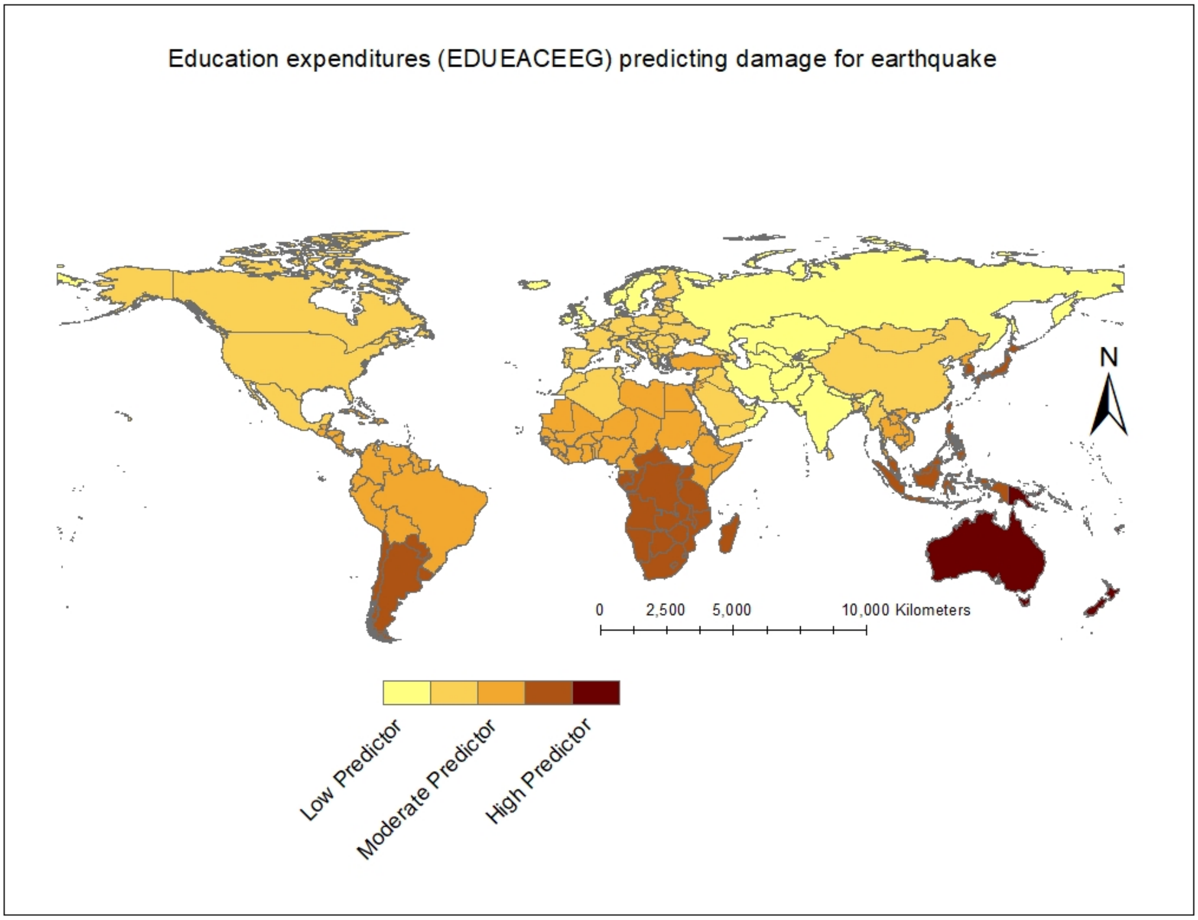



Predicting Total Damage for Age dependency ratio (POPPPSADP) as dependent variable
0
2,500
5,000
10,000 Kilometers
N
Low Predictor
Moderate Predictor
High Predictor

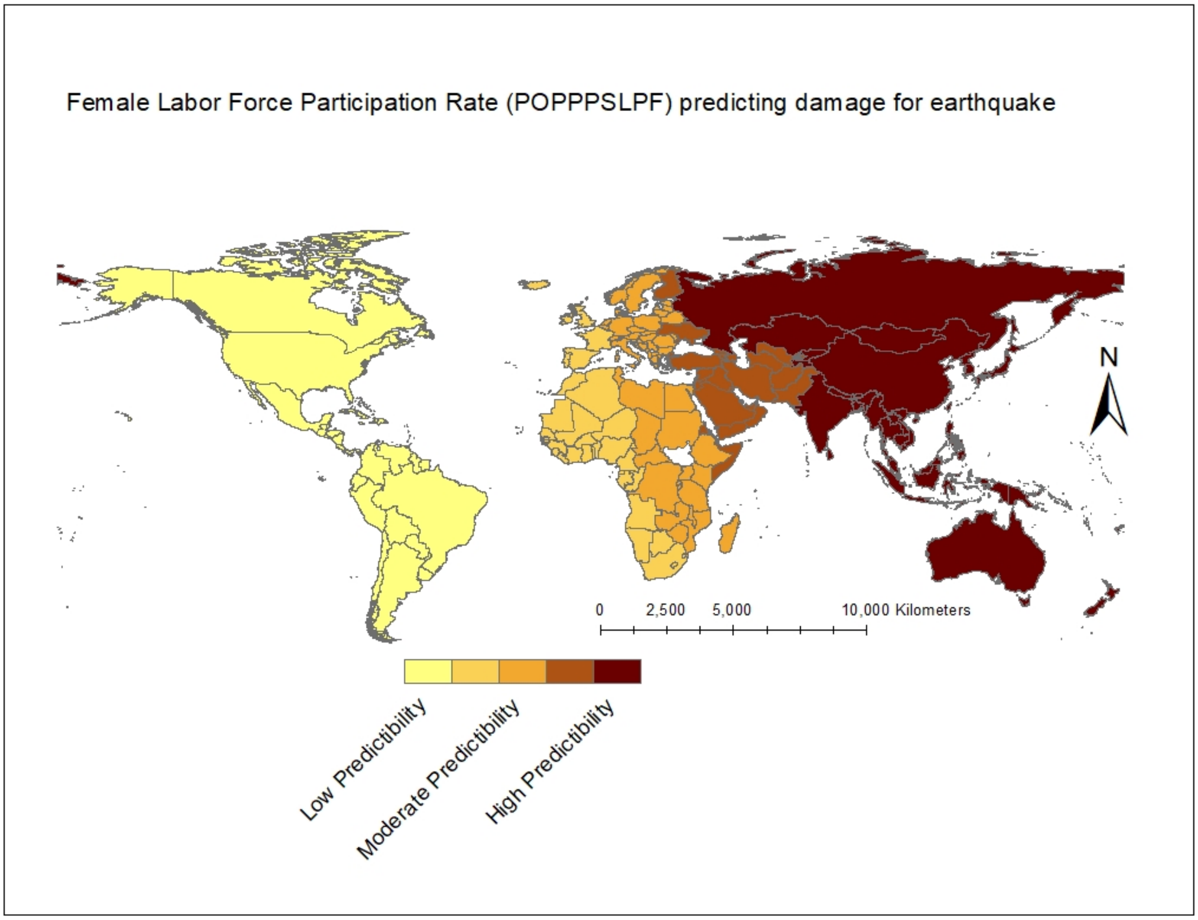


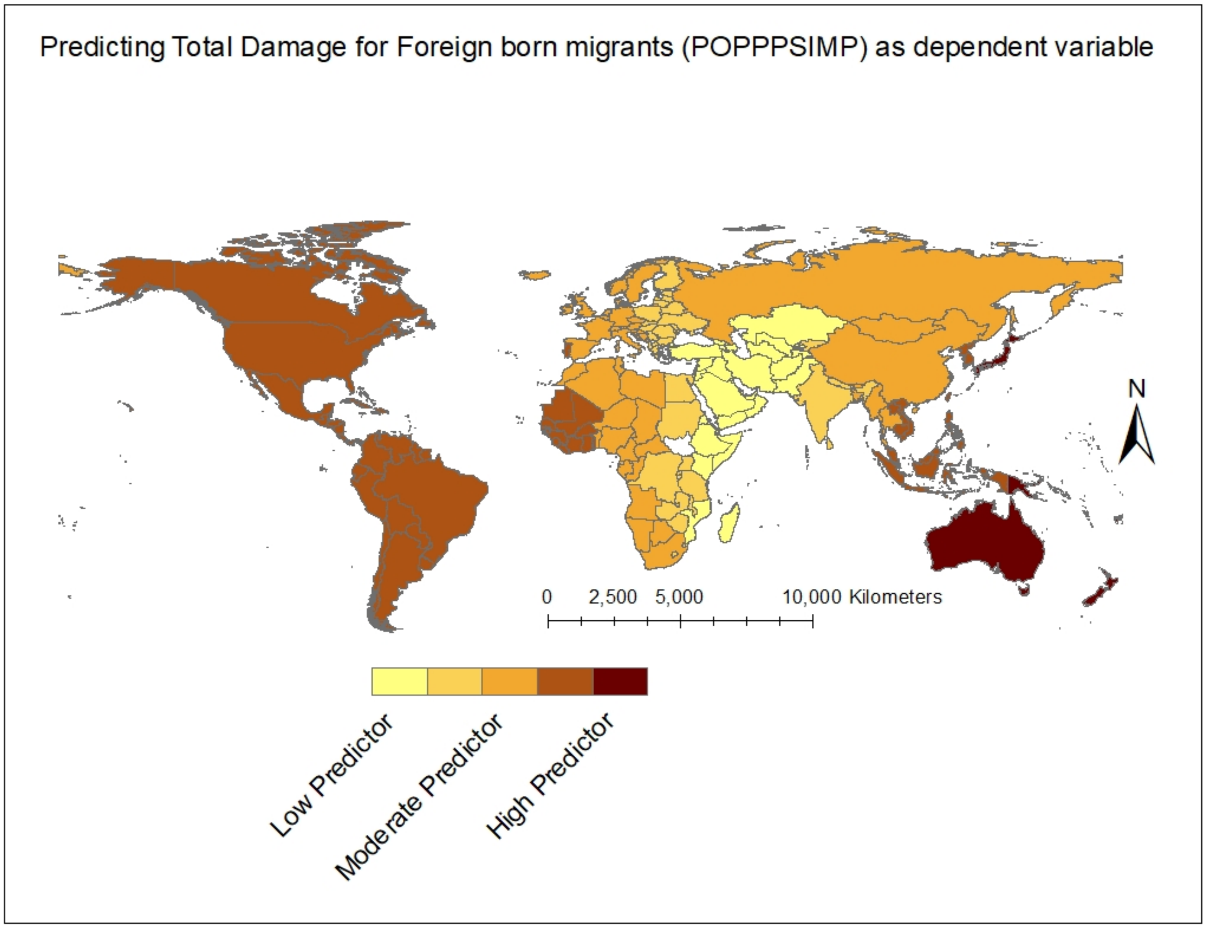
Predicting Total Damage for Percentage of the
population below income poverty line (POPVNPPIP) as dependent variable
0
2,500
5,000
10,000 Kilometers
N
Low Predictor
Moderate Predictor
High Predictor

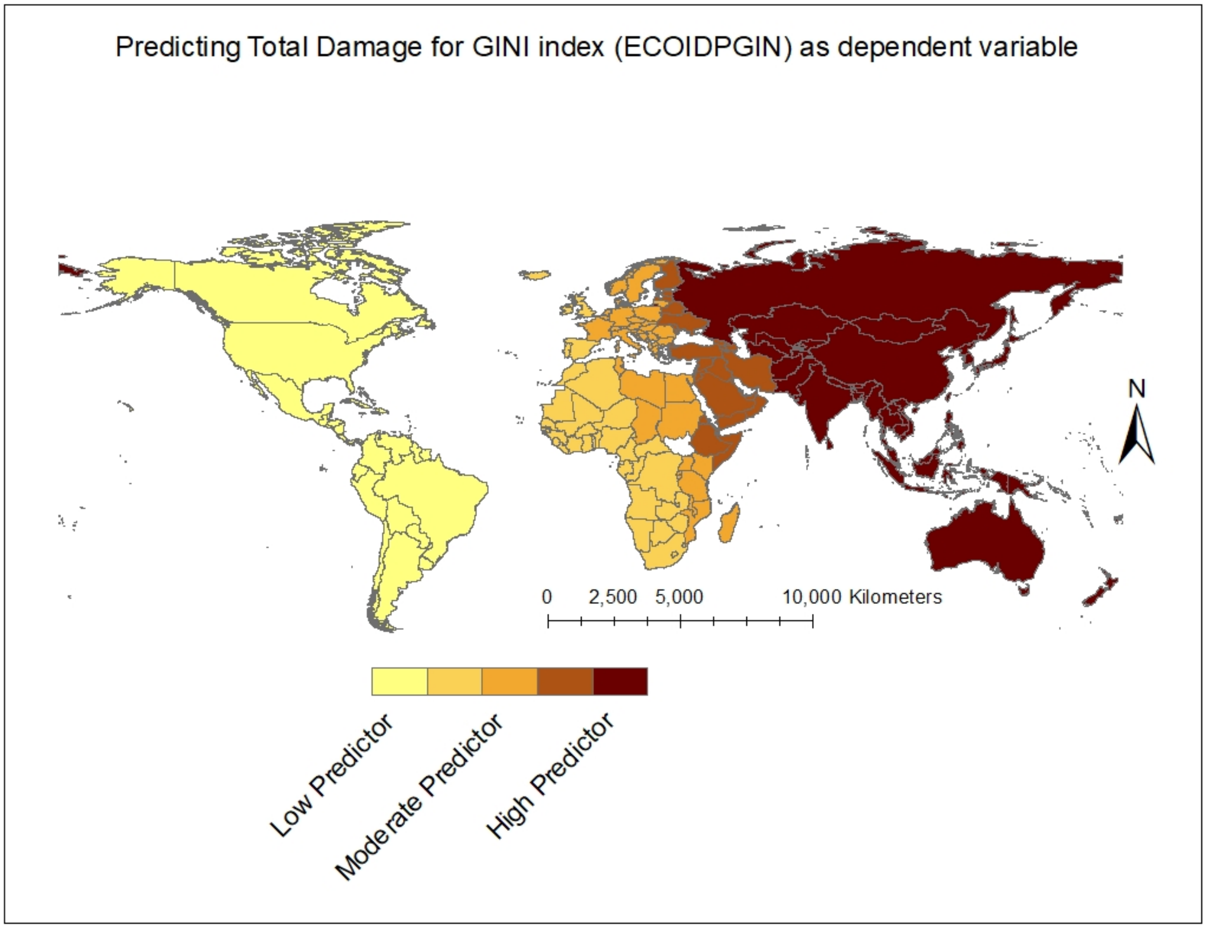

Predicting Total Damage for Crime rate (Losses due to
Theft, robbery, vandalism)(GICAVTLCP) as dependent variable
0 2,500 5,000 10,000 Kilometers
N
Low Predictor
Moderate Predictor
High Predictor

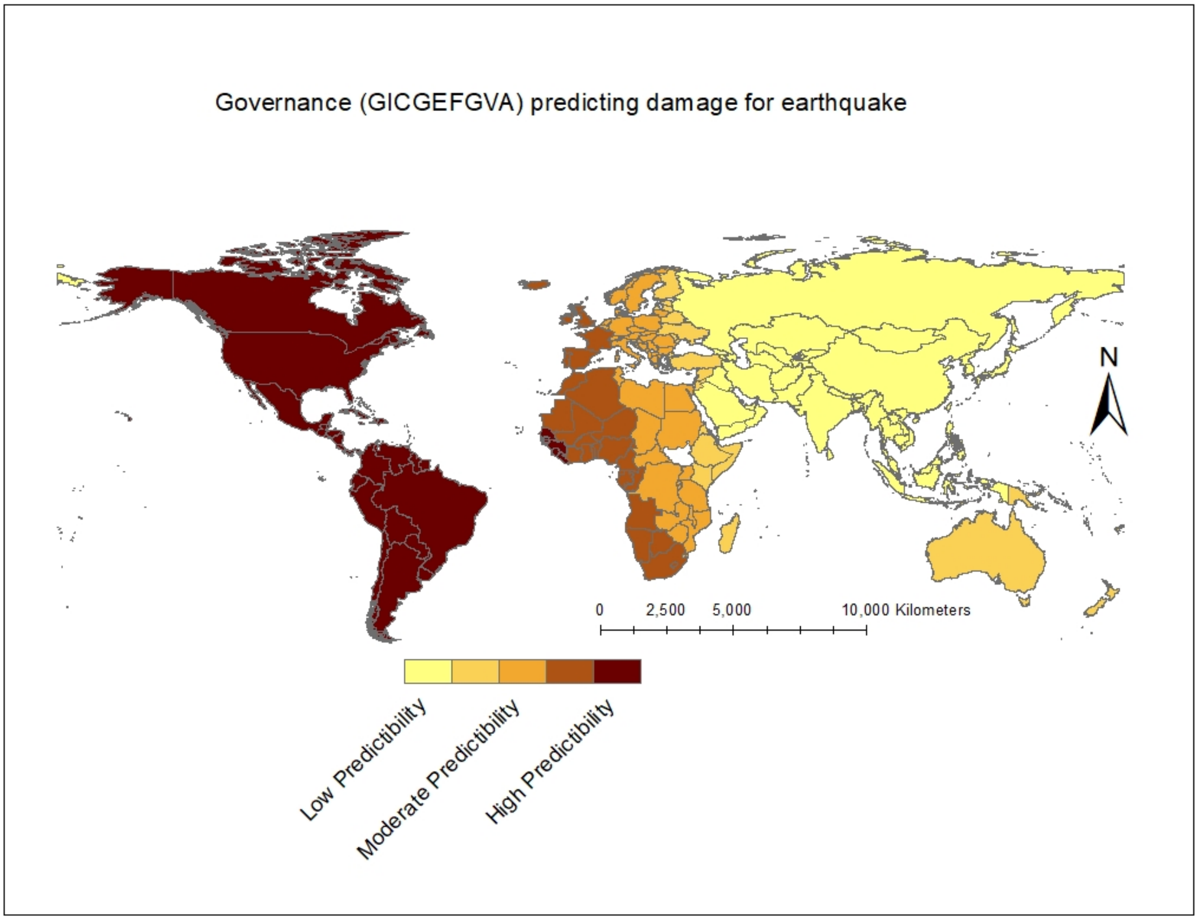


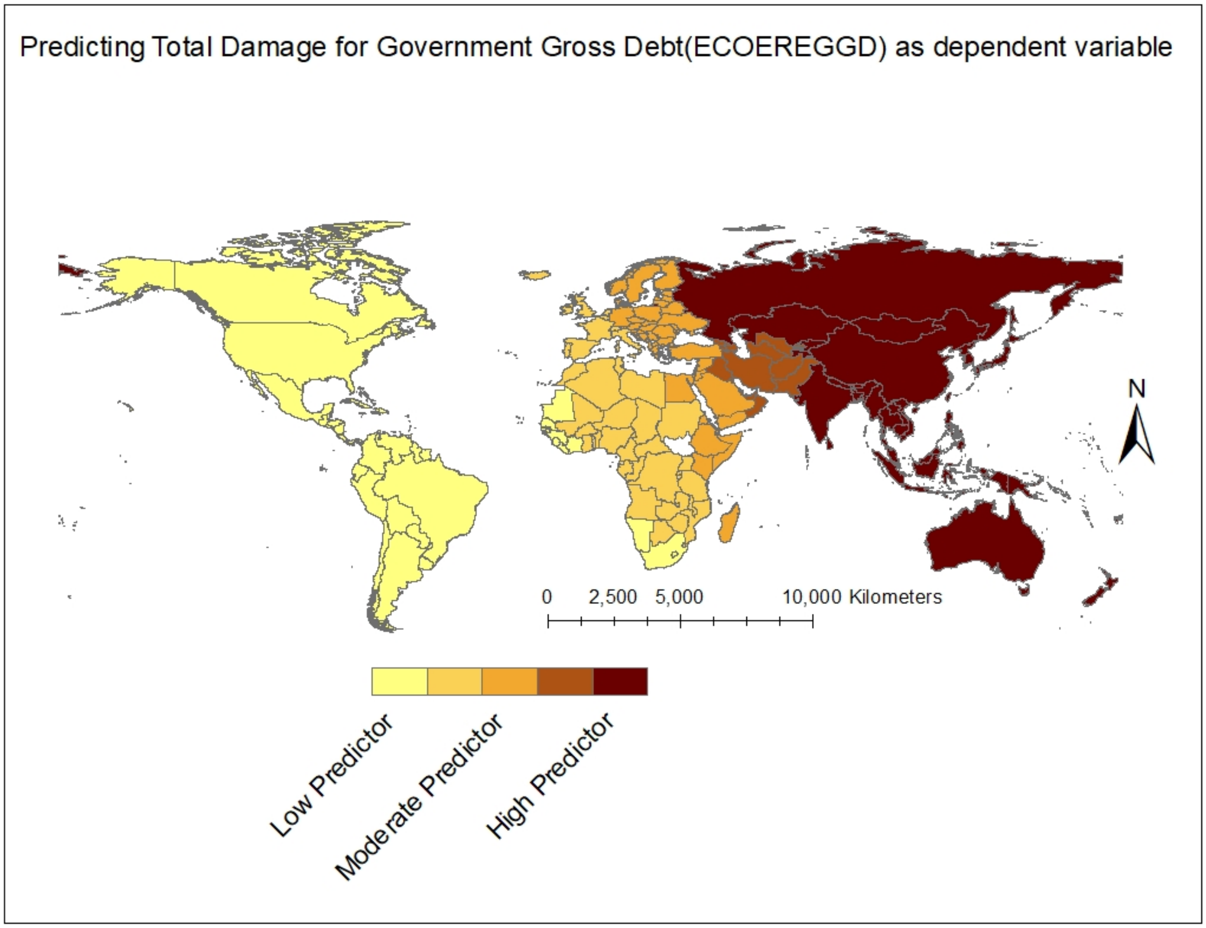
Education expenditures (EDUEACEEG) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor


Female Labor Force Participation Rate (POPPPSLPF) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictibility
Moderate Predictibility
High Predictibility

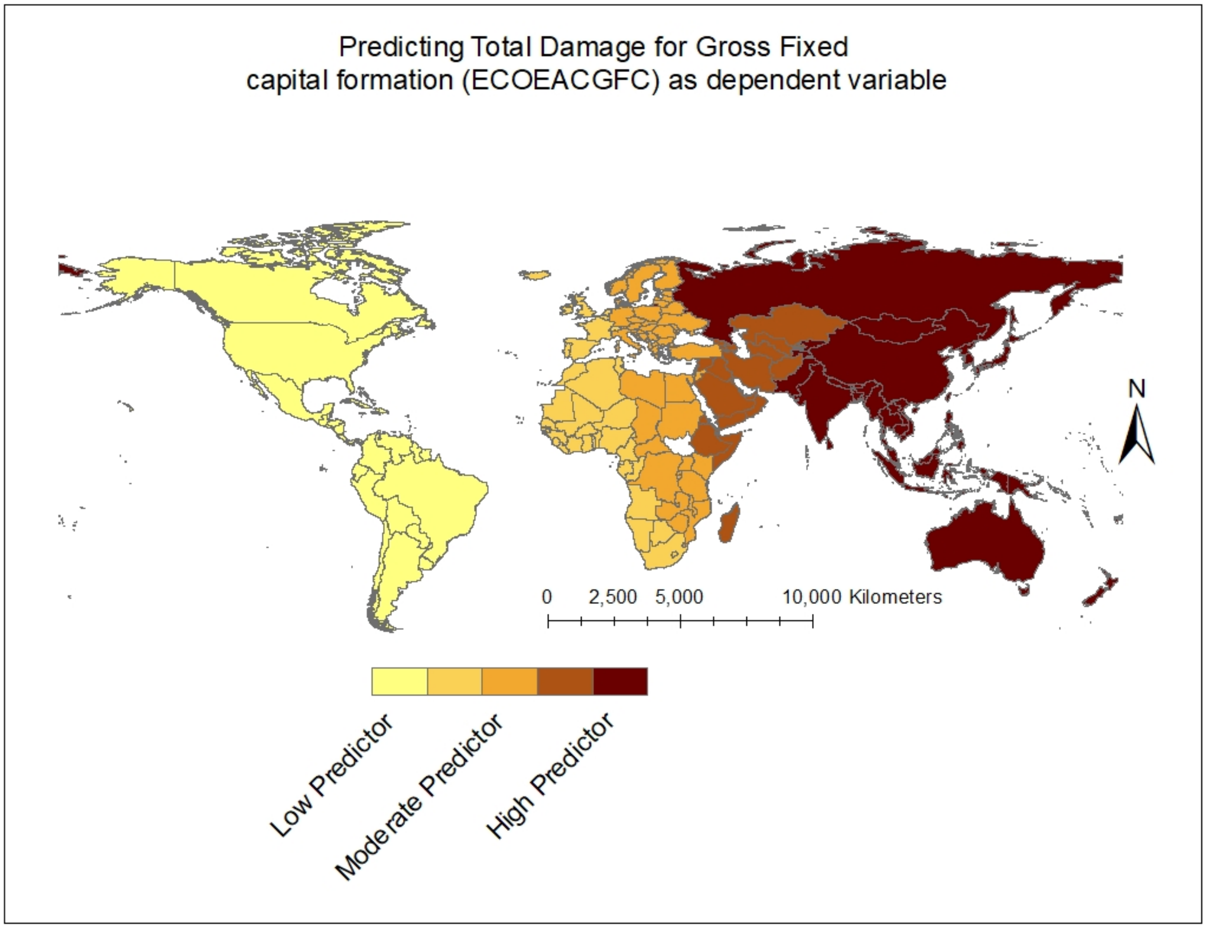

Predicting Total Damage for Foreign born migrants (POPPPSIMP) as dependent variable
N
0 2,500 5,000 10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor

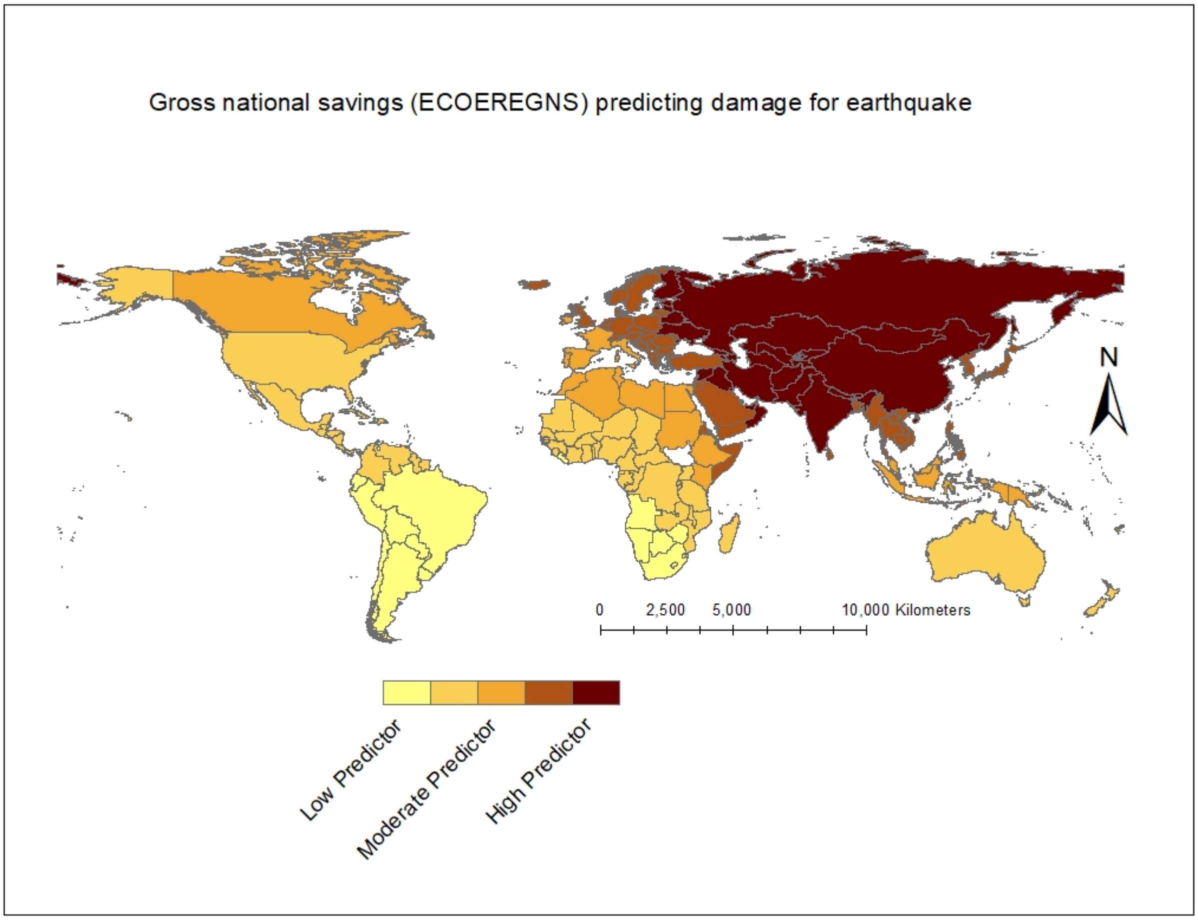

Predicting Total Damage for GINI index (ECOIDPGIN) as dependent variable
0 2,500 5,000 10,000 Kilometers
N
Low Predictor
Moderate Predictor
High Predictor

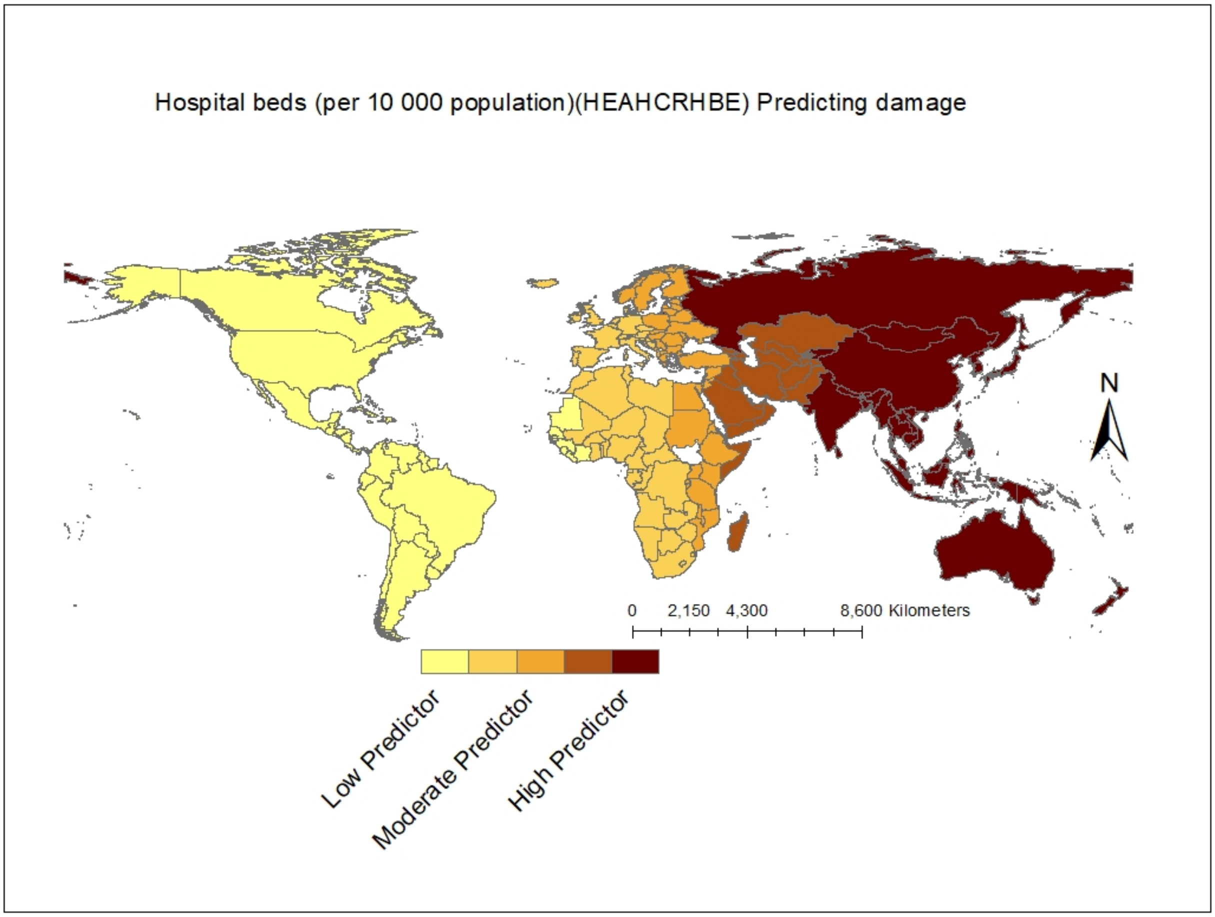

Governance (GICGEFGVA) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictibility
Moderate Predictibility
High Predictibility



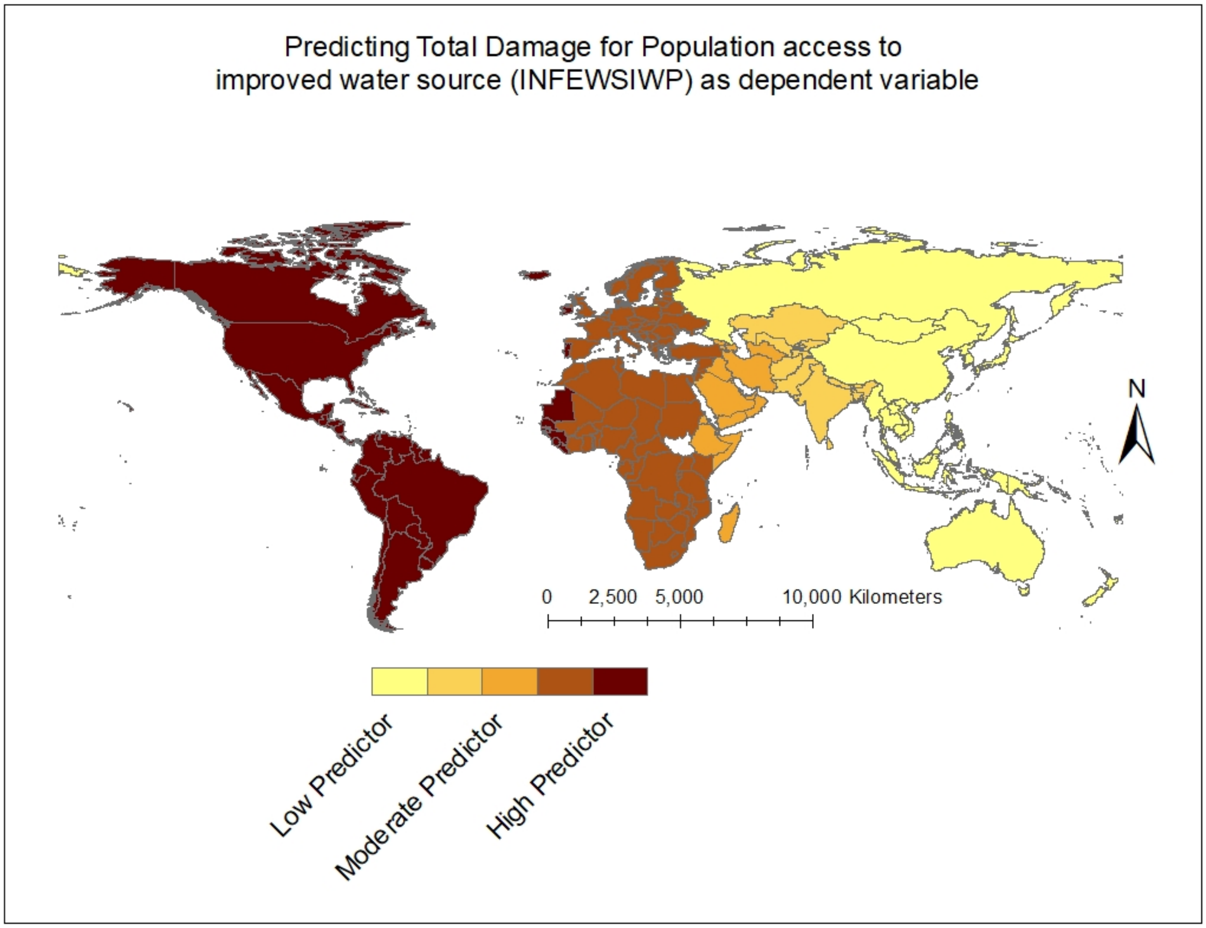
Predicting Total Damage for Government Gross Debt(ECOEREGGD) as dependent variable
N
0
2,500
5,000
10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor

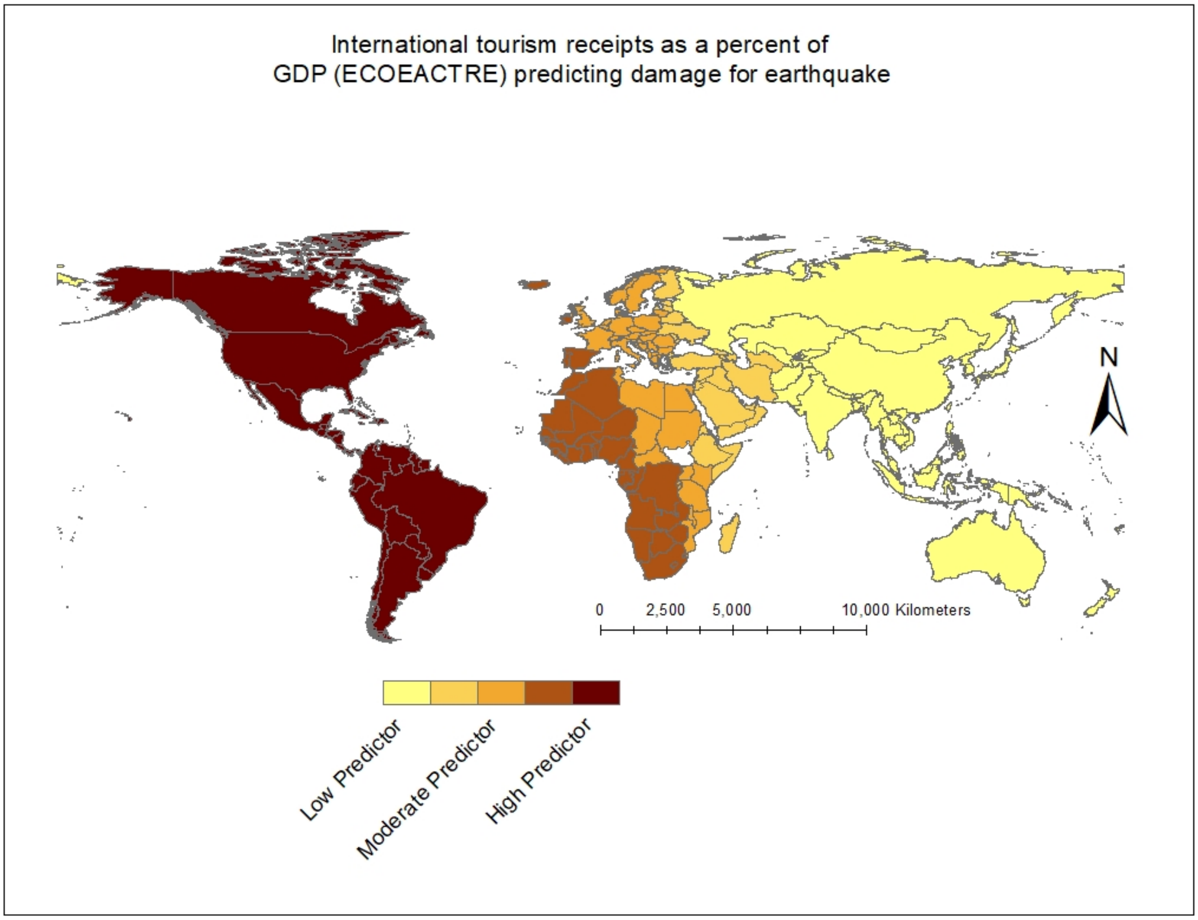

Predicting Total Damage for Gross Fixed
capital formation (ECOEACGFC) as dependent variable
N
0 2,500 5,000 10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor

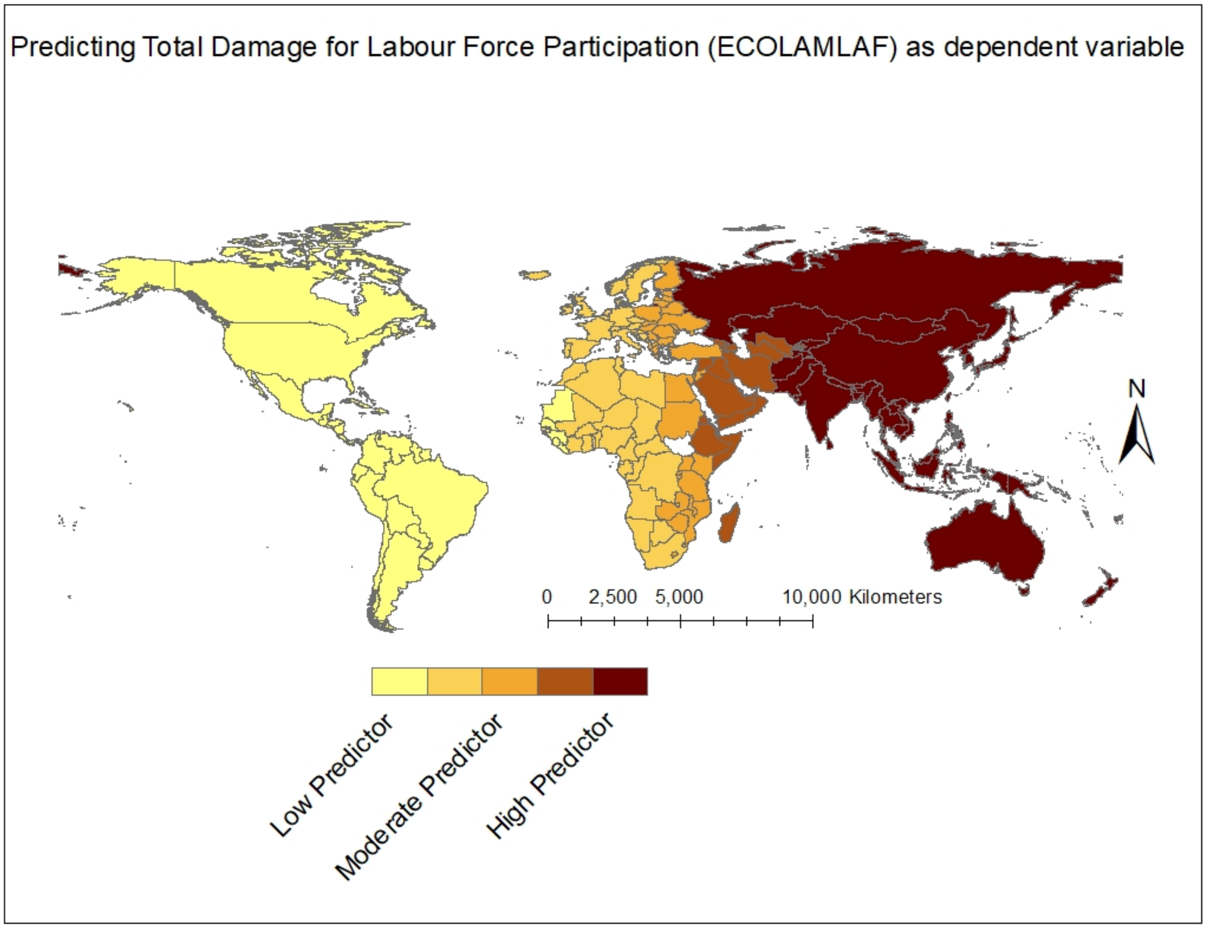

Gross national savings (ECOEREGNS) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor

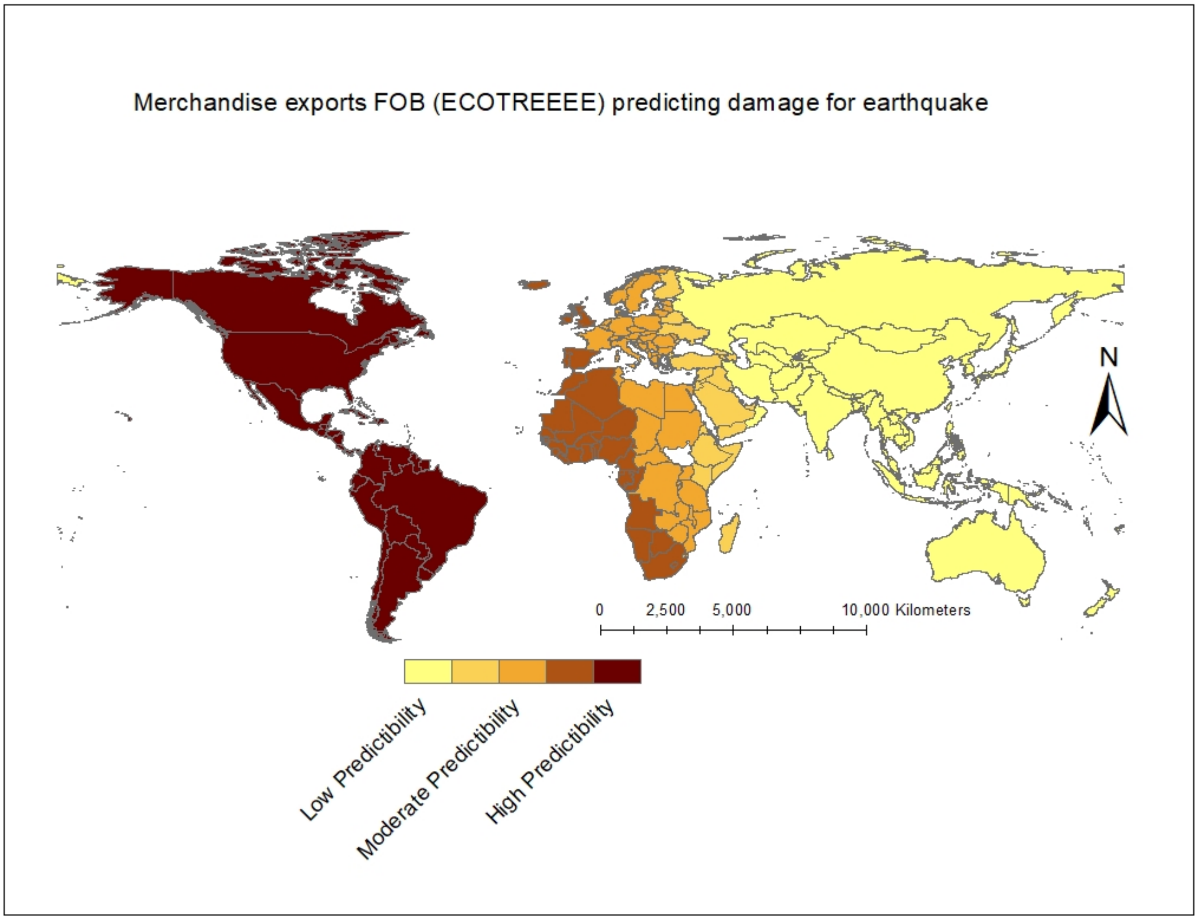


Hospital beds (per 10 000 population)(HEAHCRHBE) Predicting damage
0
2,150
4,300
8,600 Kilometers
N
Low Predictor
Moderate Predictor
High Predictor

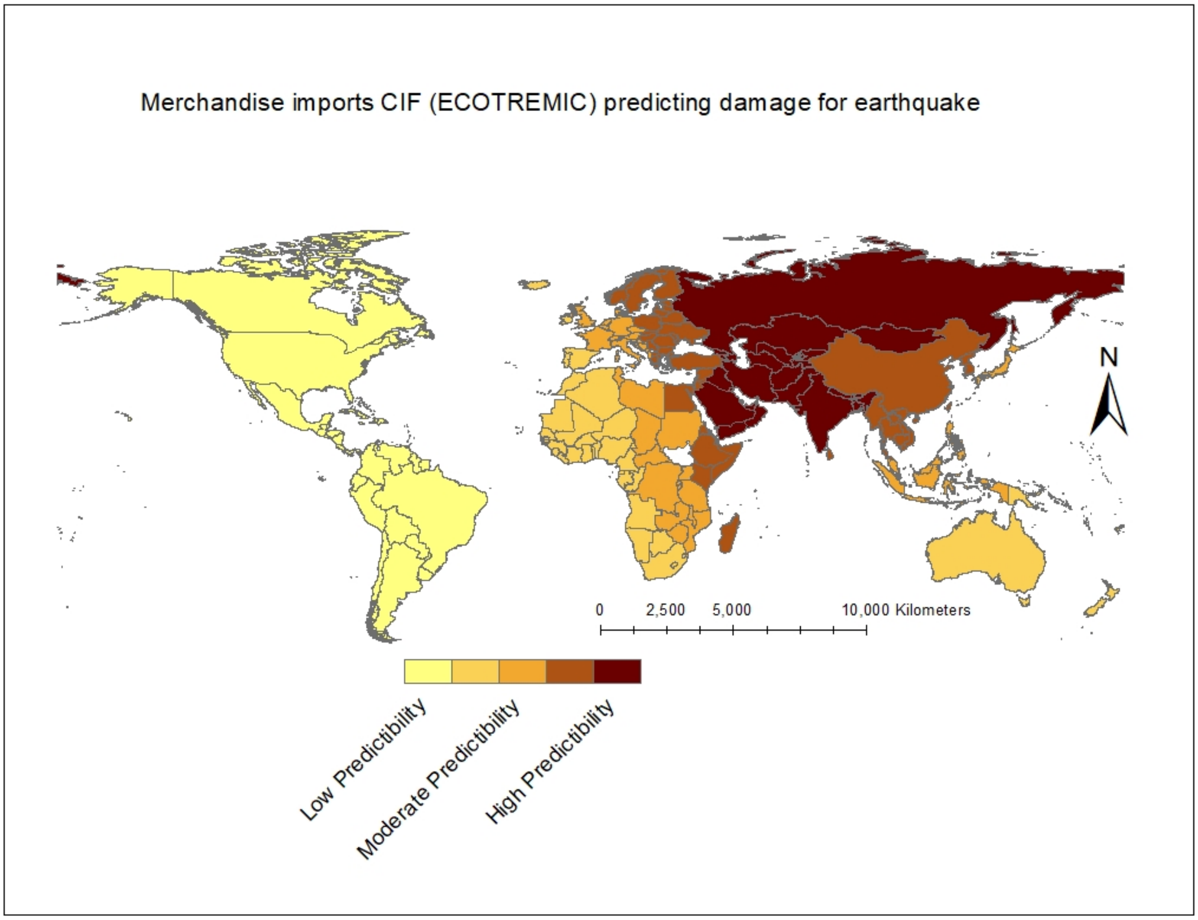

Predicting Total Damage for Population access to
improved water source (INFEWSIWP) as dependent variable
N
0 2,500 5,000 10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor

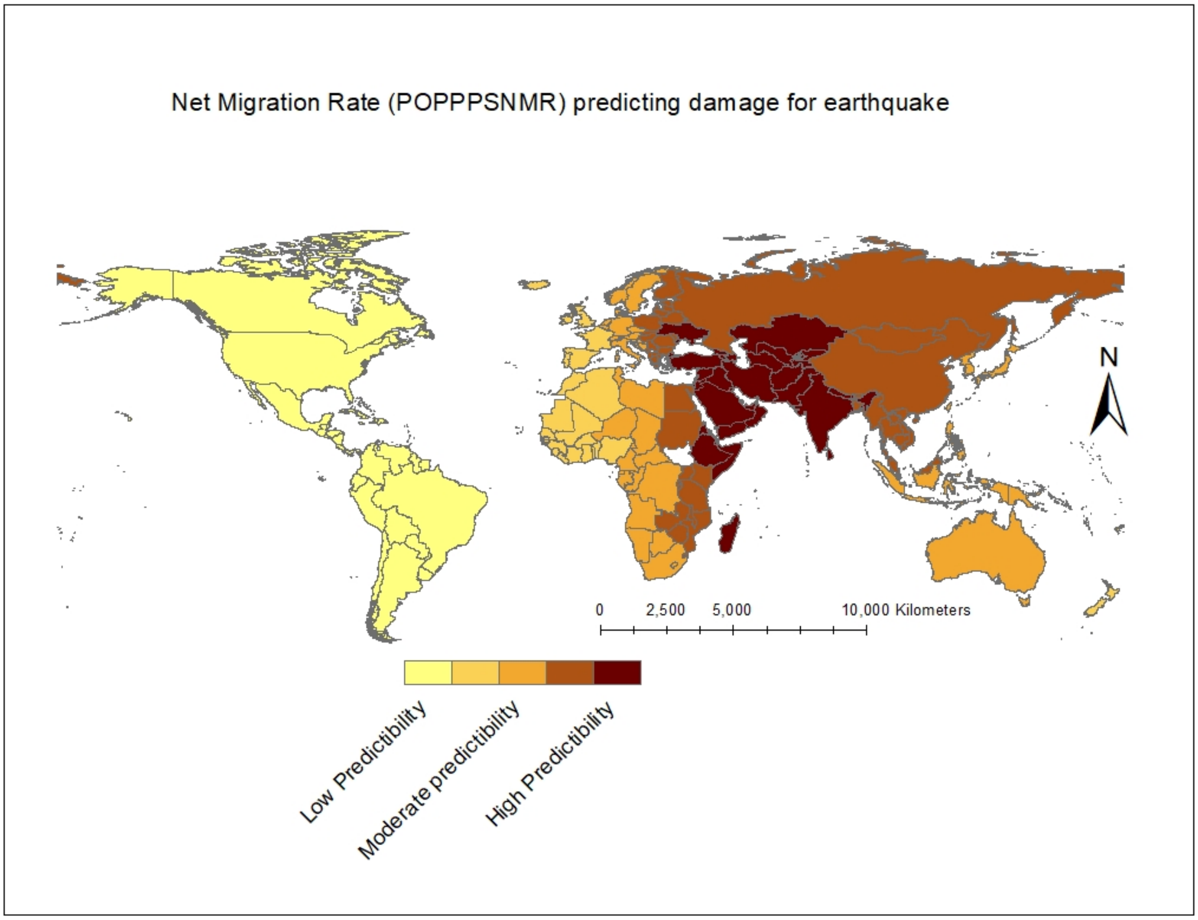

International tourism receipts as a percent of
GDP (ECOEACTRE) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor

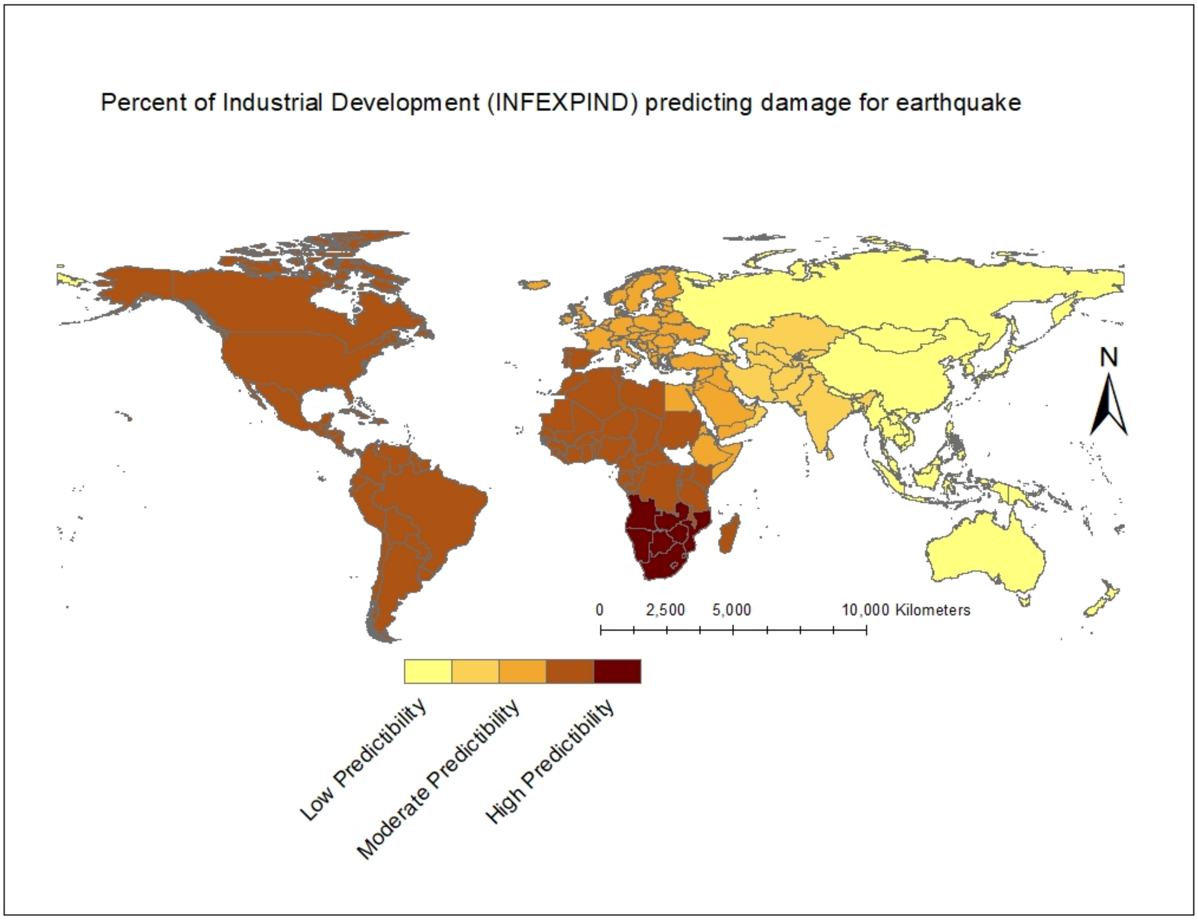

Predicting Total Damage for Labour Force Participation (ECOLAMLAF) as dependent variable
N
0 2,500 5,000 10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor



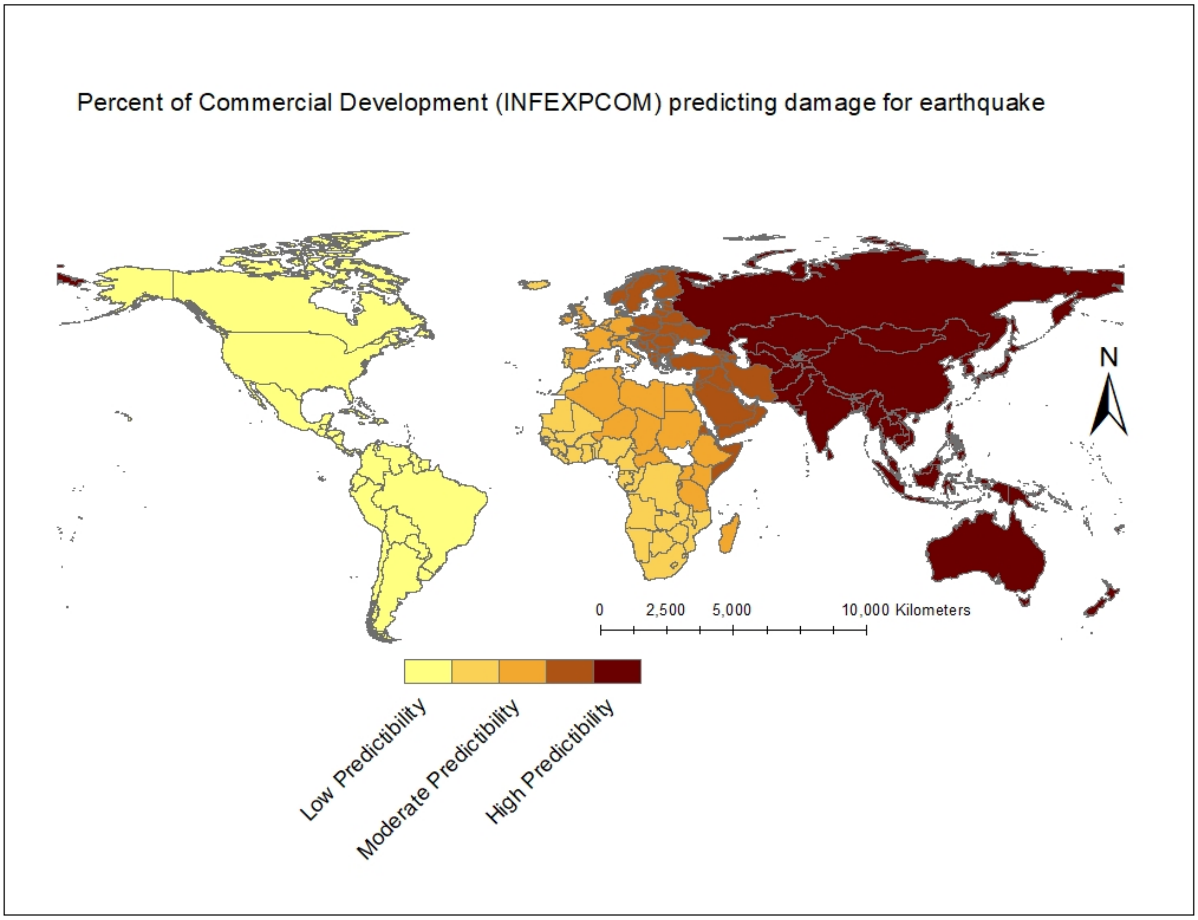
Merchandise exports FOB (ECOTREEEE) predicting damage for earthquake
N
0 2,500 5,000 10,000 Kilometers
Low Predictibility
Moderate Predictibility
High Predictibility

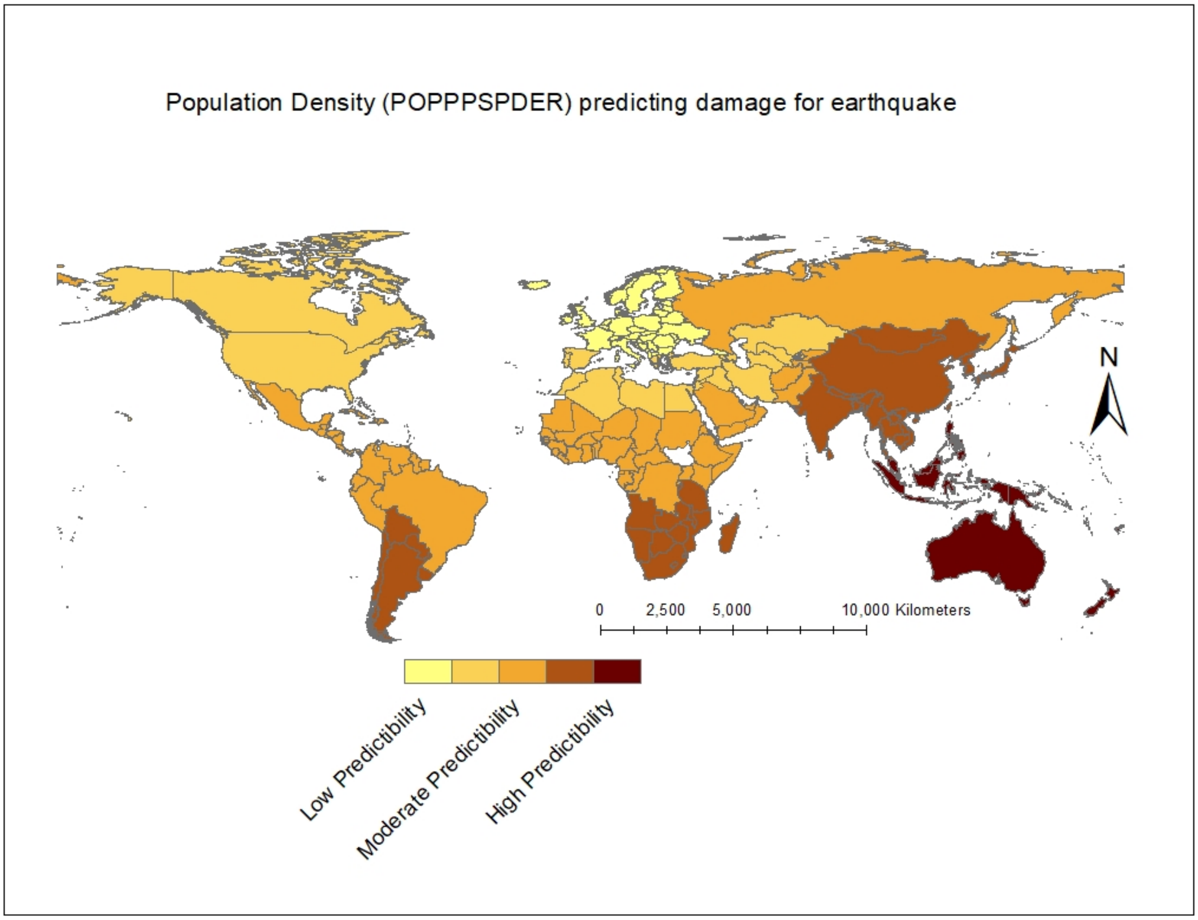

Merchandise imports CIF (ECOTREMIC) predicting damage for earthquake
N
0 2,500 5,000 10,000 Kilometers
Low Predictibility
Moderate Predictibility
High Predictibility

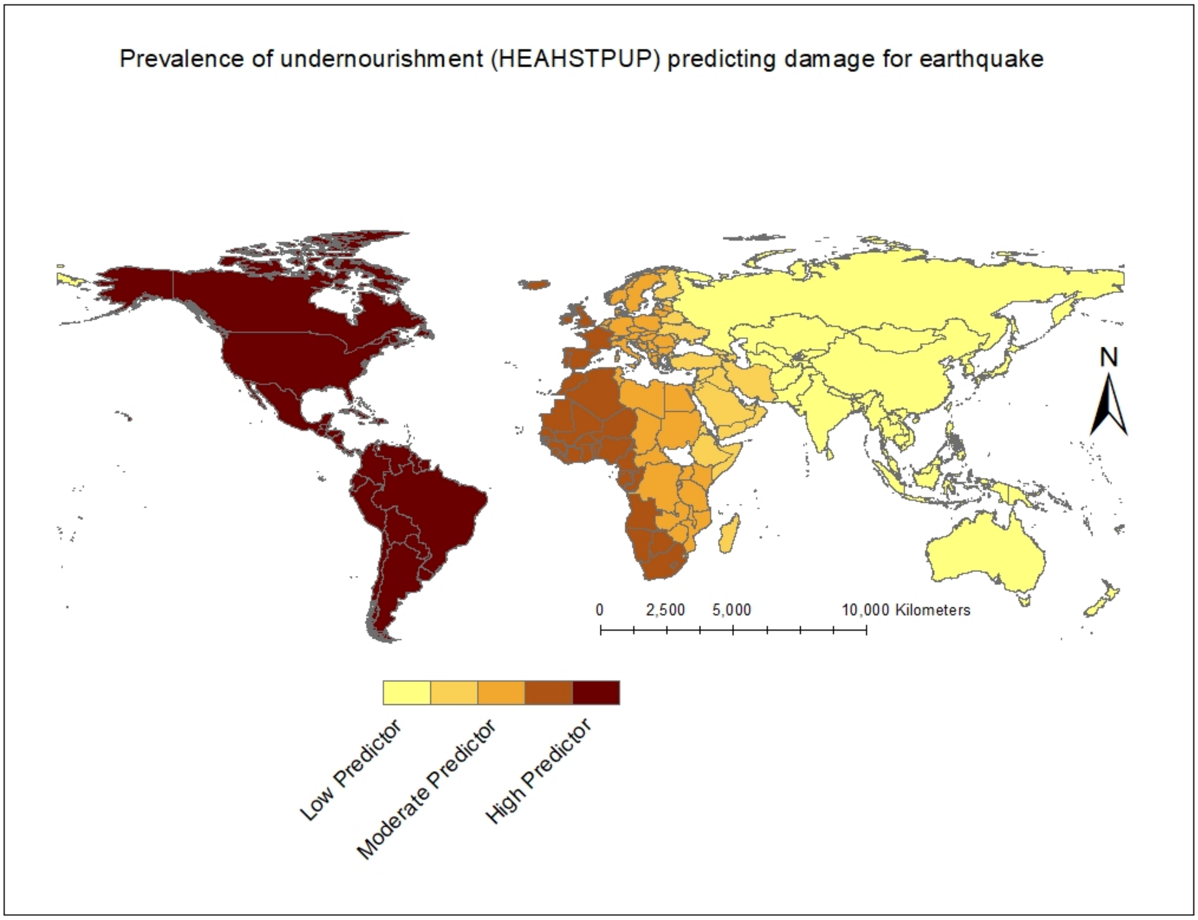

Net Migration Rate (POPPPSNMR) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictibility
Moderate predictibility
High Predictibility

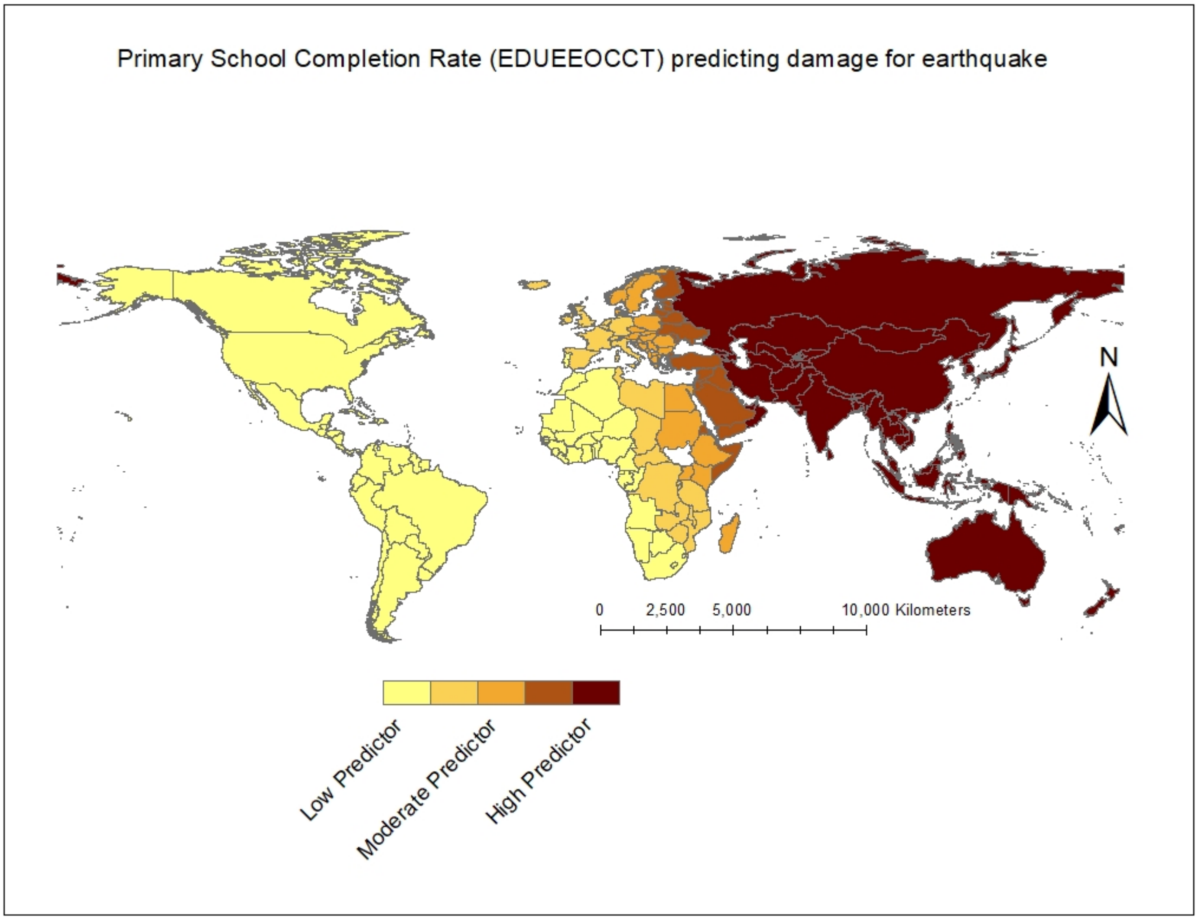


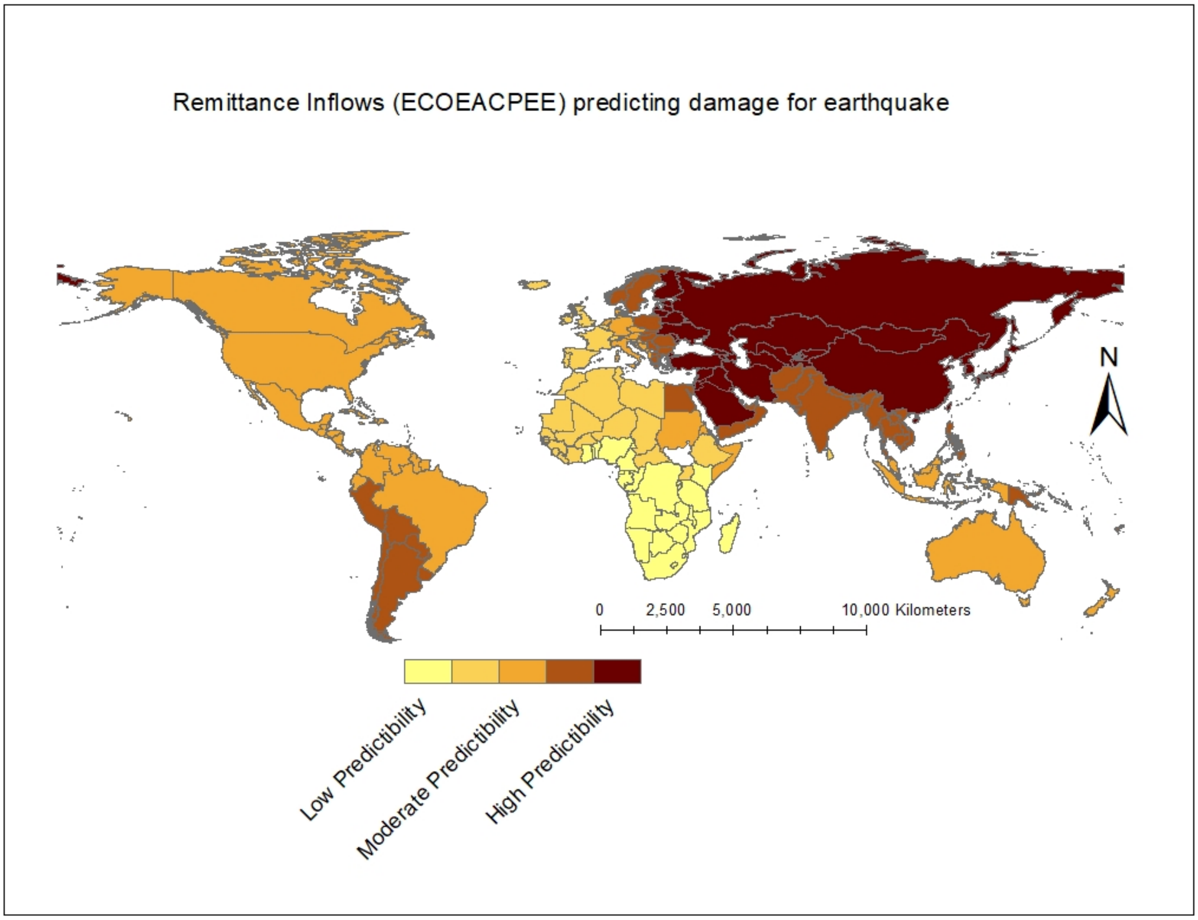
Percent of Industrial Development (INFEXPIND) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictibility
Moderate Predictibility
High Predictibility

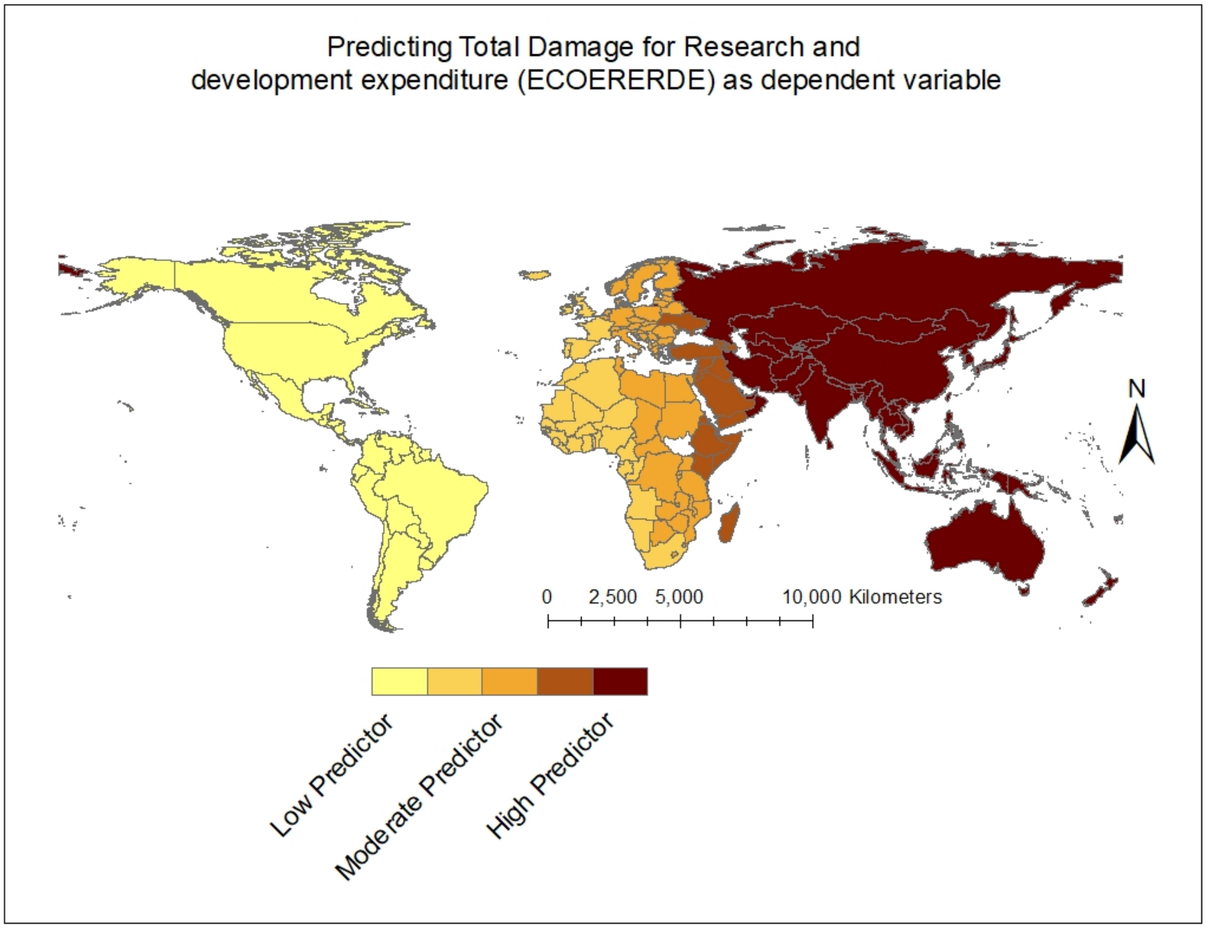

Percent of Commercial Development (INFEXPCOM) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictibility
Moderate Predictibility
High Predictibility

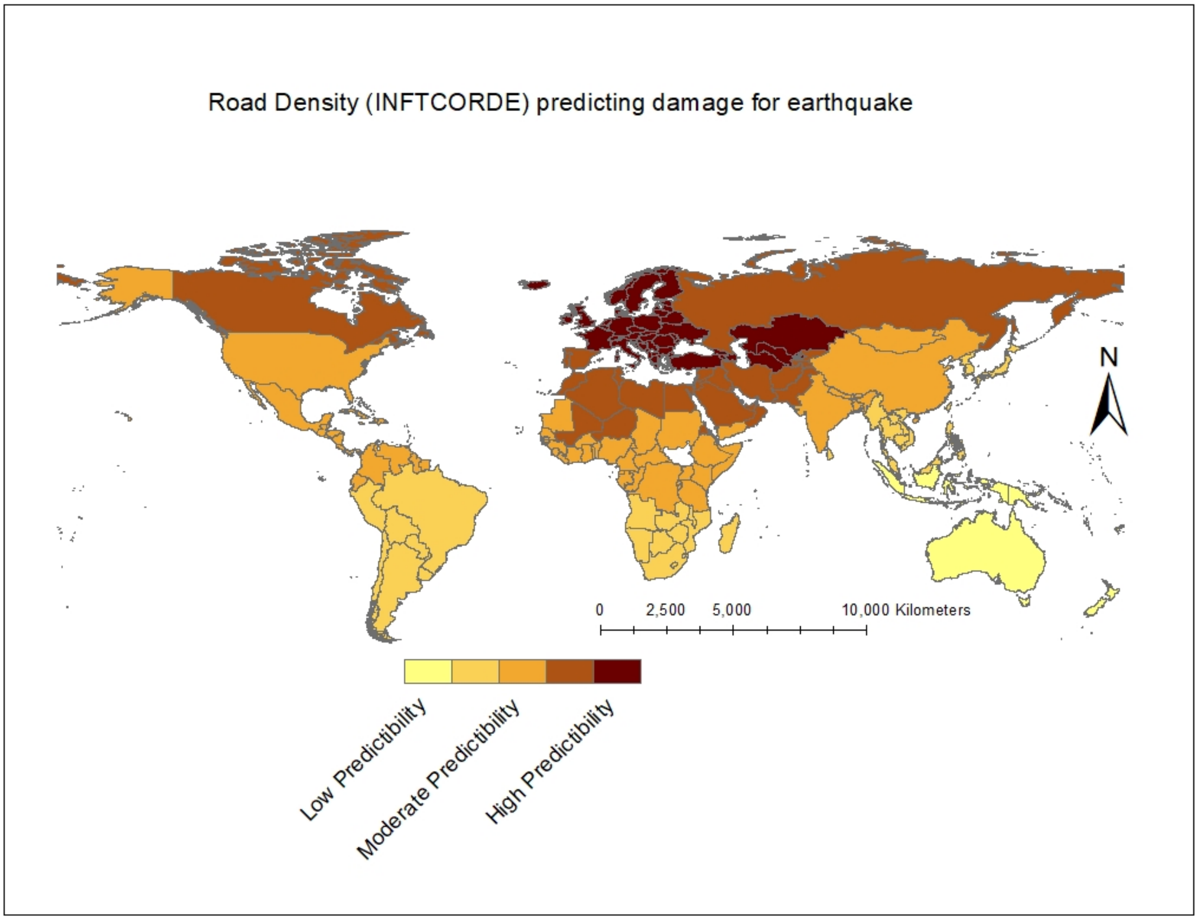

Population Density (POPPPSPDER) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictibility
Moderate Predictibility
High Predictibility

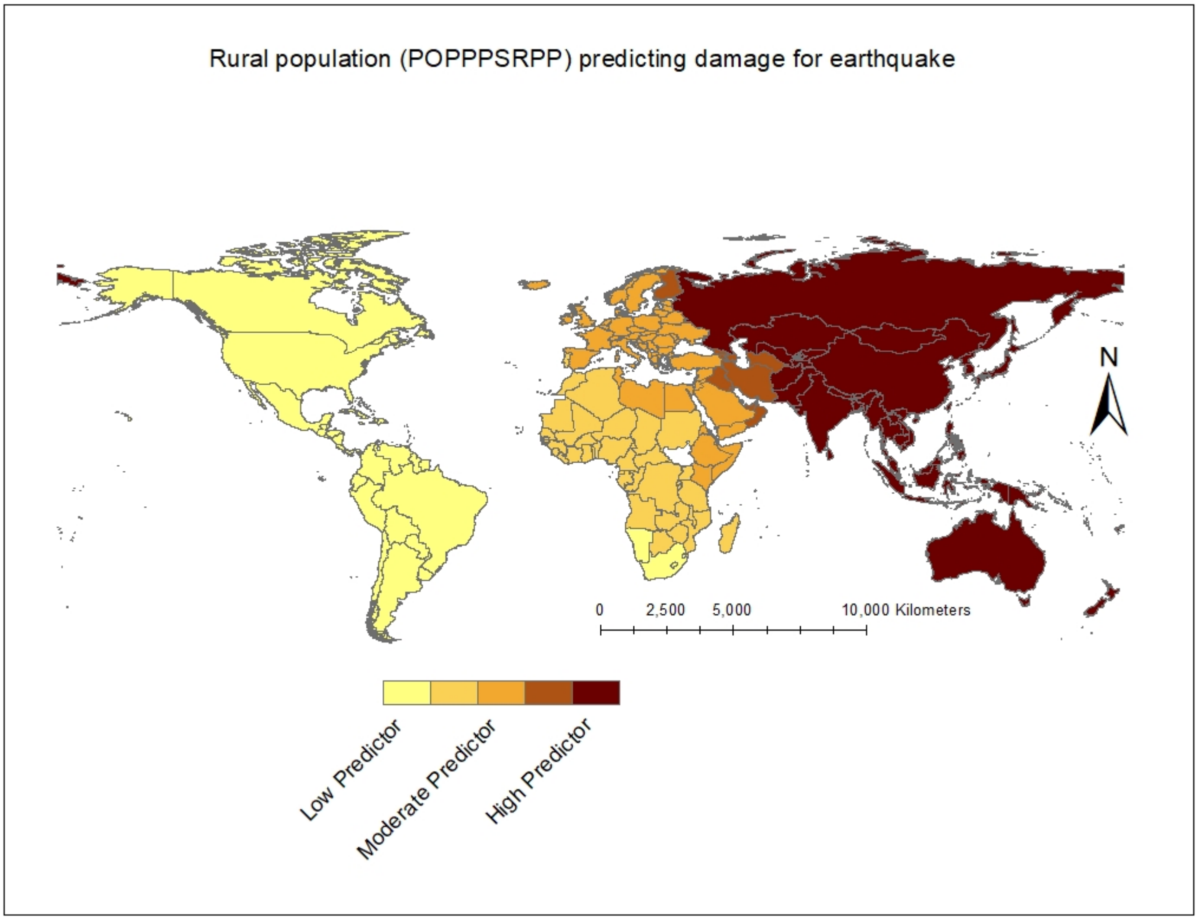

Prevalence of undernourishment (HEAHSTPUP) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor


Primary School Completion Rate (EDUEEOCCT) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor

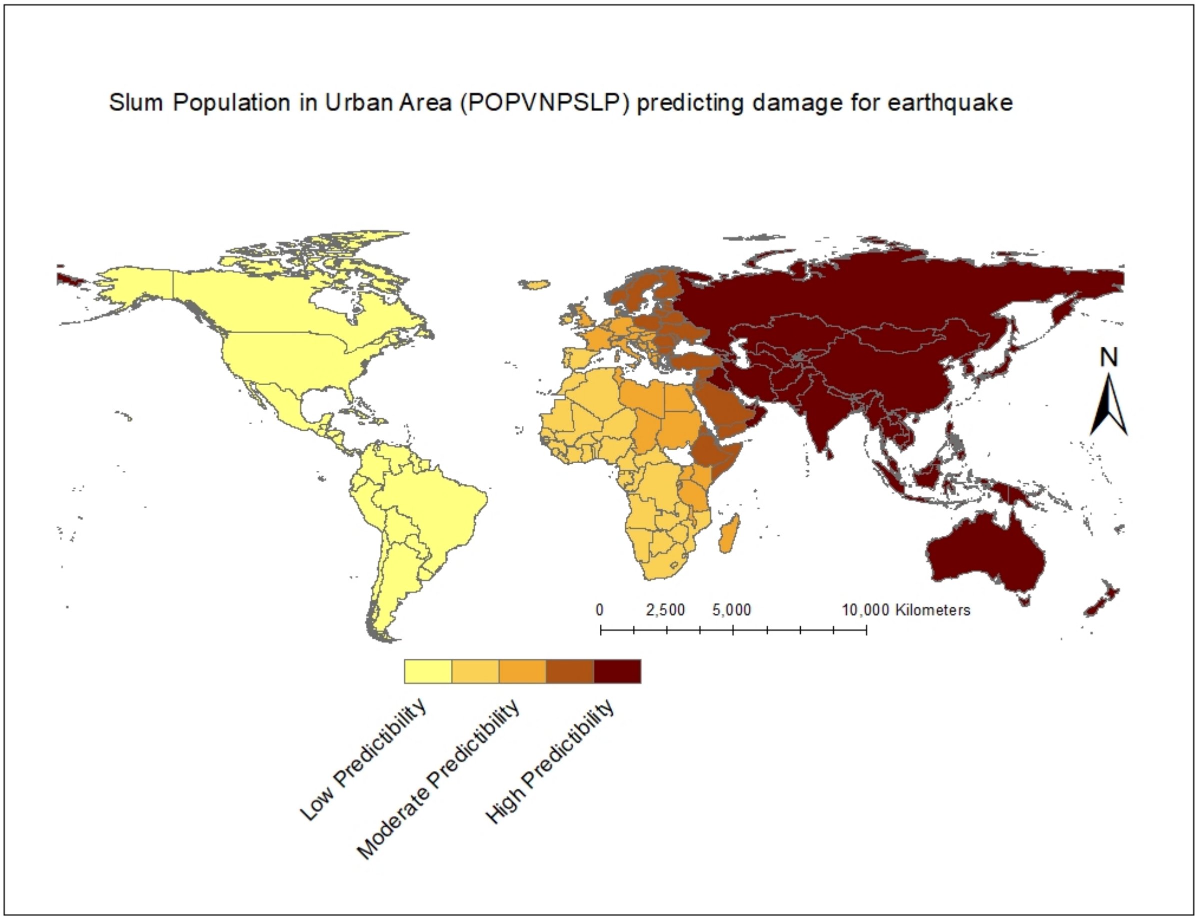

Remittance Inflows (ECOEACPEE) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictibility
Moderate Predictibility
High Predictibility

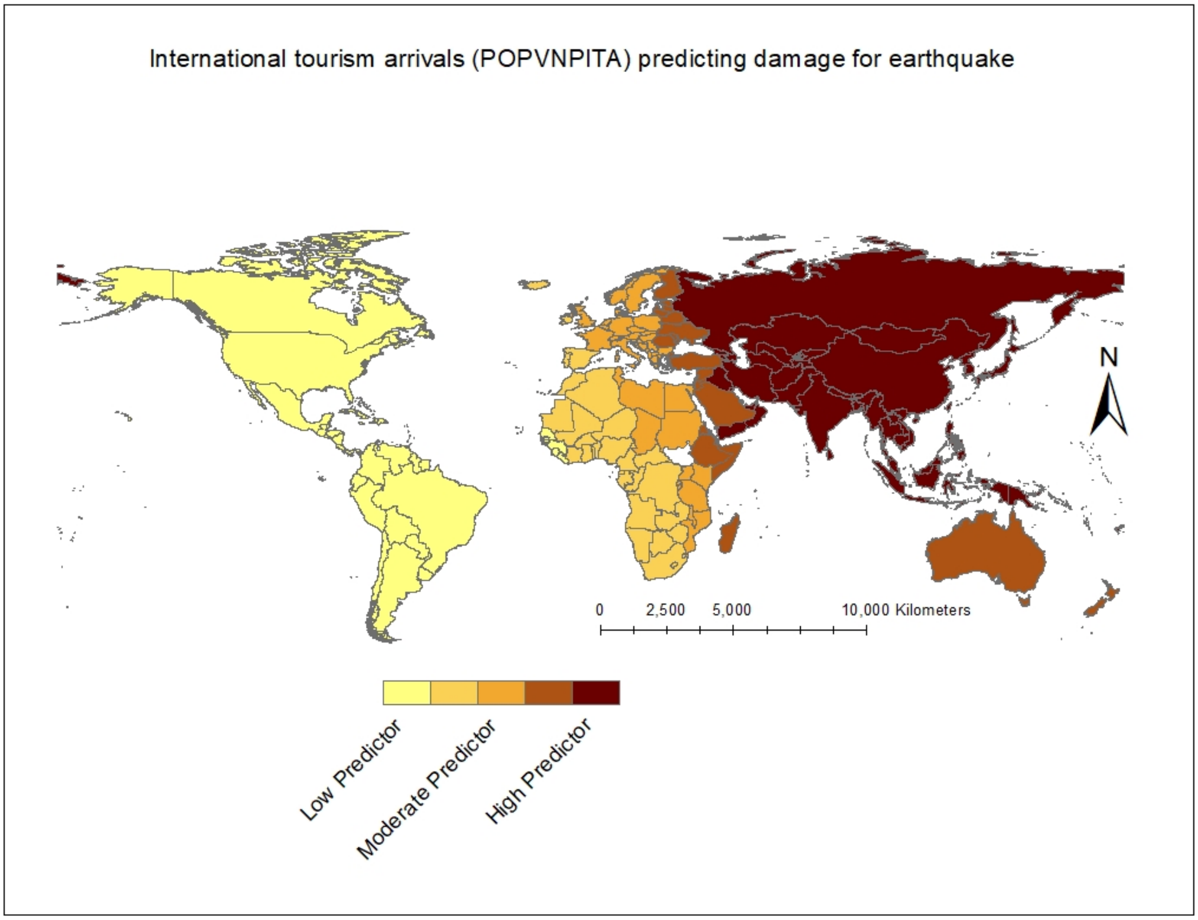

Predicting Total Damage for Research and
development expenditure (ECOERERDE) as dependent variable
N
0 2,500 5,000 10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor

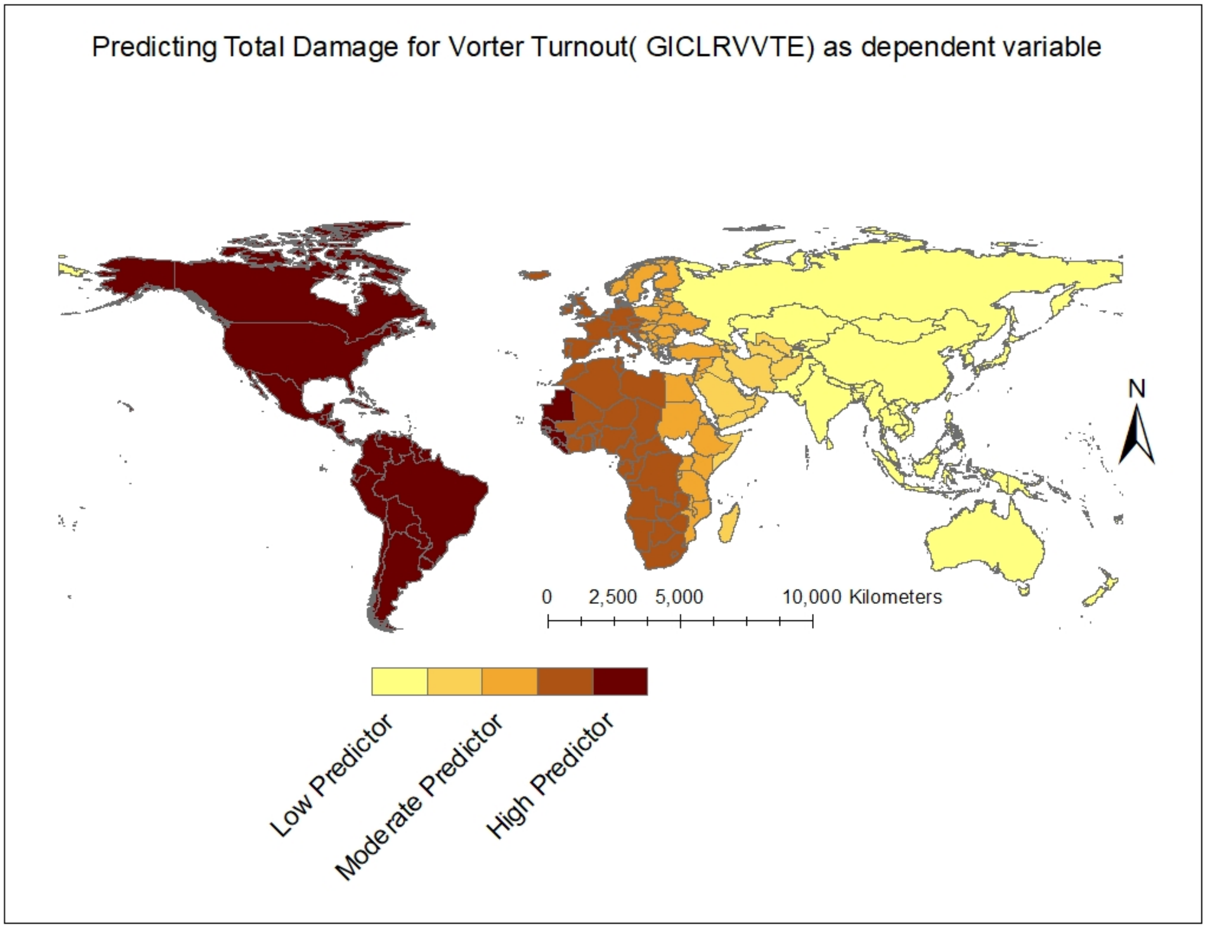

Road Density (INFTCORDE) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictibility
Moderate Predictibility
High Predictibility

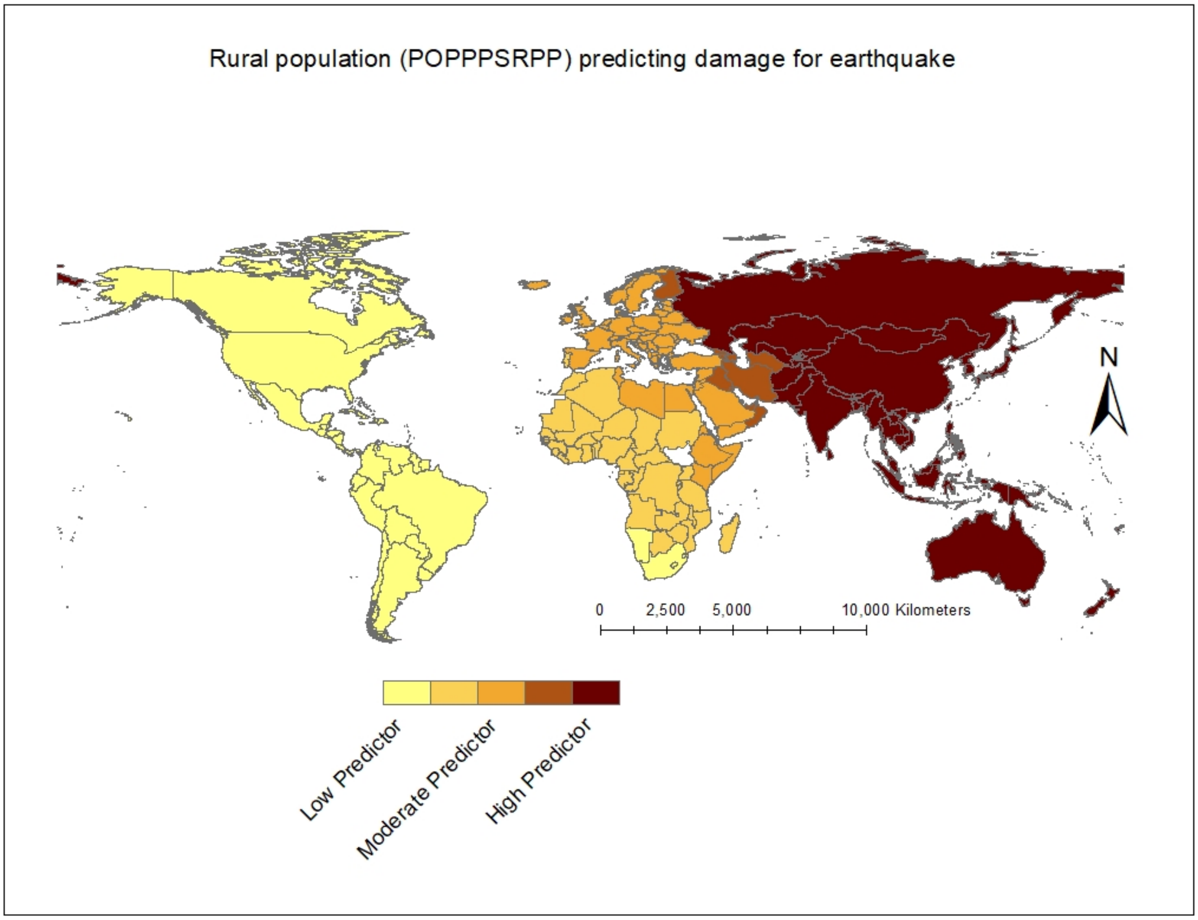


Rural population (POPPPSRPP) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor

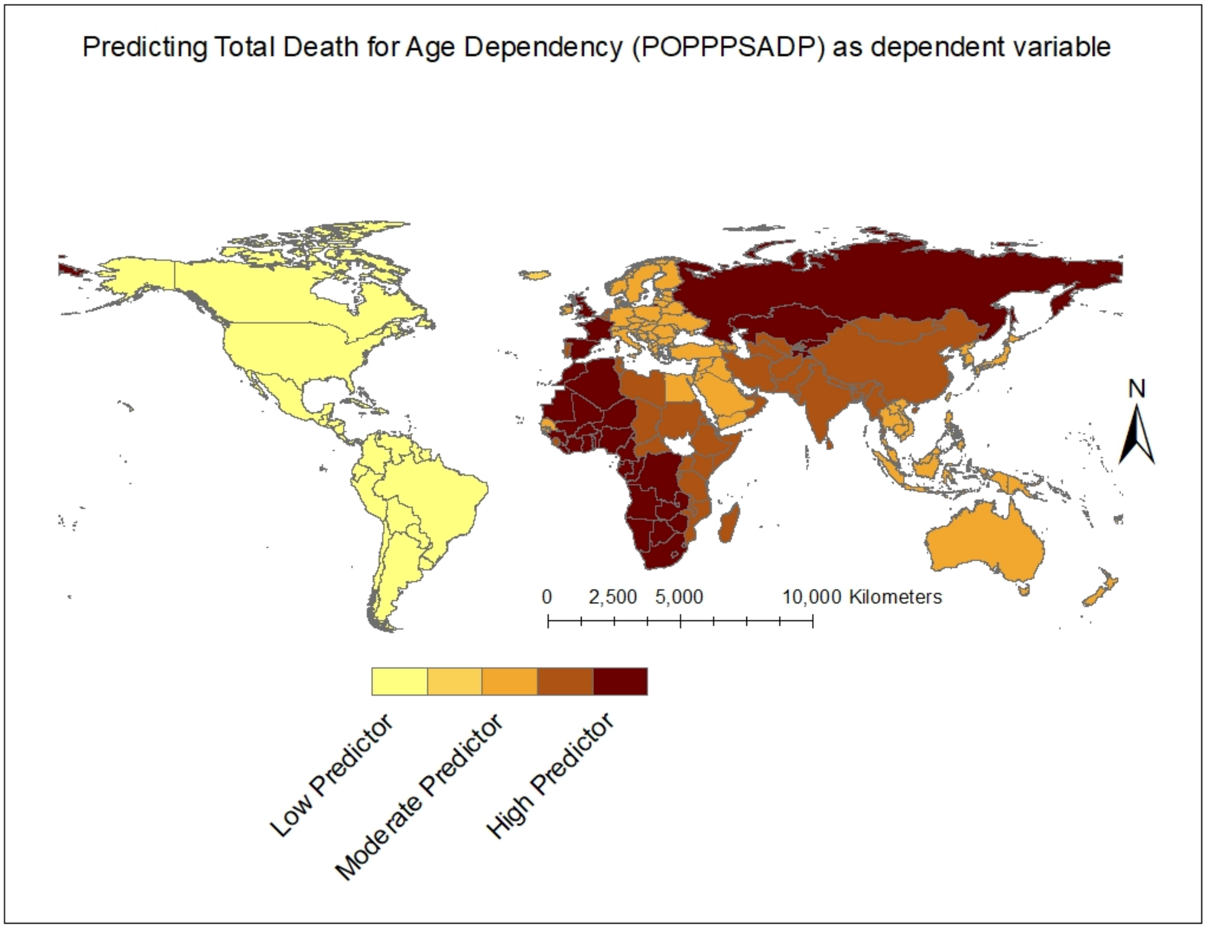

Slum Population in Urban Area (POPVNPSLP) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictibility
Moderate Predictibility
High Predictibility

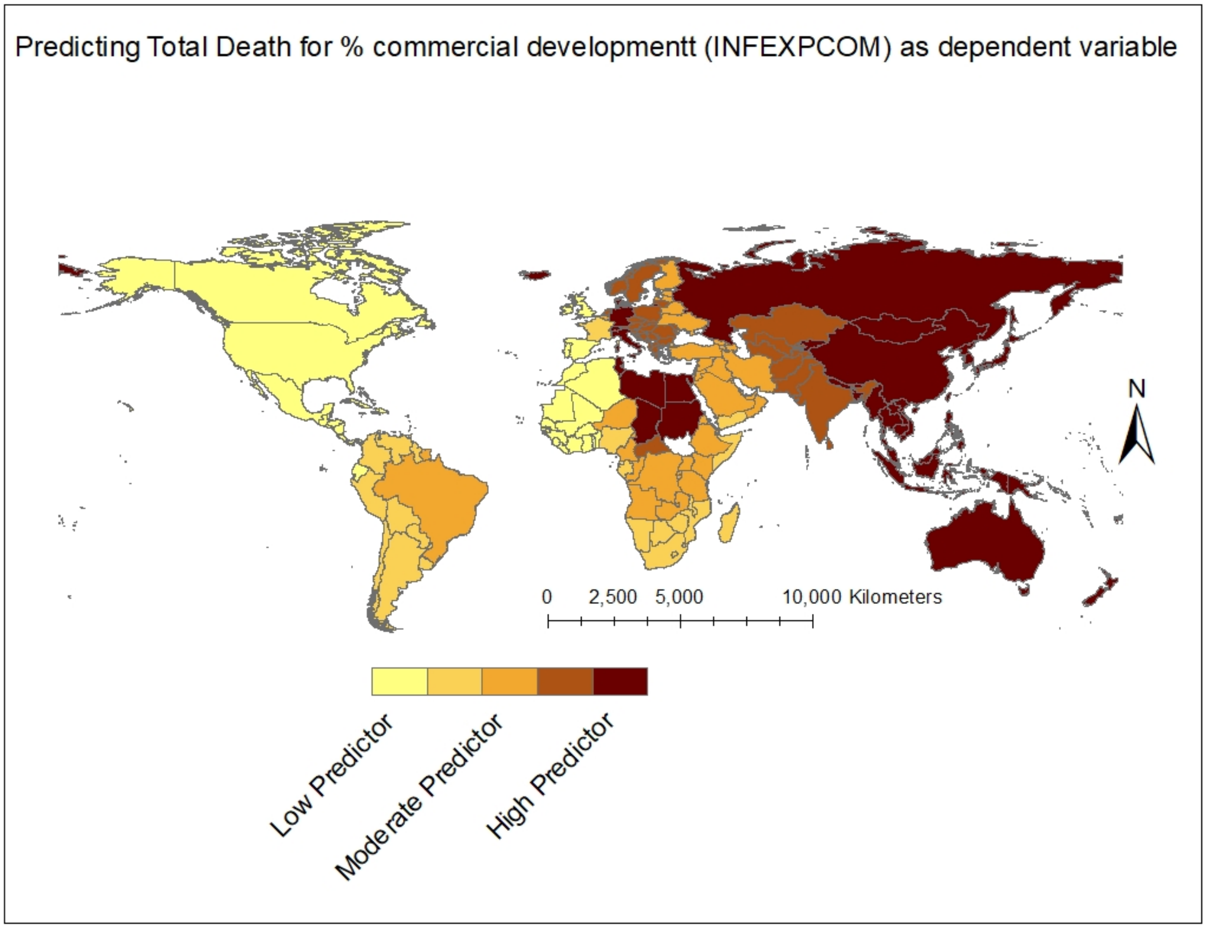

International tourism arrivals (POPVNPITA) predicting damage for earthquake
N
0 2,500 5,000 10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor


Predicting Total Damage for Vorter Turnout(GICLRVVTE) as dependent variable
N
0 2,500 5,000 10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor

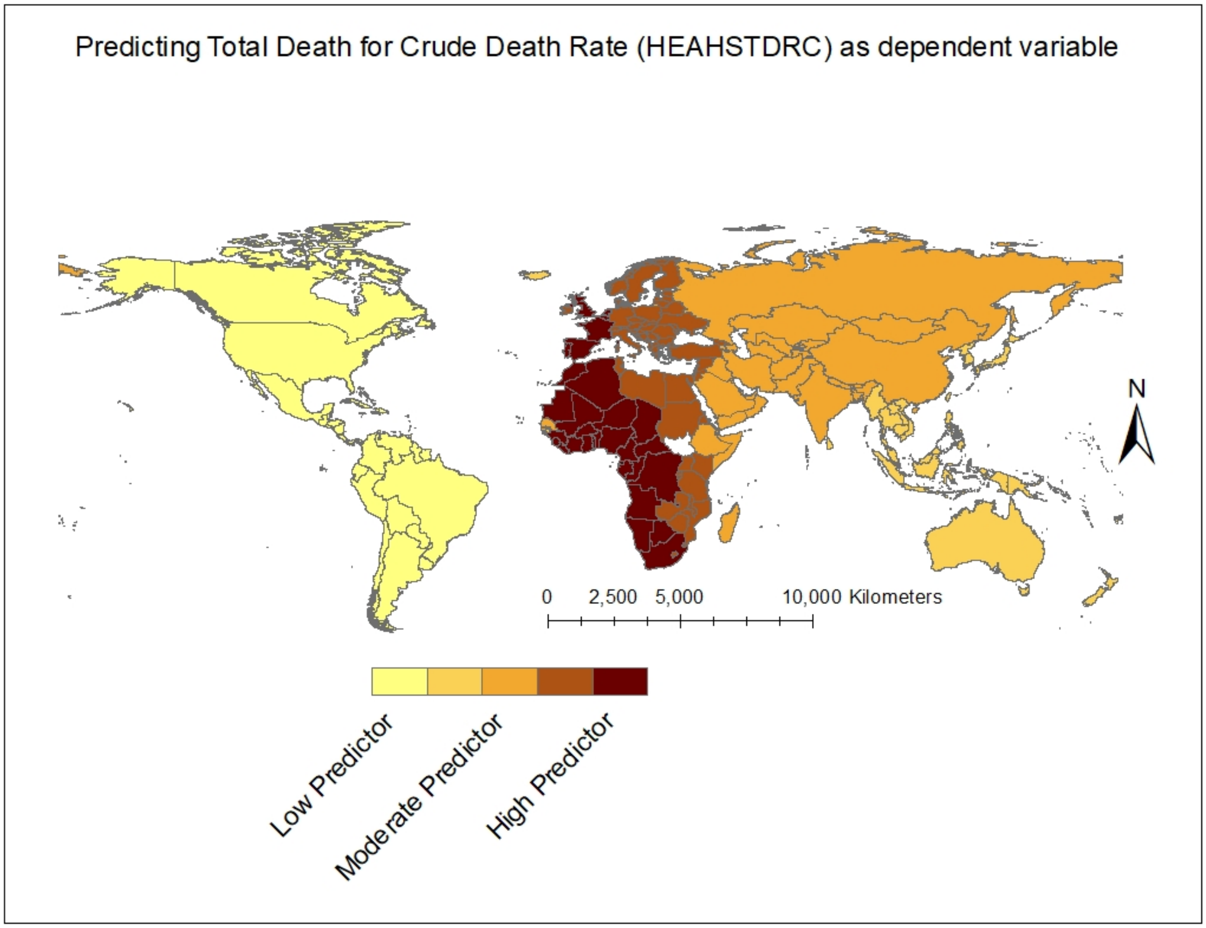

Rural population (POPPPSRPP) predicting damage for earthquake
N
0
2,500
5,000
10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor

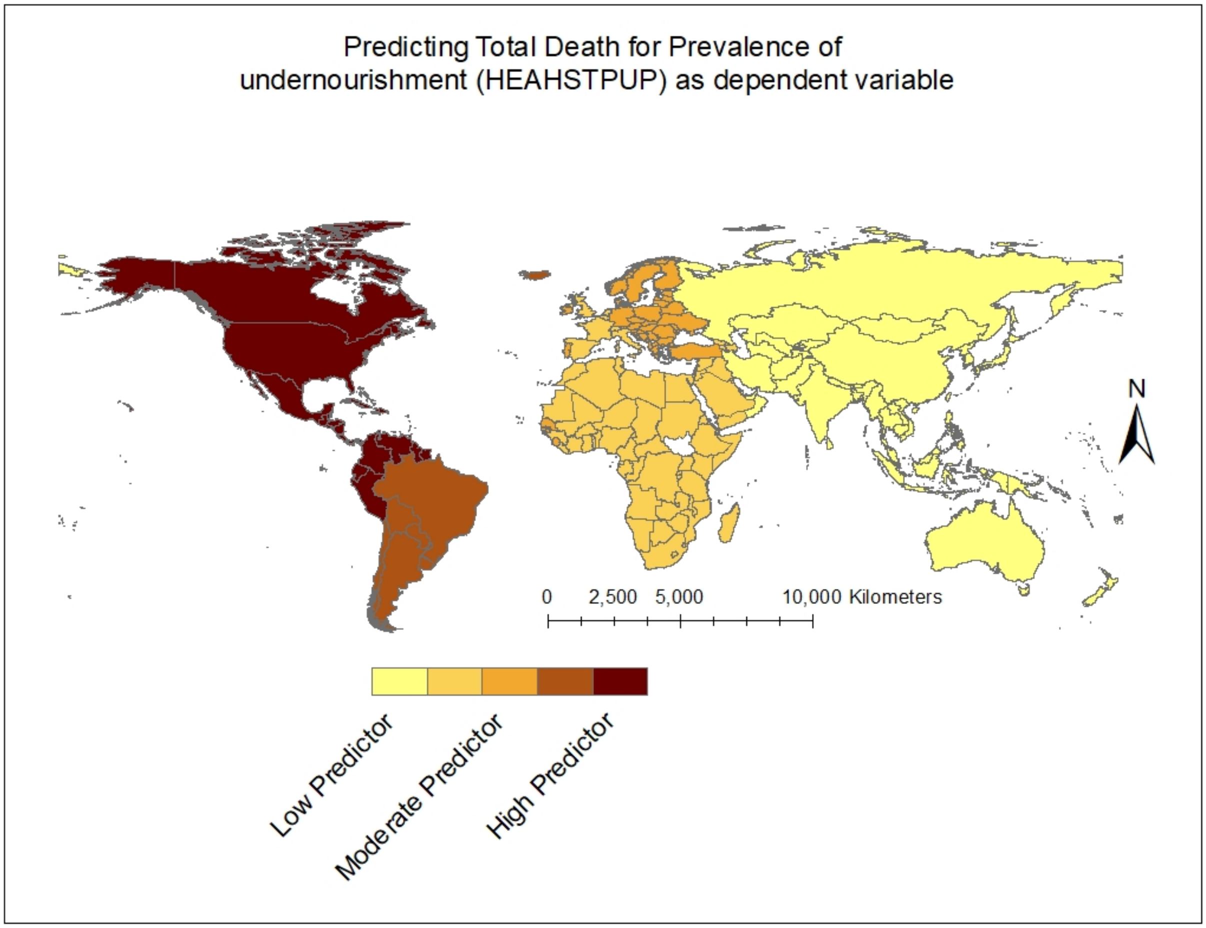
C2: Total Death as dependent variable:

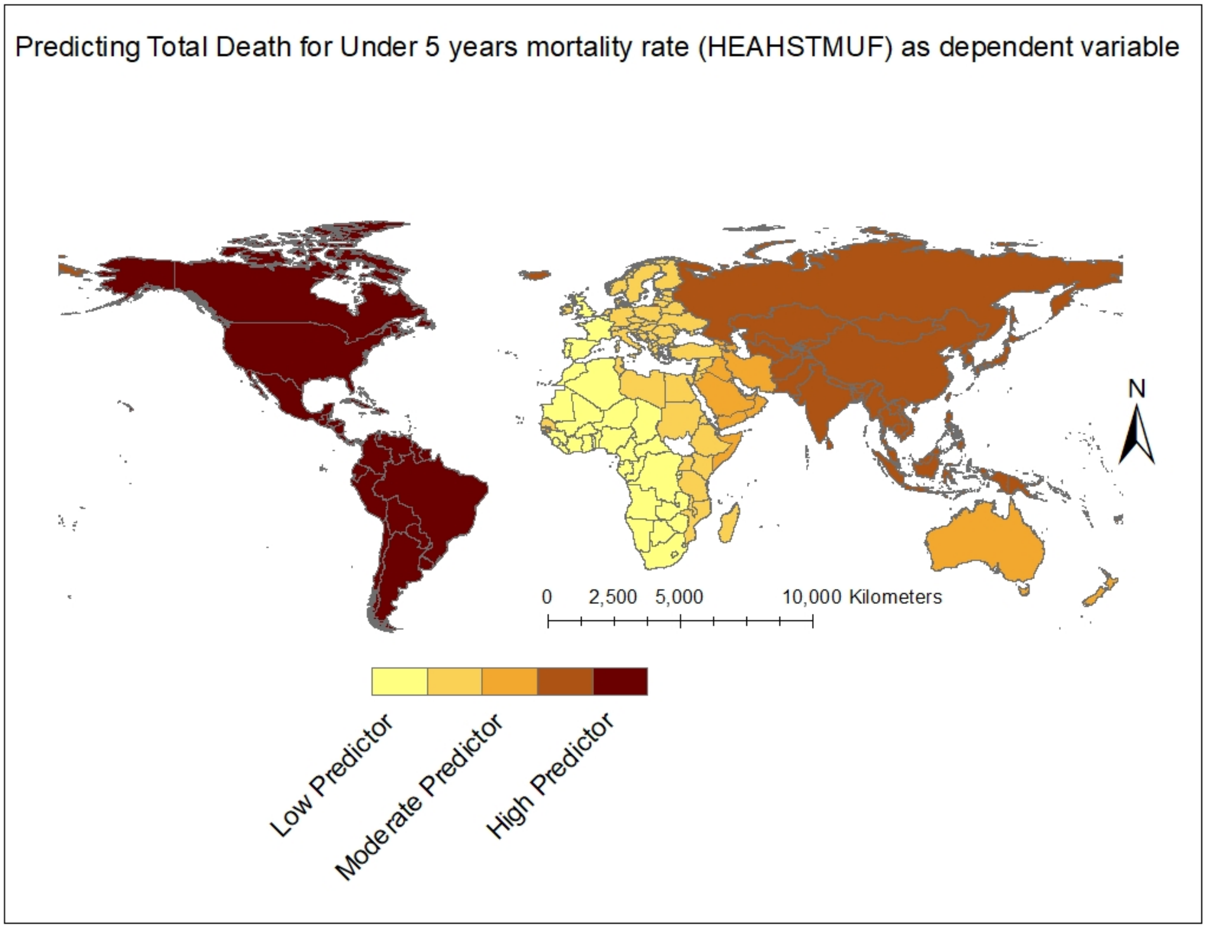


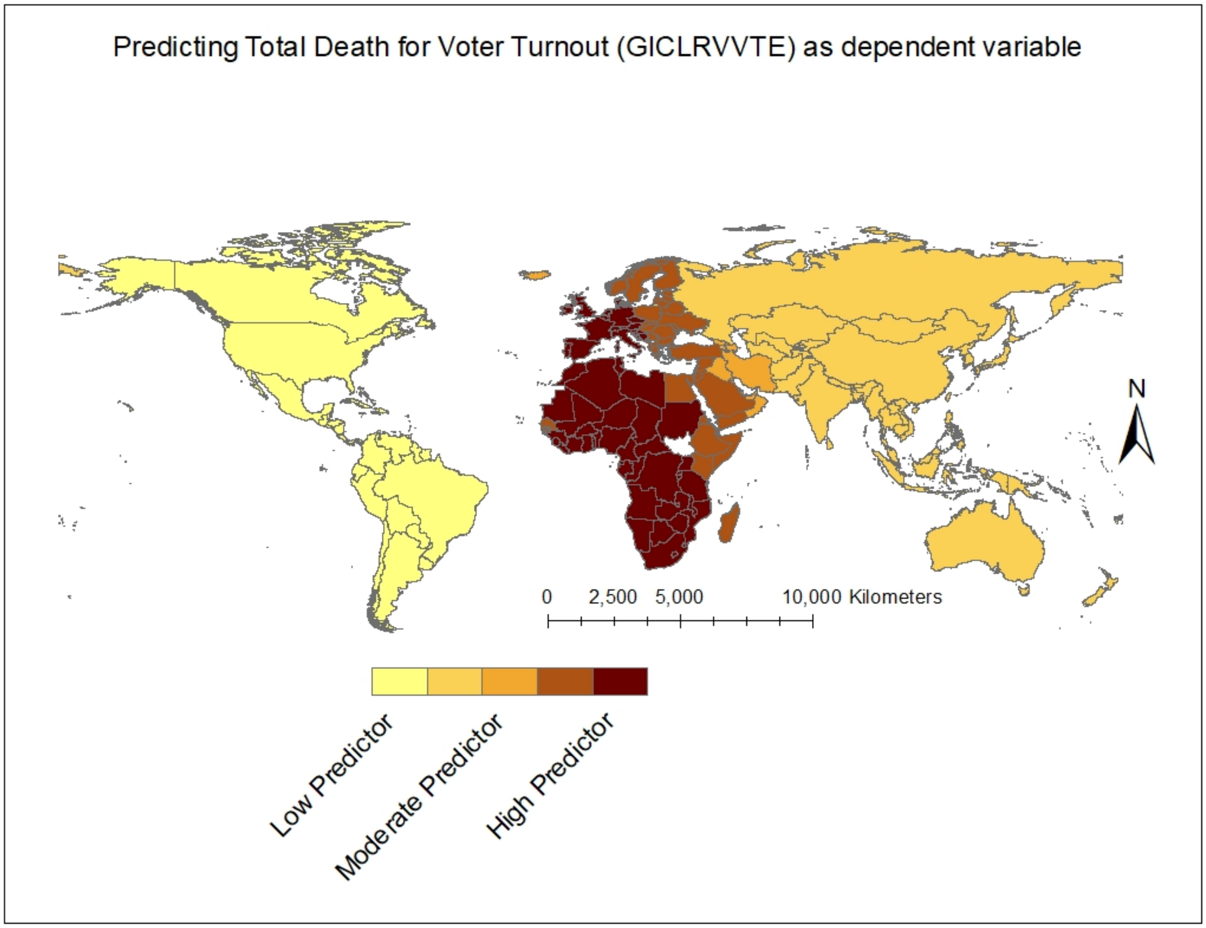


Predicting Total Death for % commercial developmentt (INFEXPCOM) as dependent variable
0 2,500 5,000 10,000 Kilometers
N
Low Predictor
Moderate Predictor
High Predictor


Predicting Total Death for Crude Death Rate (HEAHSTDRC) as dependent variable
0 2,500 5,000 10,000 Kilometers
N
Low Predictor
Moderate Predictor
High Predictor

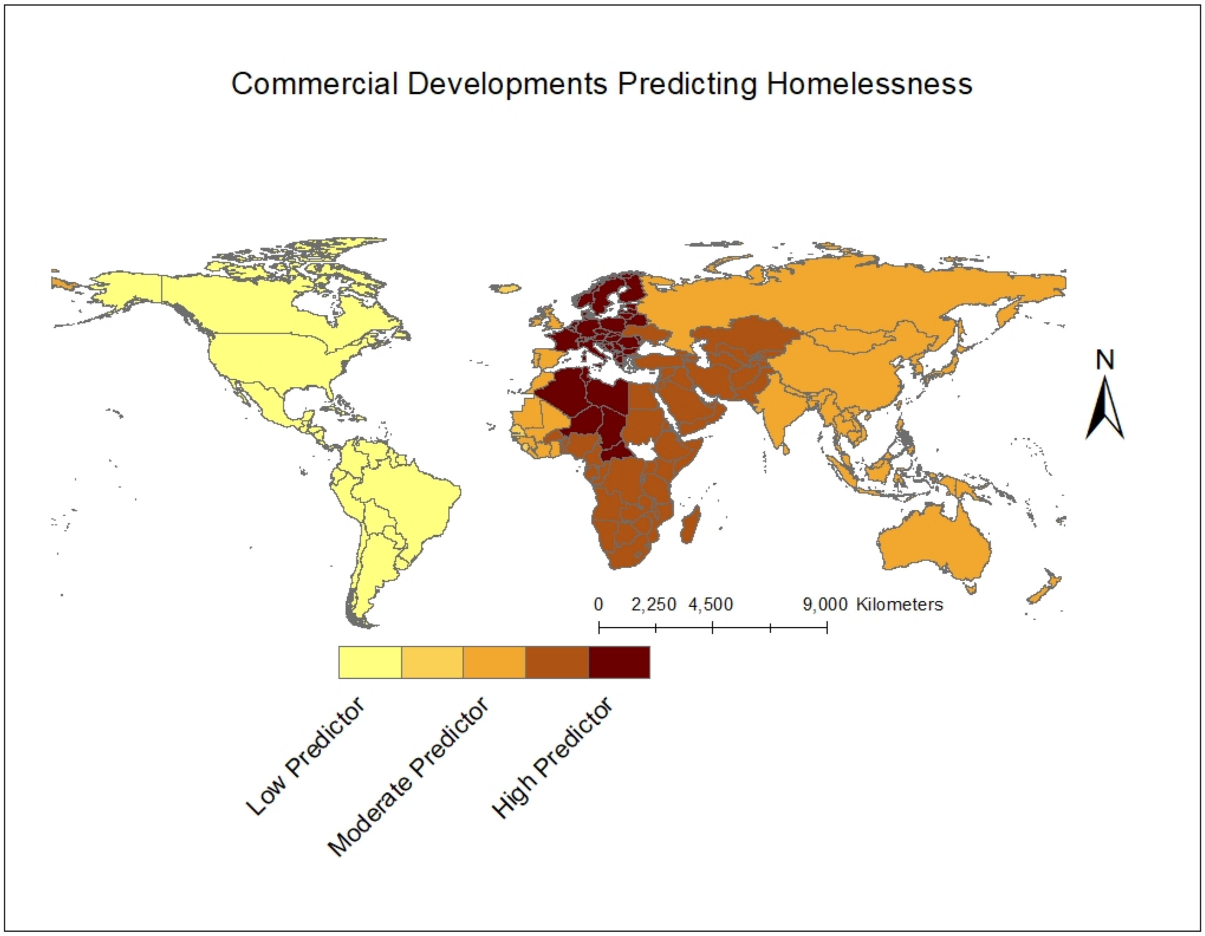

Predicting Total Death for Prevalence of
undernourishment (HEAHSTPUP) as dependent variable
N
0 2,500 5,000 10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor


Predicting Total Death for Under 5 years mortality rate (HEAHSTMUF) as dependent variable
N
0 2,500 5,000 10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor

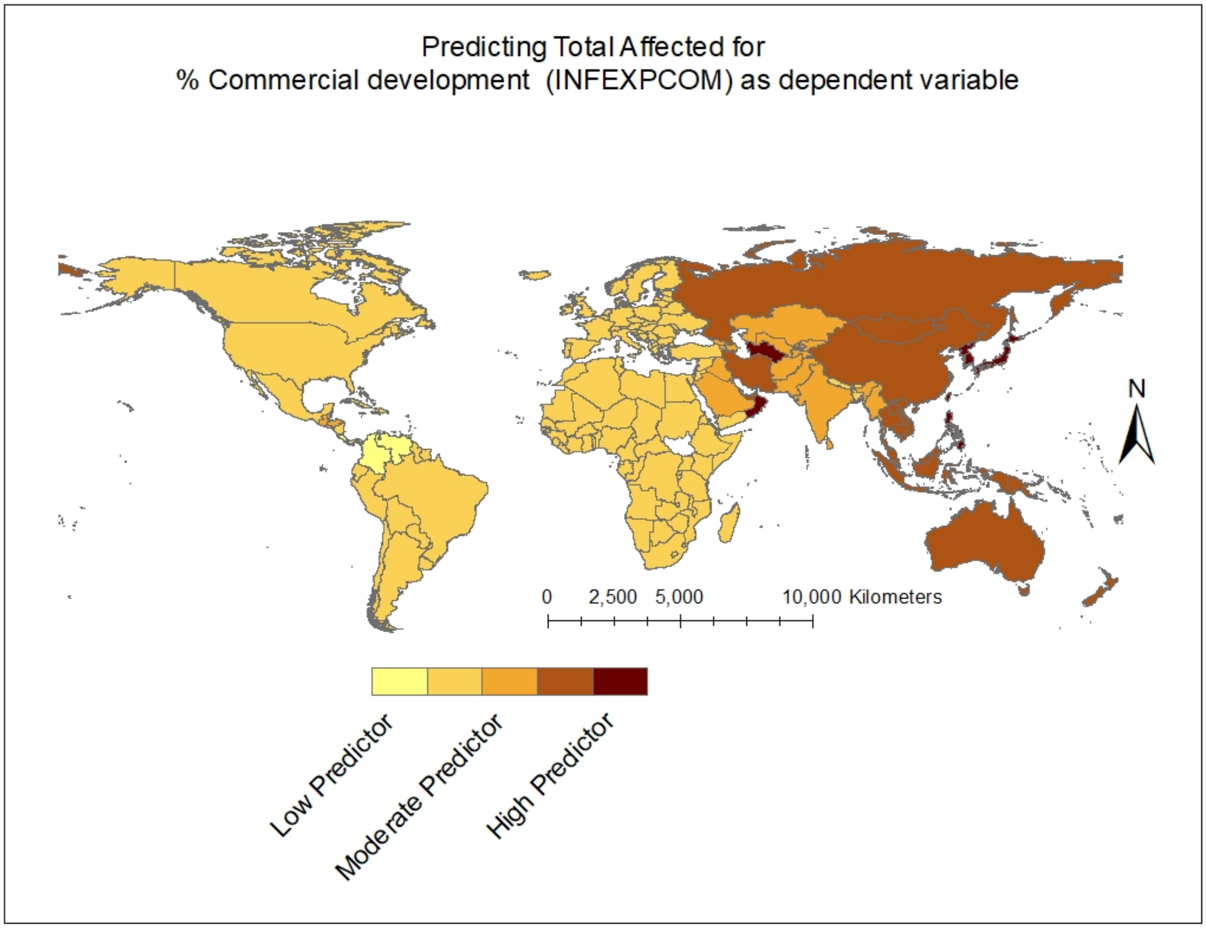


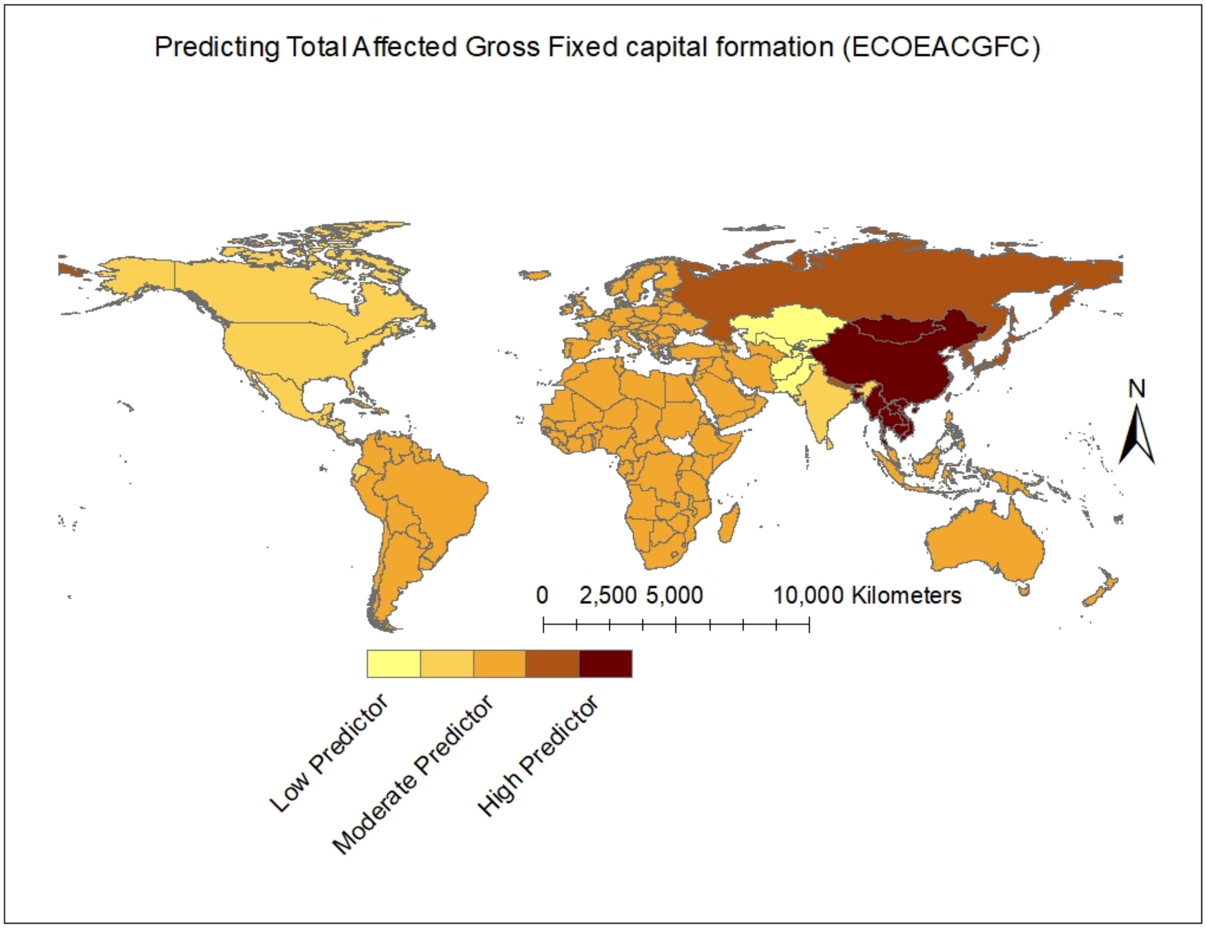
Predicting Total Death for Voter Turnout (GICLRVVTE) as dependent variable
0
2,500
5,000
10,000 Kilometers
N
Low Predictor
Moderate Predictor
High Predictor

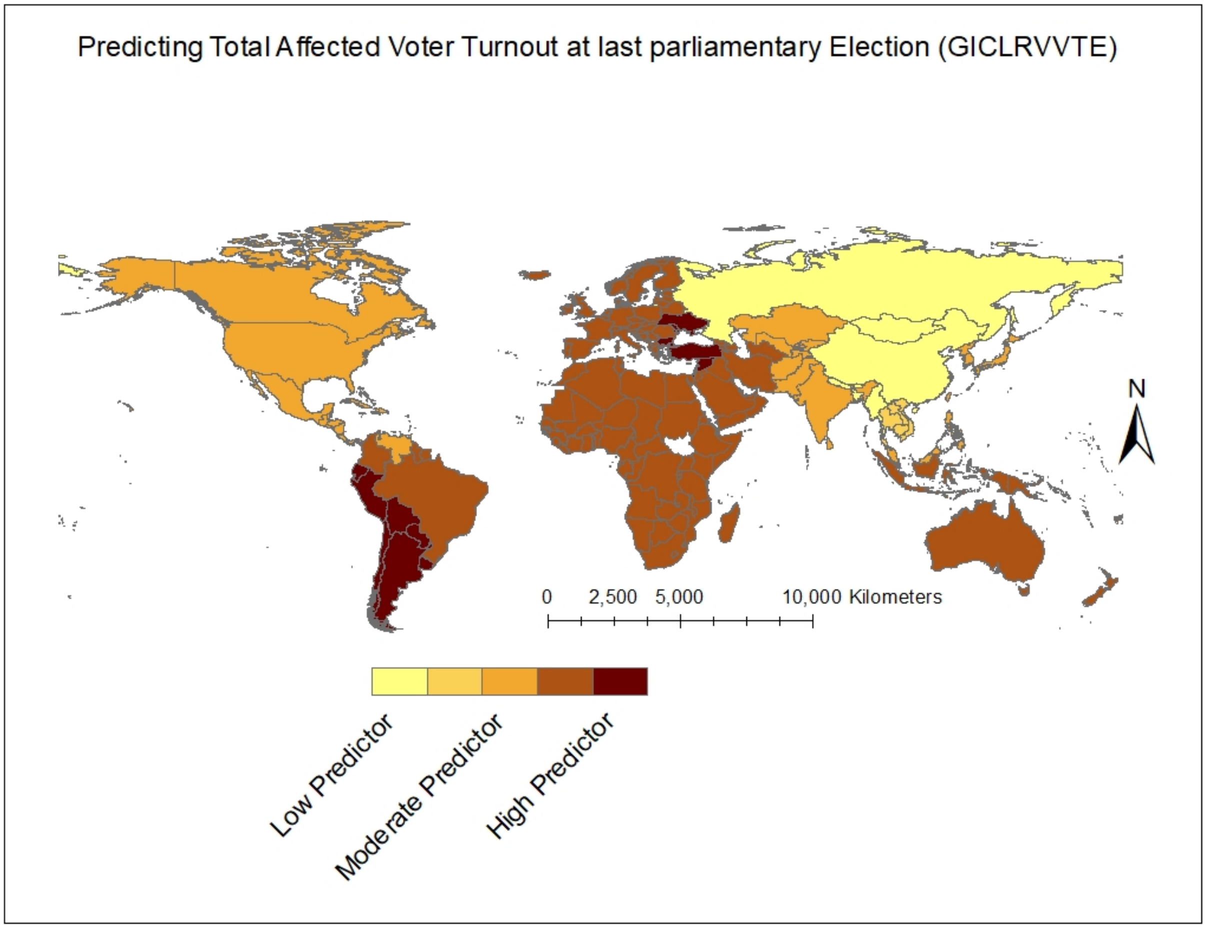
C3: Total Homeless as dependent variable:



C4: Total affected as dependent variable:




Predicting Total Affected Gross Fixed capital formation (ECOEACGFC)
0 2,500 5,000 10,000 Kilometers
N
Low Predictor
Moderate Predictor
High Predictor



Predicting Total Affected Voter Turnout at last parliamentary Election (GICLRVVTE)
N
0
2,500
5,000
10,000 Kilometers
Low Predictor
Moderate Predictor
High Predictor