The Validation and Development of Composite Indices for Measuring Vulnerability and Recovery Potential from Earthquakes

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Abstract

While many approaches for assessing earthquake risk exist within the literature and practice, it is the dynamic interrelationships between earthquake hazard, physical risk, and the social conditions of populations that are the focal point for disaster risk reduction. It is within this context that the measurement of vulnerability to earthquakes (i.e. characteristics that create the potential for harm or loss) has become a major focus area for governments, communities, and researchers. Metrics aimed at measuring vulnerability to earthquakes suffer from a number of key limitations, however. For instance, hazard and community context are often ignored, and attempts to validate metrics are largely non-existent. The purpose of this paper is to produce composite indices of the vulnerability of countries to earthquakes within three topical areas: social vulnerability, economic vulnerability, and recovery potential. To improve upon the status quo in indicators development for seismic events, our starting point was to: 1) define a set of indicators that are context specific to earthquakes as defined by the literature; 2) delineate indicators within categorical areas of vulnerability that are easy to understand and could be put into practical use by DRR practitioners; and 3) propose indicators that are validated using historical earthquake impacts. Indicators found statistically associated with historical earthquake impacts include age dependent populations, homeless and disabled populations, the under-educated, foreign migrants, the density of exposed economic assets such as commercial and industrial infrastructure, reliance on imports/exports, government debt, and purchasing power. When mapped, the geographic variations in the differential susceptibility of populations and economies to the adverse effects of damaging earthquake impacts become evident, as does differential ability of countries to recover from them.

1. Introduction

Earthquakes are one of the most devastating natural hazards that affect humanity. While the seismicity from earthquakes has remained fairly constant throughout the world, risk from earthquakes has been increasing substantially (USGS 2017). This increase is partially due to trends in population growth that have resulted in increased, and at times unplanned, urban development in seismic zones. Since it has become increasingly obvious that threats to society from earthquakes will increase in parallel with global urbanization, millions of people will continue to be vulnerable to earthquakes in the coming decades (Voigt et al. 2007; Lantada et al. 2008; Cvetkovic et al. 2015). As a result, 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). It is within this context that systematic studies of earthquake risk have been primarily assumed by scientists in the natural sciences and engineering (Cardona 2003). The latter has led to approaches for assessing and communicating earthquake risk that remain focused primarily on the potential for ground shaking, or on estimated damages to buildings, but not on social conditions that foster risk and create a differential potential for losses from earthquakes when they occur. This bifurcation in earthquake risk studies has been demonstrated by the GEM Foundation (Global Earthquake Model) through their publication of the world's first high resolution global earthquake hazard and risk maps (Pagani et al. 2018; Silva et al. 2018). Although these maps aim to deliver a comprehensive global assessment of earthquake hazard and risk, they do not 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.

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 socio-economic systems (Maskrey 1993; Lavell 1996; Bogardi and Birkmann 2004; Burton and Silva 2016; Fatemi 2017). It is within this context that GEM has taken steps toward addressing the aforementioned area of opportunity by developing a set of composite indicators for the measurement of the vulnerability of social and economic systems to earthquakes as well as the differential ability of populations to recovery from them. There is, however, no agreed-upon framework and established sets of data for measuring, understanding, and communicating earthquake vulnerabilities and recovery potential (Schmidtlein et al. 2011; Burton and Silva 2016). This is partially due to a lack of attempts to validate proxy metrics needed to measure characteristics within social and economic systems that affect loss and recovery from earthquakes. Additionally, this is due to the need to account for the context of the earthquake 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).

The purpose of this article is to provide a validated set of metrics for measuring vulnerability to earthquakes accounting for social, economic and recovery perspectives using the literature and empirical analyses. As a starting point, an exhaustive review of the literature was utilized to identify potential drivers of vulnerability within social and economic systems and recovery potential from earthquakes. This work was then coupled with a quantified accounting of global adverse impacts from earthquakes that were used to identify externally validated indicator sets that could provide a comparative assessment of vulnerability to earthquakes at multiple levels of geography. Two questions form the basis of this work:

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

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

The remainder of this article proceeds as follows. The second section describes the concept of vulnerability to natural hazards and disasters. The third section outlines the study area. The fourth section describes the methods from which a validated set of indicators is identified for measuring vulnerability to earthquakes from a social, economic, and recovery potential perspective. The fifth section describes the results whereas the remaining two sections identify caveats, research opportunities, and conclude the article.

2. The vulnerability concept

2.1. Vulnerability and social vulnerability

There is a continuing need for disaster risk reduction strategies to shift emphasis from assessing hazard events towards reducing vulnerabilities within social systems (Briceño 2015; Burton et al. 2018). Vulnerability is broadly defined as the potential to suffer loss or harm (Burton et al. 2018). The latter can include the structural vulnerability of buildings, the exposure of people and places to natural hazard events, and social vulnerability describing differential susceptibility based on social, economic and political factors (O'Keefe et al.1976; Cutter 2001; Burton et al. 2018). When applied in social science research, the term vulnerability generally describes a state of people and populations rather than of physical structures, economies, or regions of the Earth (Wisner et al. 2004). The concept of social vulnerability involves an amalgamation of factors that determine the degree to which a person's life or livelihood is put at risk by a particular event. These factors include exposure (a risk measure directly related to the proximity of people and infrastructure to hazard-prone areas), sensitivity (the degree to which people and places can be harmed), and resilience (the ability of systems to adjust to change and moderate the effects of, cope with, and recover from a disturbance) (Adger 2006; Cutter 1996; Polsky et al. 2007; Burton 2010). It is within this context that there are various demographic, economic, and social characteristics within communities that make some places more socially vulnerable to adverse hazard impacts than others (Cutter et al. 2013). Such characteristics are inherent and are borne from a myriad of inequalities that not only affect the ability of a social system to absorb hazard impacts, but differentially affect access to resources and information, housing choice and location, and the marginalization of a community's residents.

The antecedents of current efforts to model social vulnerability were derived from social indicators research (Schmidtlein et al. 2008) where there is a tradition of exploration focused on the development of proxy indicators to measure factors that aggravate or attenuate the impact of hazard events on populations. These indicators include measures of age, gender, race, socioeconomic status, and special needs populations (e.g., homeless, transients, physically or mentally challenged), non-English speaking immigrants, and seasonal tourists (Enarson and Morrow 1998; Peacock et al. 1997; Tierney 2006; Tierney et al. 2001; Burton 2010). Other measures include access to education, governance, institutional capacities, healthcare access, and elements of the built environment such as the age and density of residential, commercial, and manufacturing and industrial infrastructure (Cutter et al. 2003; Burton and Silva 2016). Indices focusing explicitly on social vulnerability include the Prevalent Vulnerability Index (Cardona 2005), the Index of Social Vulnerability to Climate Change for Africa

(Vincent 2004), the Predictive Indicator of Vulnerability (Adger et al. 2004), the Social Vulnerability Index (SoVI) (Cutter et al. 2003), and a social vulnerability index in context to river floods (Fekete 2009).

2.2 Economic vulnerability

Economic vulnerability is often defined as the exposure of an economy to exogenous shocks (Briguglio et al. 2009), such as those caused by a natural hazard impact or disaster. Most studies on economic vulnerability provide empirical evidence that small states (particularly island ones) tend to have more exposure to exogenous shocks, thereby higher levels of economic vulnerability (Guillaumont 2009; Briguglio et al. 2009). It is within this context that researchers have demonstrated that the vulnerability of an economy to exogenous shocks is a product of a number of inherent economic conditions including: 1) high degrees of economic exposure, 2) economic openness, 3) export concentration, and 4) the reliance on imports. According to Briguglio (1995) and Andrianto and Matsuda (2004), the degree of economic exposure of a country (or place) is an important variable in vulnerability analysis because the greater the exposure, the higher potential for adverse impacts exist where the recovery of an economy from a damaging hazard event may be increasingly dictated by external conditions. A high degree of economic openness renders a place susceptible to economic impacts from hazards that are a function of the size of a country's domestic market and amount of exports and the availability of resources within a country to produce goods and services following an event (Briguglio et al. 2009). Regarding export concentration, dependence on a narrow range of exports gives rise to risks associated with lack of diversification (Cutter et al. 2003), whereas dependence on strategic imports would expose an economy to shocks with regard to the availability and costs of such imports (Briguglio et al. 2009).

2.3 Disaster recovery and resilience

A number of studies such as Burton (2015) and Despotaki et al. (2018) have demonstrated that recovery from damaging hazard impacts, such as those caused by an earthquake, depend not only on the extent of the damage to the built environment, but also on the extent of the resilience of the damaged communities. Burton (2015) directly linked the recovery of communities to the disaster resilience concept and proposed a set of 41 indicators for measuring the resilience of communities to natural hazards along the Mississippi Gulf Coast, USA. Resilience can be defined as the ability of social systems to prepare for, respond to, and recover from natural hazards and disasters (Cutter et al. 2008), and it is within this context that resilient communities are less vulnerable to hazards and disasters than less resilient communities.

Holling (1973) was perhaps the first to describe resilience within the field of ecology. Holling defined resilience as the ability to absorb change and disturbance and still maintain the same relationships that control a system's behavior. Timmerman (1981) was likely the first to describe the concept in natural hazards and disaster research where he described resilience as the measure of the capacity of a system, or part of a system, to absorb impacts or recover from a damaging event. Since the publication of the work of Holling and Timmerman, the concept of resilience has gained acceptance in a variety of fields, and conceptual models used to describe and measure resilience within the literature are plentiful. These include models that describe resilience as a set of networked capacities (Norris et al. 2008; Sherrieb et al. 2010) and those that relate the concept to what are now referred to as manufactured, financial, human, social, and natural capital (Aldrich 2012; Alawiyah et al. 2011; Miles and Chang 2011). Other conceptual models include the description of attributes of particular systems such as the economy (Rose 2007), governance (Tierney 2012) and critical infrastructure (Bruneau and Tierney 2007). Place-based models for measuring community resilience also occur within the literature (e.g., Cutter et al. 2008). Place-based models not only account for the conditions within societies that make people vulnerable to natural hazards, they also account for proximity to potential hazard events and loss potential.

3. Study area

Since the primary impetus for conducting this research was the identification of indicators for the global measurement of social and economic vulnerability to earthquakes, as well as recovery potential, the study area is the whole world (*N*=193 countries). Here, we included all countries with populations of 200,000 or more for our data collection and analysis. Countries that are disputed or non-UN member states (e.g., Kosovo, Northern Cyprus) were not considered for our investigation. Disputed countries or non-UN member states and those with less than 200,000 population typically had no data reported, thereby prompting their exclusion. It's important to note that the validation and delineation of indicators for this study was conducted at the country level, comparing one country to another in terms of their social vulnerability, economic vulnerability, or recovery potential. Public policy development and planning to reduce earthquake risk often occurs at the sub-national level, however. While we are sensitive to this major caveat, we conducted our study at the global level: 1) to create a baseline of composite indicators that can be integrated with GEM's country level assessments of hazard and risk; 2) because freely attainable and reliable data on adverse earthquakes impacts that can be used for validation are only available at the country level for the world; and 3) it is anticipated that the measurement framework developed here can be adopted for more local level analyses.

4. Methodology

Perhaps the most popular method to assess characteristics that affect the vulnerability of countries to earthquakes is through the construction of composite indices (also referred to as composite indicators). An indicator is a quantitative or qualitative measure derived from observed facts that model the reality of a complex situation (Freudenberg 2003). Indicators can reveal the relative position of the phenomena being measured (e.g. most vulnerable, least vulnerable), can illustrate the magnitude of a change over time (a little or a lot), and can illustrate the direction of change (increasing or decreasing) (Cutter et al. 2010). A composite indicator is the mathematical combination of individual indicators or thematic sets of indicators that represent different dimensions of a concept that cannot be fully captured by any individual indicator alone (Nardo et al. 2008). A composite indicator generally measures multi-dimensional concepts that cannot be captured with a single indicator; thus, composite indicators have been considered ideal tools to quantify characteristics of hazard vulnerability and recovery (Cutter et al. 2010; Burton 2015).

The application of composite indicators for measuring social vulnerability is not new, and the scientific literature outlines several steps for index construction (see Nardo et al. 2008; Tate 2012). These steps typically include the identification of relevant variables, multivariate analysis, aggregation of individual indicators into composite indicators, and the linking of variables to an external validation metric. These steps make up our methodology and are described in the sub-sections below.

4.1 Selection of vulnerability indicators

To choose indicators contextually exclusive for modeling vulnerability to earthquakes from a social, economic, and recovery perspective, we performed a literature review. The literature review focused on empirical studies describing vulnerability processes and outcomes in the context of severe natural hazard impacts and earthquakes. Using Web of Science and Google Scholar, we applied search terms such as "natural hazard" or "earthquake" and "social vulnerability" or "vulnerability" and "disaster recovery" or "resilience". The article selection process resulted in more than three hundred peer-reviewed papers that were collected and compiled into a digital library. These papers were reviewed to identify characteristics identified in the literature as either affecting recovery processes from damaging hazard events or contributing to and/or reducing the social and economic vulnerabilities of countries, regions, cities, and populations, considering earthquakes in particular. This review of the literature was conducted to develop a "wish list" of variables that could be applied exclusively to measure social vulnerability and economic vulnerability to earthquakes as well as recovery potential from damaging earthquakes. This wish list consisted of approximately 440 potential proxy indicators.

To transcend from the "wish list" to actual data collection, three equally important criteria had to be met for a variable to be considered fit for our index construction. First, variables needed to be of consistent quality and freely available from sources such as the World Bank and the United Nations. The second criterion was that variables needed to be scalable or available at multiple levels of geography to encourage more local-level analyses. The third criterion made it essential that variables were justified based on the literature regarding the variable's relevance to social vulnerability, economic vulnerability, or recovery potential. Out of the 440 potential proxy indicators on the "wish list", 78 of them were deemed fitting based on their availability and the three criteria outlined above. Our initial set of indicators are delineated in Table 1 along with their sources to justify consideration for further analysis. Each indicator was binned into one or more of the composite index categories (social, economic, recovery) based on how each variable was citied within the literature or based on the authors' expert opinion.

The first index category, social vulnerability, was designed to capture the differential capacities of populations to reduce their risk from earthquakes where the linking of social capacities with demographic attributes 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 exhibit higher social vulnerability than communities lacking these characteristics (Tierney et al. 2001; Cutter et al. 2003; National Research Council 2006). Other relevant indicators within the index include in-migration from foreign countries, population density, an accounting of slum populations, and international tourist arrivals (Cutter et al. 2000).

The economic vulnerability category was designed primarily to measure the potential for economic losses within a country due to the exposure of a country's economy to exogenous shocks. The category is also an appraisal of the ability of a country to respond to shocks to its economic system (Briguglio et al. 2009). Relevant indicators for measuring exposure to economic losses and the potential for economic shocks include the density of exposed economic assets such as commercial and industrial infrastructure (Cutter et al. 2003, Briguglio et al. 2009). Metrics used to measure the ability of a country to withstand shocks to its economic system include reliance on imports/exports, government debt, and purchasing power (Briguglio et al. 2009). The economic vulnerability category also considers the economic vitality of countries. Since the economic vitality of a country can be directly related to the vulnerability and resilience of its populations, the category includes metrics aimed at measuring economic characteristics such as single-sector economic dependence, income inequality, and employment status (Cutter et al. 2003, Briguglio et al. 2009).

The third category, recovery and reconstruction potential, is very closely aligned with the concept of disaster resilience (see Cutter et al. 2008). The disaster resilience concept includes conditions that are inherent and that will allow communities within a country to absorb impacts and cope with a damaging earthquake event, such as the density of the built environment, education levels, and political participation

(Cutter et al. 2010; Burton 2015). Resilience also encompasses post event processes that facilitate a population's ability to reorganize, change, and learn in response to a damaging earthquake (Cutter et al. 2008, Burton 2015). Thus, enhancing a country's resilience to earthquakes is to improve its capacity to anticipate threats, to reduce its overall vulnerability, and to allow its communities to recover from adverse impacts from earthquakes when they occur.

Table 1: Potential indicators for social vulnerability assessment

Indicator Category	**Variable**	**Justification**
Social; Economic	Population density (people per sq. km)	Boruff and Cutter 2007; Birkmann 2007; Guillard-Goncalves et al 2014
Social; Recovery	% of population living in slums	Cardona 2005; Rufat et al. 2015
Social; Economic; Recovery	% of population with a disability	Adger et al. 2004; Guillard-Goncalves et al 2014; Chang 2001
Social; Economic; Recovery	Unemployment rate	Cardona 2005; Sherrieb et al 2010; Cutter et al. 2008
Economic; Recovery	GDP growth rate	Choi and Fisher 2003; Gall 2004
Social; Recovery	Road density	Holand et al. 2011; Cutter et al. 2003
Social; Recovery	Adult mortality rate	Rufat et al. 2015; Cardona 2005
Social; Economic; Recovery	% of population under 15 years of age	Holand et al. 2011; Cardona 2005; Burton 2015
Social; Economic; Recovery	% of population over 65 years of age	Holand et al. 2011; Cardona 2005; Burton 2015
Social; Recovery	Hospital beds per capita	Burton 2009; Cardona 2005; Kates et al. 2006
Social; Recovery	Female labor force participation rate	Cutter et al. 2003; Burton 2015
Social; Recovery	Governance (Voice and Accountability Index)	Brooks et al. 2005
Social; Economic; Recovery	Median income (USD)	Cutter et al. 2003; Cutter et al. 2008; Burton 2015
Social; Economic	Average debt per capita (USD)	Cardona 2005; Pelling and Uitto 2001
Economic	% building infrastructure that is commercial development	Guillard-Goncalves et al 2014

Economic	% building infrastructure that is industrial development	Cutter et al. 2003
Social; Economic; Recovery	Building density	Burton 2015; Cutter et al. 2010; Cardona 2005
Social; Economic; Recovery	Average household size	Mendes 2009; Guillard-Goncalves et al 2014; Rufat et al. 2015
Social; Economic; Recovery	% female headed households	Cutter et al. 2003; Guillard-Goncalves et al. 2014; Burton 2015
Social; Recovery	Universal health care service coverage index	Adger et al. 2004; Cutter et al 2010; Burton 2015
Social; Recovery	% of population without basic sanitation access	Adger et al. 2004; Guillard-Goncalves et al. 2014
Social; Recovery	Age dependency ratio	Holand et al. 2011; Cardona 2005; Burton 2015
Social; Economic; Recovery	Illiteracy rate	Adger et al. 2004; Guillard-Goncalves et al. 2014; Pelling and Uitto 2001
Social; Economic; Recovery	Net migration rate	Holand et al. 2011; Guillard-Goncalves et al. 2014; Kates et al. 2006
Social; Economic; Recovery	Government Effectiveness Index	Brooks et al. 2005; Geis 2001
Social	Birth rate	Mendes 2009
Social; Recovery	Crime rate (theft, robbery, vandalism)	Kotter and Friesecke 2009
Social; Economic	Gross fixed capital formation	Cardona 2005; Cutter et al. 2008
Recovery	Environmental Sustainability Index	Cardona 2005
Economic	Foreign direct investments	Briguglio 1995
Social; Economic; Recovery	GDP per capita	Boruff et al. 2005; Rufat et al. 2015; Fukultat et al. 2009;
Social; Economic; Recovery	GINI index	Adger et al. 2004; Mayunga 2007; Cutter et al. 2010
Social; Economic; Recovery	International tourism receipts as a percent of GDP	Guillard-Goncalves et al 2014; Cutter et al. 2008; Kumpulainen 2006
Social; Economic; Recovery	% population with electricity access	Boruff and Cutter 2007; Guillard-Goncalves et al. 2014; Kates et al 2006
Social	Number of refugees per capita	Uekusa 2017
Social	Life expectancy at birth	Brooks et al. 2005

Social; Economic; Recovery	Inflation rate	Cardona 2005; Choi and Fisher 2003
Economic	Merchandise exports FOB	Cardona 2005
Economic	Merchandise imports CIF	Cardona 2005
Social; Economic	General government gross debt	Boruff et al. 2005
Social; Economic	Gross government revenue	Cardona 2005
Recovery	Research and development expenditures	Kumpulainen 2006; Burton 2015
Social	% population that is a foreign-born migrant	Cutter et al. 2003; Guillard-Goncalves et al. 2014
Social; Recovery	Crude death rate	Rufat et al. 2015; Cardona 2005
Social; Economic	GDP composition by sector - industry	Cutter et al. 2003; Holand et al. 2011; Kates 2006
Social; Recovery	Education expenditures per capita	Mayunga 2007
Social; Economic	GDP composition by sector - services	Cutter et al. 2003; Holand et al. 2011; Kates 2006
Social; Economic; Recovery	% population in poverty	Cutter et al. 2003; Morrow 2008; Burton and Silva 2015
Economic	GDP at purchasing power parity per capita	Fukultat et al. 2009
Social; Recovery	% of population without a secondary education or higher	Cutter et al. 2003; Burton 2015
Recovery	Remittance inflows in USD	Adger et al. 2004
Social; Recovery	% voter turnout at last parliamentary election	Holand et al. 2011; Cutter et al. 2010
Social; Recovery	% of working aged population employed in industry	Holand et al. 2011; Kates et al. 2006
Social; Recovery	% of working aged population employed in services	Cutter et al. 2010
Social; Economic; Recovery	% of households with motor vehicle access	Van Vandt 2012; Cutter et al. 2010; Burton 2015
Social; Recovery	Cellular phone subscriptions per capita	Colten 2006; Cutter et al. 2010
Social	Fixed broadband internet subscribers per capita	Allaire 2016
Social	Mortality rate (under 5 years)	Mendes 2009
Social; Recovery	Mean years of schooling	Holland et al. 2011; Cardona 2003; Burton 2015
Social	% of children out of school (primary)	Guillard-Goncalves et al. 2014
Social	Ratio of literate males to females ages 15-24	Adger et al. 2004; Guillard-Goncalves et al. 2014; Pelling and Uitto 2001

Social; Recovery	Primary school completion rate	Guillard-Goncalves et al. 2014
Social; Recovery	% rural population	Fekete 2009; Cutter et al. 2016
Social; Economic; Recovery	% population with access to improved sanitation facilities	Adger et al. 2004; Guillard-Goncalves et al. 2014
Social; Economic; Recovery	% population with access to an improved water source	Adger et al. 2004; Guillard-Goncalves et al. 2014; Hagenlocher et al. 2016
Social; Economic	Health expenditures per capita	Adger et al. 2004; Gall 2003
Social; Recovery	Physicians per capita	Cutter et al. 2003; Cutter et al. 2010
Social	International tourism arrivals per capita	Kumpulainen 2006
Social	% population that is undernourished	Kumpulainen 2006
Social; Economic; Recovery	Gross national savings	Shaw 2009; Morrow 2008; Kates et al. 2006
Social; Economic; Recovery	GDP per capita	Adger et al. 2004; Burton 2009; Fukultat et al. 2009
Social	Infant mortality rate	Mendes 2009
Social	Gross education enrollment ratio, secondary	Holland et al. 2011; Cardona 2003; Burton 2015
Social	Gross education enrollment ratio, primary	Holland et al. 2011; Cardona 2003; Burton 2015
Social	Gross education enrollment ratio, tertiary	Holland et al. 2011; Cardona 2003; Burton 2015
Social; Economic; Recovery	% adult labor force participation	Cutter et al. 2003; Guillard-Goncalves et al. 2014; Burton 2015
Social; Economic; Recovery	International tourism receipts as a percentage of total exports	Guillard-Goncalves et al. 2014; Cutter et al. 2008; Kumpulainen 2006
Social; Economic; Recovery	Ratio of males to females	Cutter et al. 2000; Fukultat et al. 2009; Cutter et al. 2010

Once the 78 potential proxy indicators were identified, the raw data was collected. The primary source of the data was the GEM 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 vulnerability concept. Figure 1 illustrates the data sources and the different proportions they contributed to the socio-economic database. Here, 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.

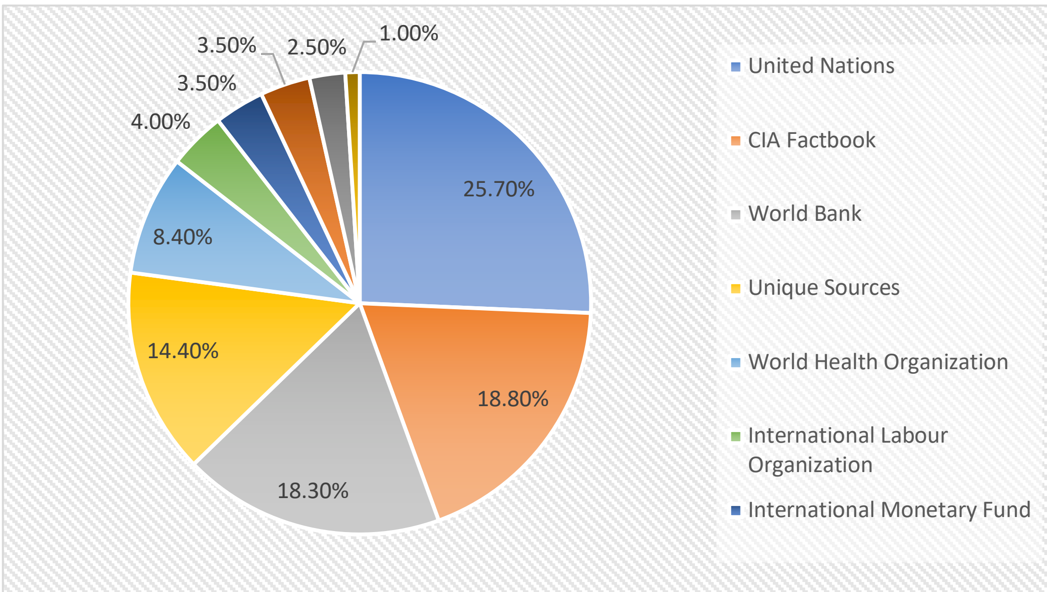

Figure 1. Sources and their percent contribution to the GEM social vulnerability database. Adapted from: Power et al. (2014)

4.2 Multivariate analysis

The quality of composite indicators depends not only on the methods used in the construction process, but also on how well the variables may measure the underlying concept (Nardo et al 2008; Tate 2012). For this reason, a multivariate analysis was conducted prior to attempting to validate the indicators and aggregating them into composite indices. The multivariate analysis was accomplished to distinguish potentially relevant from non-relevant data and to reduce potential measurement redundancies. As a primary step, the raw data was transformed into comparable scales using either percentage, per capita, and density functions where the transformation type was based on how a particular variable was described in the literature (see Table 1) or based on the author's expert judgement. The data was then standardized using a Min-Max rescaling scheme to render the indicators commensurate (i.e. 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 worst rank for an indicator score and 1 being the best rank). A seventy-eight by seventy-eight-dimension correlation analysis was conducted as a third step using all of the data. Here, we utilized a non-parametric correlation analysis because preliminary testing of the data revealed a large number of non-parametric and non-linear relationships between variables. During the correlation step, twenty-five variables were interpreted as highly correlated (Spearman's R >0.700). These variables were eliminated from further consideration to avoid subjectively choosing one variable over another for inclusion in subsequent analyses. The remaining fifty-three variables were considered appropriate for the final validation step described in the sub-section below.

4.3 Indicator validation

To date, there has been little systematic research on the relationship between economic losses and other adverse impacts such as fatalities from earthquakes and social and economic vulnerability. Such a research gap restricts the ability of researchers to forecast the social consequences of earthquakes (Schmidlein et al. 2011). For this reason, we focused on the statistical association between our vulnerability indicators on a country by country basis and the adverse impacts from historical earthquakes. The EM-DAT Emergency Events Database (CRED 2009), which contains core data on the occurrence and effects of over 22,000 natural hazard impacts and disasters from 1900 to the present, provided our external validation metrics. From the EM-DAT database, we collected data from damaging earthquake events that conformed to at least one of four criteria: 1) had at least 10 fatalities, 2) had 100 people or more affected, 3) had a declaration of a state of emergency, and/or 4) had a call for international assistance. This data selection accounts for classes of earthquakes that are strong or greater, but also considered moderate earthquakes that were damaging (i.e., MMI >=5.0). It was within this context that four external validation metrics were created considering events spanning nearly two decades (2000-2018): a) losses from damaging earthquakes per country in $USD, b) fatalities caused by earthquakes per capita, (c) homelessness caused by earthquakes per capita, and d) total affected populations from earthquakes. These were standardized to account for time (i.e. by dividing the total losses by the timeframe in which the losses occurred) and population change (i.e. by averaging the total population during the timeframe for the per capita calculations)

To identify the variables that are associated with the adverse impacts form earthquakes, and thereby validated, a multivariate regression modelling procedure was utilized. A regression analysis was chosen for the validation portion of this research since regression provides a simplistic view of the relationship between variables and provides measures of statistical significance, strength, and direction of the association between variables. Four regression models were calibrated. These incorporated the four adverse impact metrics (losses, fatalities, homelessness, impacted) as response variables and the proxy variables to represent the social vulnerability concept ($X1_i$ $X2_i$...X_i) and economic vulnerability concept ($X1_i$ $X2_i$...X_i) as predictor variables. This approach allowed for the prediction of Y_i (each of the earthquake impact outcomes) that was based on the pre-existing social and economic conditions within countries $X1_i$ $X2_i$...X_i. For this research, an ordinal logistic regression model (sometimes referred to as a *cumulative logit* model) was utilized since preliminary testing of the data showed a violation of regression's linearity and normality assumptions, meaning a non-linear/non-parametric procedure needed to be sought. An ordinal logistic regression can only be calibrated when dependent variables have more than two dichotomous classes that are ordered, however. For this reason, the values for each of the earthquake impact variables were reclassified into continuous intervals with equal probabilities using quantiles and four data classes (1, 2, 3, 4). A value of 1 was assigned to countries with their impact data values falling within the first quartile, a value of 2 was assigned to data classes falling within the second quartile, and so on. As opposed to fitting a straight line to the data, a logistic regression applies maximum likelihood estimation after transforming the dependent variable into a logit variable (Fox 2000). A logit variable is the natural log of the odds of a dependent variable equalling a certain value, meaning the logit model is based on the odds of a certain value (or event) occurring, a country experiencing an increased economic loss potential from earthquake due to characteristics driving its social or economic vulnerability for example.

It's important to note that measures of recovery from damaging earthquake events are highly localized (e.g., Despotaki et al. 2018). To date, quantified recovery studies from natural hazard impacts in general are very few and have been conducted at the neighbourhood, city and regional level only. These include a study of housing losses and recovery problems following the 1994 Northridge Earthquake (Comerio 1997), a spatial and temporal analysis of the recovery from the 2014 Napa California Earthquake (Despotaki et al. 2016), a five-year analysis of the recovery from Hurricane Katrina (Burton et al. 2011; Burton 2015), and the analysis of exposure and recovery disparities in New Jersey following Hurricane Sandy (Cutter et al. 2014). Since there is no acceptable and justifiable data to externally validate the recovery index at the global level, only the social and economic vulnerability indices were used in the external validation step. The selection of indicators for the recovery index was based on literature citations only, which is an accepted form of validation.

5.0 Results

5.1 Model validation results

The regression analyses to select a set of indicators revealed that thirty-six indicators might be fit for measuring global social and economic vulnerability (Table 2). The decision on fitness for purpose for indicators to be included in our final composite indices was based on the statistical significance of each individual variable ($p \leq 0.050$). If a variable was found statistically significant, it was considered valid, and the indicator was included in one or more of our final composite indices.

The parameter estimates denoted by B relate the earthquake impact variables to the parameters selected to measure characteristics of social and/or economic vulnerability. The order of the importance of the variables is highlighted by their regression coefficients. The R-square statistics for the models range from 0.270 to 0.601 leaving an average of 63 percent of the variance unexplained. The lowest explanatory power (i.e., 0.270) is attributed to the annual homelessness caused by damaging earthquakes model. The annual losses from damaging earthquakes model accounts for the highest explanatory power (i.e., 0.601). The total fatalities and total affected models explain 0.337 and 0.272 percent of the variance, respectively.

The results of the annual losses from damaging earthquakes model suggests that building density, population density, and GDP per capita are the strongest predictors of earthquake losses globally as a function of our selected social and economic vulnerability indicators. This finding is directly related to country wealth and the amount of infrastructure in harm's way. It is within this context that wealth enables communities to absorb losses. However, the value, quality, and density of residential construction affects potential losses and recovery where expensive homes are costly to replace (Cutter et al. 2003). Conversely, the results demonstrate that countries with high percentages of populations in poverty, or with high levels of inequality, are also likely to experience economic losses from earthquakes. This finding is noteworthy because poverty and inequality often directly relates to the poor and marginalized being located in high hazard zones as well as the type of infrastructure they inhabit (Cutter et al. 2003; Burton 2010).

The results of the annual fatalities from damaging earthquakes regression model suggest that population density, building density, population in poverty, population living in slums, under 5-years of age mortality rate, and undernourishment are all predictors of fatalities from earthquake events. Here, the extent to which populations have sufficient assets and financial resources to mitigate against, prepare for, and respond to damaging earthquake events will affect mortality rates from earthquakes. When large segments of a society are poor, for instance, it is less plausible to expect residents to be have funds for adherence to building codes, building mitigation, emergency preparation, and the facilitation of resources to assist residents during search and rescue operations (Morrow 2008). The results show that age is also a predictor of fatalities. This is because extremes of age (the very young and very old) have mobility constraints or mobility concerns that impede movement out of harm's way (Cutter et al. 2010). Expenditures on education, research and development spending, and voter participation are also statistically significant indicators that contain a negative beta coefficient, meaning that for every one unit increase in one of these variables, fatalities are expected to decrease. It is within this context, that education and the ability to affect public policy translates directly into populations that are more resilient to the impacts of natural hazard events (Burton 2015).

For the prediction of homelessness, the results of the annual homelessness from damaging earthquakes regression model demonstrates that population density and building density are the best predictors for homelessness. With the increased density of property in harm's way, the chances of being displaced from a hazard event increase (Burton 2015). Moreover, the loss of residential infrastructure may place an insurmountable financial burden on communities that lack the financial resources to rebuild, and those that are renters may lack sufficient shelter options when lodging becomes uninhabitable or too costly to afford (Cutter et al. 2003). GDP and populations in poverty are also statistically associated with homelessness. A high socioeconomic status increases the ability of populations to absorb and recover from losses, decreasing the chance of homelessness. People with a low socioeconomic status, however, are economically and socially marginalized and will require support in pre- and post-disaster periods (Morrow 1999; Cutter et al. 2003).

Predictors for total populations that are impacted from earthquakes include inequality, age, population density, building density, death rate, poverty, and populations living in slums. Gross fixed capital formation, labour force participation, voting, and remittances are all predictors of a decreased impact to populations overall. Here, the ability to reduce impacts is a function of economic vitality, community involvement, involvement in the political process, and personal support. All are key drivers of disaster preparation and the ability to recover from damaging events when they occur (Burton 2015).

Table 2. Index validation results for: 1) earthquake losses, 2) earthquake fatalities, 3) total homelessness, 4) total impacted

	B **Losses**	***B*** **Fatalities**	***B*** **Homeless**	***B*** **Impacted**
Inflation rate	*ns*	*ns*	*ns*	*ns*
Research and development expenditures	-0.111*	-0.017*	-0.133**	-0.017**
General government gross debt	0.143***	*ns*	*ns*	*ns*
Gini index	0.244**	0.221***	0.174**	0.177***
Environmental Sustainability Index	*ns*	*ns*	*ns*	*ns*
% population with electricity access	*ns*	-0.033*	*ns*	*ns*
Age dependency ratio	*ns*	0.304*	*ns*	0.157
% population that is a foreign-born migrant	0.068*	0.019*	0.023*	0.016*
% adult labor force participation	-0.021*	0.011*	-0.023*	-0.011*
Foreign direct investments	*ns*	*ns*	*ns*	*ns*
Gross fixed capital formation	0.183*	*ns*	*ns*	-0.287***
Crime rate (theft, robbery, vandalism)	*ns*	0.238*	*ns*	*ns*

% voter turnout at last parliamentary election	-0.199**	-0.251***	-0.164***	-0.198***
% population with access to an improved water source	*ns*	*ns*	-0.122*	0.092*
% population in poverty	0.322**	0.422***	0.254***	0.334***
Physicians per capita	*ns*	*ns*	*ns*	*ns*
Net migration rate	*ns*	*ns*	*ns*	0.030*
Population density (people per sq. km)	0.332***	0.577***	0.308***	0.388***
% of population living in slums	*ns*	0.302**	*ns*	0.394***
Unemployment rate	-0.034*	-0.046*	*ns*	*ns*
GDP growth rate	*ns*	*ns*	*ns*	*ns*
Road density	0.226***	*ns*	*ns*	*ns*
Female labor force participation rate	-0.008*	*ns*	*ns*	-0.101***
Governance (Voice and Accountability Index)	-0.297***	*ns*	*ns*	*ns*
% infrastructure that is commercial development	0.104***	*ns*	*ns*	*ns*
% infrastructure that is industrial development	0.082***	*ns*	*ns*	*ns*
Building density	0.475***	0.565***	0.486***	0.545***
Average household size	0.101**	0.114***	*ns*	0.026*
% female headed households	*ns*	*ns*	*ns*	*ns*
GDP per capita	0.377***	-0.104***	-0.252***	-0.099***
Illiteracy rate	*ns*	*ns*	0.044*	0.067*
Median income (USD)	*ns*	*ns*	*ns*	*ns*
Remittance inflows in USD	*ns*	-0.233	*ns*	-0.093*
Merchandise exports FOB	-0.178*	*ns*	*ns*	*ns*
Merchandise imports CIF	0.076*	*ns*	*ns*	*ns*
% working aged population employed in industry	*ns*	*ns*	*ns*	*ns*
% working aged population employed in services	*ns*	*ns*	*ns*	*ns*
Gross national savings	-0.107***	*ns*	*ns*	*ns*
% of population without a secondary education or higher	*ns*	*ns*	*ns*	*ns*
GDP composition by sector - industry	*ns*	*ns*	*ns*	*ns*
Cellular phone subscriptions per capita	*ns*	*ns*	*ns*	*ns*
Gross government revenue	*ns*	*ns*	*ns*	*ns*
International tourism receipts as a percent of GDP	-0.011*	*ns*	*ns*	*ns*
Ratio of males to females	*ns*	*ns*	*ns*	*ns*
Education expenditures per capita	-0.232**	-0.133*	*ns*	-0.112**
Mortality rate (under 5 years)	0.000***	0.551**	*ns*	*ns*
Primary school completion rate	0.009*	*ns*	*ns*	-0.021*
GDP composition by sector - services	*ns*	*ns*	*ns*	*ns*
Crude death rate	*ns*	0.256*	0.136*	0.232**
% population that is undernourished	*ns*	0.400**	*ns*	0.322*
Number of refugees per capita	*ns*	*ns*	*ns*	*ns*
International tourism arrivals per capita	*ns*	0.117*	*ns*	0.022*

% rural population	*ns*	*ns*	*ns*	*ns*
Note: For all models, significance >= 0.05; pseudo R2 = 0.601, 0.337, 0.270, 0.272 (Nagelkerke). *Significant at 0.05 **Significant at 0.01 ***Significant at 0.001				

5.2 Spatial distribution of global social vulnerability

Up until this point, this article has been concerned exclusively with the identification of a validated set of variables for measuring aspects of global social vulnerability, economic vulnerability, and recovery potential from earthquakes. To display the relative vulnerability to earthquakes throughout the world, we created our three composite indices using the variables identified as being statistically associated with one or more of the earthquake impacts (see Table 3). Variables that did not demonstrate statistical significance were not considered fit for use in an index. The assignment of specific variables to an individual index, and the directionality regarding how each variable contributes to its index (for example a high percent poverty increases a country's social vulnerability whereas a high GDP decreases a country's social vulnerability), were based on: 1) how a variable was cited within the literature (e.g., if a variable was cited in the literature as contributing economic vulnerability, it was placed in the economic vulnerability index); 2) the variable's statistical association with the outcome measures; and c) the expert opinion of the authors. For these reasons, some variables overlap because they were considered ideal proxy variables for more than one of the indices.

The method of aggregation to derive each of the final composite indices is the equally weighted average of all variable scores within each index. The standardized variable scores within each index were averaged to reduce the influence of a differential number of variables within each index contributing unevenly to the mapped outputs. Each averaged index score was then rescaled between 0 and 1 and mapped. Before aggregating the data, we chose to apply equal weights to each indicator because there was no theoretical or practical justification for the allocation of importance across indicators for this particular case study that considers every country in the world.

Table 3. Final composite indices with directionality

Variable	Social Index	Economic Index	Recovery Index
Research and development expenditures	–	–	(+)
General government gross debt	–	(+)	(-)
Gini index	(+)	(+)	(-)
% population with electricity access	–	–	(+)
Age dependency ratio	(+)	(+)	(-)
% population that is a foreign-born migrant	(+)	–	(-)
% adult labor force participation	(-)	(-)	(+)
Gross fixed capital formation	–	(-)	–
Crime rate (theft, robbery, vandalism)	(+)	–	–
% voter turnout at last parliamentary election	–	–	(+)
% population with access to an improved water source	(-)	–	–
% population in poverty	(-)	–	(-)
Net migration rate	(+)	–	(-)
Population density (people per sq. km)	(+)	–	–
% of population living in slums	(+)	–	–
Unemployment rate	(+)	(+)	(-)
Road density	–	(-)	(+)
Female labor force participation rate	–	(-)	–
Governance (Voice and Accountability Index)	–	–	(+)
% building infrastructure that is commercial development	–	(+)	–
% building infrastructure that is industrial development	–	(+)	–
Building density	(+)	(+)	–
Average household size	(+)	–	(+)
GDP per capita	(-)	(-)	(+)
Illiteracy rate	(+)	–	(-)
Remittance inflows in USD	–	(-)	(+)
Merchandise exports FOB	–	(+)	–
Merchandise imports CIF	–	(+)	–
Gross national savings	–	(+)	(-)
International tourism receipts as a percent of GDP	–	(+)	(-)
Education expenditures per capita	(-)	(-)	(+)
Mortality rate (under 5 years)	(+)	–	–
Primary school completion rate	(-)	–	(+)
Crude death rate	(+)	–	–
% population that is undernourished	(+)	–	–
International tourism arrivals per capita	(+)	–	–
% rural population	–	–	(-)

The aggregated composite index scores used to create the social vulnerability, economic vulnerability, and recovery potential maps (Figures 2-4, respectively) provide a comparative assessment of the overall susceptibility of populations to adverse earthquake impacts and the recovery potential of societies from damaging earthquake events worldwide. For the economic and social vulnerability maps, the countries symbolized in dark red have the highest levels of vulnerability. Countries symbolized in dark red on the recovery potential map have the lowest recovery potential. When mapped, the geographic variations in the differential susceptibility of populations and economies to the adverse effects of damaging earthquake impacts becomes evident, as does differential ability of countries to recover from them.

The aggregated composite index scores visualized using the social vulnerability map (Figure 2) provides a comparative assessment of the potential within social systems for losses or harm throughout the world. The results demonstrate that a number of African countries spanning Central and Sub-Saharan Africa as well as South Asian countries such as Afghanistan have the highest potential for adverse human impacts from earthquakes. Some South Asian countries such as Pakistan, India, Bangladesh and Southeast Asian countries such as Myanmar also demonstrate high levels of social vulnerability. It is within this context that countries with high social vulnerability scores, as per the data, tend to have high unemployment rates, high numbers of slum populations, high illiteracy rates, low GDP's per capita, and low levels of government effectiveness. These high vulnerabilities tend to occur in developing countries where social and economic marginalization are arguably widespread. These are the countries of potential risk management concern since they have populations that may not have the ability to prepare for, respond to, and recover from damaging earthquake events when they occur. On the other hand, predominantly developed countries such as the United States and Canada, Australia and European countries such as the United Kingdom, Germany, Norway, Sweden and Finland have low vulnerability scores. These countries will likely demonstrate a higher degree of earthquake resilience than the more socially vulnerable nations mentioned above.

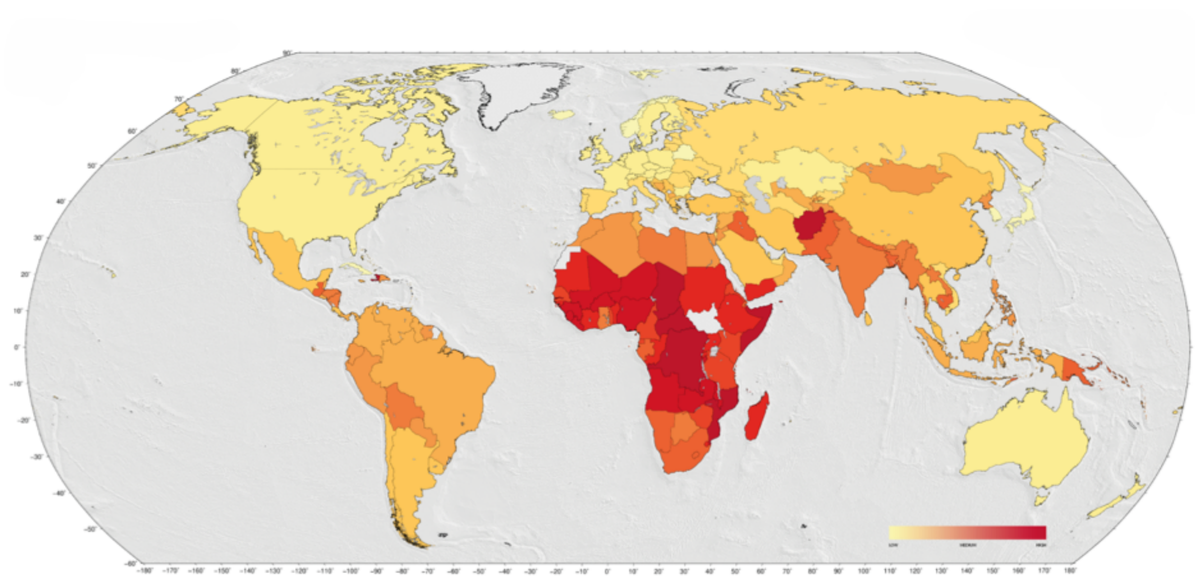

Figure 2: Global social vulnerability index

Figure 3 demonstrates the worldwide potential for economic impacts as a result of each country's comparative economic vulnerability. The results show that most of the African countries including Mauritania, the 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 some Middle Eastern countries such as Iraq, Syria and Yemen also share a high economic vulnerability to earthquake hazards. From the data, it should be noted that some countries that score high on economic vulnerability demonstrate 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 could contribute to a significantly hampered recovery following an earthquake event (Cutter et al. 2003). Other countries such as those that score in the moderate range (the U.S. and China for example) have a high density of commercial and industrial assets. On the other hand, developed countries including Australia, Canada, and some European countries including Norway, Sweden, Finland, Germany and Poland have a low economic vulnerability, comparably.

It should be noted that countries such as Nepal and Kazakhstan have low levels of economic vulnerability as per the composite index. Kazakhstan is an upper middle-income country with one of the lowest total infrastructure densities in the world, which heavily affects its comparative index score. The country also has a very low inequality rate and a very low level of government debt, comparatively. In addition, Kazakhstan has very little reliance of imports and exports, comparatively. Nepal is a low-income country with very little high-density building exposure outside of the Kathmandu Metropolitan City. The country is an agricultural nation with very little commercial and industrial infrastructure exposure, yet the structure of the Nepali economy is shifting from agriculture with increased migration to urban areas as well as increased migration abroad where Nepal received approximately 25.1 percent of its GDP in FY 2017/18 from remittances (OEC 2019). Nepal also has a relatively low unemployment rate, as per the data, and has a very low dependence on imports and exports where the country's main imports are petroleum products (petrol, diesel, LPG), gold, rice, telecommunications equipment, and construction equipment, mainly from India, China, and France (OEC 2019).

Although impacts to the country may be severe, they have less to lose in terms of economic possessions which equates to less overall economic vulnerability, in this case, as the economic vulnerability index is geared heavily towards measuring economic assets exposure.

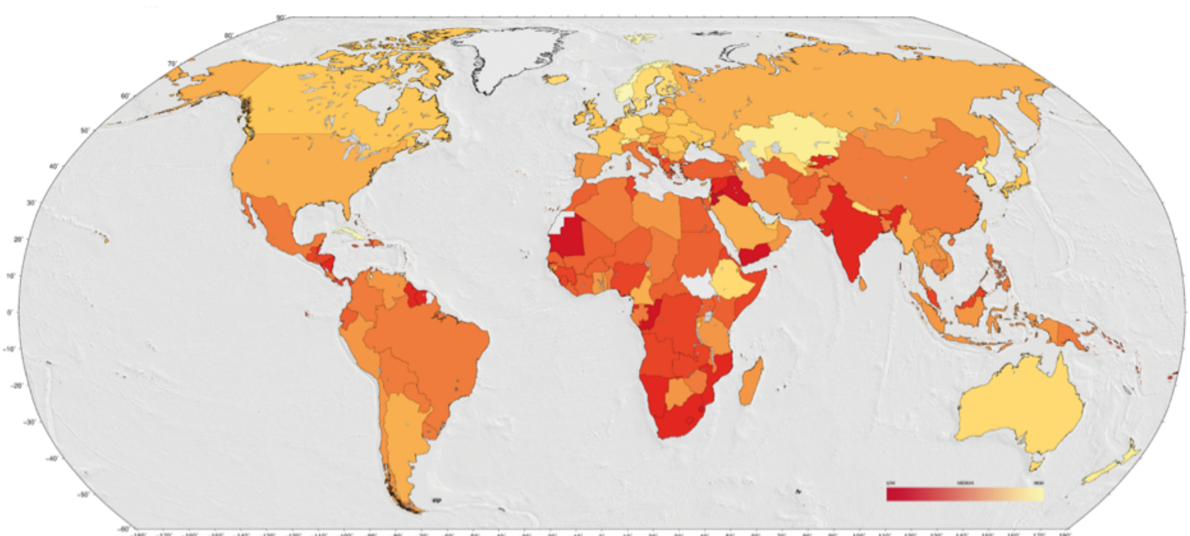

Figure 3. Global economic vulnerability index

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 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 South Asian countries such as Pakistan and Afghanistan show the lowest potential for recovery. The data reveals that the countries with the highest recovery potential typically have low unemployment rates, higher level of governance, higher number of hospital beds per capita, higher GDP’s per capita, higher gross national savings, and lower government debt.

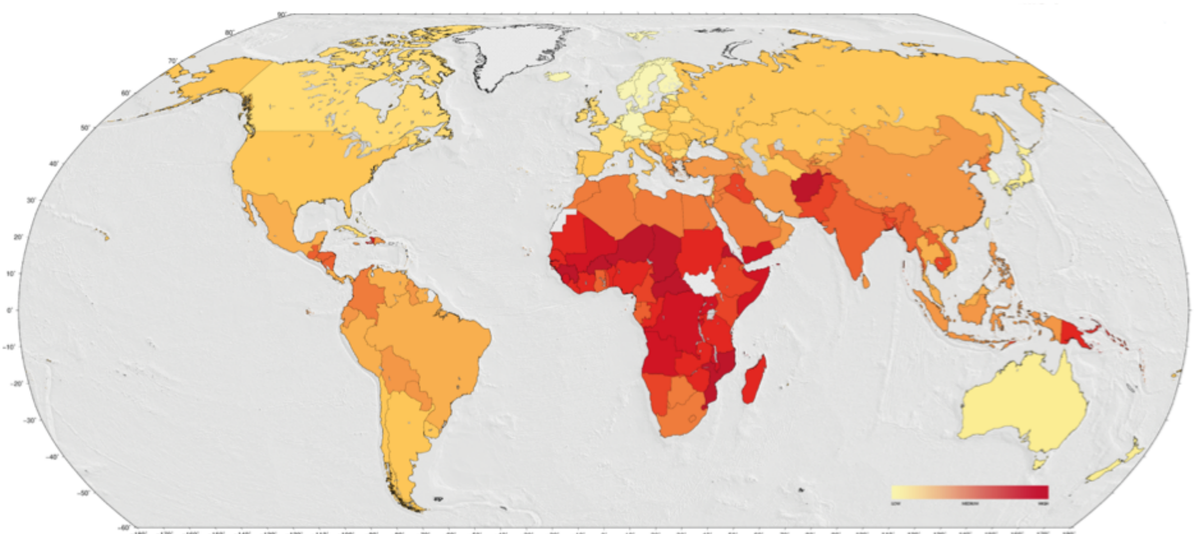

Figure 4. Global recovery and reconstruction index

5.3 Integrated risk assessment

6.0 Discussion

The vulnerability concept helps to explain the reasons behind differential consequences experienced from earthquakes. The development of composite indices of vulnerability to earthquakes is useful for benchmarking, public policy development, and planning for earthquake risk reduction. The development of such metrics 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-brushed first assessment of the vulnerability of countries to earthquake events considering social characteristics that will lend to more detailed analysis at the sub-country level and for an increased understanding of place-specific factors affecting the social and economic vulnerability of populations, as well as the recovery potential of communities from earthquakes. Academic research on 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 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 different places, yet these studies often lack hazard context, and there rarely are attempts to validate the findings.

For better understanding the 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 vulnerability to earthquakes and choices made in the modelling process were tenuous (Rufat et al. 2015). The methods applied, and the results obtained for this study, highlight several gaps in knowledge regarding the construction of composite indicators of 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.

6.1 Missing or incomplete data

One of the challenges in the construction of composite indices is that data is not always reported by all countries equally. Imputation of missing data is therefore important because it is a necessary step for conducting statistical operations and robust comparisons. 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. 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.

6.2 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 paper considered country comparisons, but to influence public policy for earthquake disaster risk reduction, 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 vulnerability and/or recovery 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.

6.3 Model sensitivity and uncertainty

The outcomes of this research depends largely on the variables selected and construction decisions used for the development of the three composite indices.. Each decision, such as which variables to include, 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 gauge 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 indicator scores when modelling parameters such as the variables chosen for the modeling are changed. Uncertainty analysis may then be followed by a sensitivity analysis which quantifies the proportional contribution of each modeling decision to the overall uncertainty of the model (Tate 2012).

7.0 Conclusion

Although earthquakes are one of the most devastating natural hazards that affects humanity, there are few studies that objectively measure social characteristics of earthquake risk considering validated metrics of vulnerability. Moreover, there is no agreed-upon framework and established sets of data to measure vulnerability to earthquakes. The purpose of this study was to produce composite indices representing the vulnerability of countries from earthquakes within three topical areas (social vulnerability, economic vulnerability, recovery and reconstruction potential).

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 where people live, work, and socialize. It is here that an increased understanding of the social characteristics of populations at risk from earthquakes leads to a perspective on earthquake risk that allows stakeholders to:

- mainstream the vulnerability concept into policy discussions on reducing earthquake losses and damage;
- utilize vulnerability assessments (social and economic) 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
- recognize that the causes and solutions for reducing earthquake impacts are found in human-environmental interactions.

Although there has been a multitude of studies to quantify risk and vulnerability from earthquake hazards, very few attempts have been made to integrate economic aspects, human impact potential, and recovery potential. This study has attempted to address these aspects to quantify earthquake vulnerability at a global scale using a thematic composite index-based modeling 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.

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