Agricultural and Forestry Sciences

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November 27, 2018

Dear Editor Dr. Paolo Tarolli

Thank you for considering our paper for a fourth revision. In this fourth submission, we submit a revised version of our paper with changes accepted, an abstract and in this file the response point by point to the comments and the changes to the article, and a revised version with changes that are not accepted. We hope that after this third revision we have clarified the reviewer comments that have centered mainly in the selection of the variables to construct the social vulnerability index. We did not intend to explain the factors that model social vulnerability neither to assume that a PCA based social vulnerability index is the definite way to describe social vulnerability in an evacuation process. However, we understand the concern of the reviewer and we addressed the comments in the following pages.

With all the best,

Dr. Marcelo Somos-Valenzuela

Corresponding author

Comment Reviewer 1, third revision

Comment 1: This manuscript continues to lack in demonstrating the choice and the validity of the variables chosen for the social vulnerability to evacuation. The authors argue that are widely considered in the computation of the index per se but not for evacuation purposes. I would consider socio-demographic characteristics rather than economic ones. How can income burden the capacity to evacuate?

Response Comment 1:

In the case of floods, we found few studies that seek to understand the relationship between evacuation and socioeconomic variables. For example, Henry et al., (2017) analyzed the relationship between income disparity and disaster information collection, and the resulting impacts on peoples' vulnerability after the 2011 Chao Phraya River Flood in Thailand. They found that among different demographic and socioeconomic variables, income was the strongest predictor of the population's decision to evacuate during the flood ($p<0.01$). They concluded that "…among those respondents affected by the flood, it could be seen that lower-income respondents had a higher tendency not to evacuate their homes" (page 5).

Furthermore, Medina & Moraca (2016) conducted a study to identify factors that influence the decision to evacuate upon flood warning by authorities in the province of Bukidnon, Philippines. They found that household income, measured as poverty, was a significant factor to explain whether families will evacuate upon advices by local authorities. According to Henry et al., (2017) household income is linked to different levels of access and use of information during flood evacuation and that could be one of mechanisms how income influences the decision making process to evacuate. They said "lower-income respondents tended to also utilize lower technology modes, such as radios and loudspeakers, in contrast to the internet-based modes used by higher-income respondents. Lower-income respondents also tended to be less aware of the government hotline…" (page 9). Moreover, research in social psychology and education show that wealthier families are more likely to take informed decisions because they have better access to information and more experience with choices and alternatives (Levin, 1998). Instead, low-income families have less access to information and are less likely to use official channels to make decisions (Ladd, 2002).

References

Henry, M., Kawasaki, A., Takigawa, I., & Meguro, K. (2017b). The impact of income disparity on vulnerability and information collection: an analysis of the 2011 Thai Flood. Journal of Flood Risk Management, 10(3), 339–348. https://doi.org/10.1111/jfr3.12144

Ladd, H. (2002). School Vouchers: A Critical View. Journal of Economic Perspectives, 16(4), 3–24.

Levin, H. (1998). Educational vouchers_ Effectiveness, choice, and costs.pdf. Journal of Policy Analysis and Management, 17(3), 373–392.

Lim, M. B., Lim, H., Piantanakulchai, M., & Uy, F. (2016). A household-level flood evacuation decision model in Quezon City, Philippines. Natural Hazards, 80(3), 1539–1561. https://doi.org/10.1007/s11069-015-2038-6

Medina, M., & Moraca, J. (2016b). Should I Stay or should I Go? Determinants of Evacuation upon Flood Warning among Households in a Flood Prone Area in Bukidnon, Philippines. International Letters of Natural Sciences, 50, 70–75. https://doi.org/10.18052/www.scipress.com/ILNS.50.70

Therefore, we modified the document as follow:

In page 3 lines 25 to 29 the document originally said:

"Huang, Lindell, & Prater (2016) analyzed 49 studies conducted since 1991 linking evacuations to hurricane warnings and they concluded that demographic variables have a minor or inconsistent impact on household evacuations. In the case of floods, however, we have not found any studies that link demographic and socioeconomic variables to the evacuation process.”

Now it says:

“Huang, Lindell, & Prater (2016) analyzed 49 studies conducted since 1991 linking evacuations to hurricane warnings and they concluded that demographic variables have a minor or inconsistent impact on household evacuations. In the case of floods, however, we found few studies that seek to understand the relationship between evacuation and socioeconomic variables. For example, Henry et al., (2017) analyzed the relationship between income disparity and disaster information collection, and the resulting impacts on peoples’ vulnerability after the 2011 Chao Phraya River Flood in Thailand. They found that among different demographic and socioeconomic variables, income was the strongest predictor of the population’s decision to evacuate during the flood ($p<0.01$). They concluded that “…among those respondents affected by the flood, it could be seen that lower-income respondents had a higher tendency not to evacuate their homes.” Furthermore, Medina & Moraca (2016) conducted a study to identify factors that influence the decision to evacuate upon flood warning by authorities in the province of Bukidnon, Philippines. They found that household income, measured as poverty, was a significant factor to explain whether families will evacuate upon advices by local authorities.

Comment 2: The capacity of people to evacuate less or faster is related to mobility factors, family interactions, community organization and information, distance from security points, etc. This makes me still skeptical in consideration of these variables and the outcomes of the current manuscript. Please justify it strongly. As you are proposing a new index, the choice and justification of the variables are essential.

Response Comment 2:

What the reviewer is pointing out here is the ability of the people to reach a safer area when the decision of evacuate has been taken. We did not use the variables in that context. We used them only to determine how social vulnerability affects the time when people decide to leave. As we mentioned in the comment 1 (above), there are not too many studies that seek to understand the relationship between the moment in which people decide to evacuate a river flood prone area and the population's demographic and socioeconomic characteristics. However, the literature found shows similar variables than this study. For example, Lim et al., (2016) pointed out "…that evacuation decision can be determined by a combination of household characteristics and capacities to cope with flood and hazard-related factors. Significant factors to evacuation decision include household characteristics (gender, educational level, presence of children less than or equal to 10 years old, and number of years living in the residence), capacity-related factors (house ownership, number of floors, type of house material), and hazard-related ones (distance from source of flood, level of flood damage, and source of warning)". Furthermore, Medina & Moraca (2016) found that "college education, having children below 5 years in the household, poverty, and depth of flood experienced positively influences a family's decision to evacuate upon flood warning in the study area". Finally, Henry et al. (2017) concluded that household income is the most relevant predictor, among other demographic and socioeconomic variables, to explain why people evacuate during flood in the 2011 Chao Phraya River Flood in Thailand.

The following table shows those variables that studies cited here have found relevant to explain whether population evacuate or stay at home during a flood evacuation (left side) and the variables used by this study (right side).

Previous studies on river flood evacuation	**Current study (RETSVI)**
Gender	Women
Educational level	Population with primary education Population with college education Illiterate population

Presence of children	Children less than 1 year old
Poverty	Population with health insurance Informal settlement Household without electricity Indigenous population
Household income	Household with 5 or more rooms Population with “white collar jobs” Jobs in the manufacturing sector Jobs in the commerce sector Jobs in the construction sector Adult population divorced
House ownership, number of floors, type of house material	House rented Independent houses
	*Population with disabilities *Population older than 65 years old

* These variables do not appear in studies of flood evacuation, (Henry et al., 2017; Lim et al., 2016; Medina & Moraca, 2016), but people with disabilities and elderly are more vulnerable according of the literature of social vulnerability post disaster. We decided to add them as part of the social vulnerability index because both variables affect the mobility and the time of reaction during a flood evacuation.

Although the variables that we selected to construct the social vulnerability index coincided with previous studies on evacuation to river flood events, it is important to mention again that the goal of this paper is not to prescribe a social vulnerability index within the ReSTVI methodology.
“The objective of this work is to propose a conceptual model ‘The Response Time by Social Vulnerability Index (ReTSVI)’ methodology that allows for the inclusion of social vulnerability into the traditional evacuation/mobilization models and it moves away from

traditional methods that combined social vulnerability and hazard magnitude by ranking in a matrix system that results in qualitative assessment.” (page 6, lines 2 -6).

Comment3: Also, I would recommend adding the response 2 to reviewer 2 in the manuscript.

Response Comment 3: We include the response 2 to reviewer 2 from the second revision in the discussion section Page 13 Line 29 after “Insert Figure 9”.

Minor issues:

Minor issues 1: Line 20-21 (abstract) I suggest to rephrase the sentence, it sounds odd.

Response minor issue 1:

The paper originally said: “The result of example of application have no statistical significance, which should be considered in a real case of application. Using a methodology such as ReTSVI could allow to combine social and physical vulnerability in a qualitative framework for evacuation, although, first more research needs to be done to understand the socioeconomic variables that explain the differences in evacuation rate. “

After the professional proofreader edition the paper now says: “The result of the application example has no statistical significance, which should be considered in a real case of application. Using a methodology such as ReTSVI could make it possible to combine social and physical vulnerability in a qualitative framework for evacuation, although more research is needed to understand the socioeconomic variables that explain the differences in evacuation rate.”

Minor issue 2: In the abstract and conclusion, it is still mentioned the physical vulnerability. Do the authors include physical components in addition to the social ones?

Response minor issue 2:

In the conclusion we wrote "the physical vulnerability or the characteristics of an inundation event"

In the abstract we wrote "Using a methodology such as ReTSVI could allow to combine social and physical vulnerability in a qualitative framework for evacuation"

Yes, we include a physical model that describe the characteristics of an inundation Page 8, which provides the exposure and time to respond as well as the intensity of the flood although the intensity is not used in ReTSVI. Finally, knowing the intensity of the flood and the number of people that did not evacuate, we can estimate the number of people that can perish on a flood, which is not part of this study, but it can be one of the applications of this methodology.

Minor issue 3: I would recommend adding to the manuscript the results of the Bartlett's Sphericity test.

Response minor issue 3: We added it as Table 2 and renumbered the following tables.

Minor issue 4: Check carefully through the manuscript verbs tense consistency

Response minor issue 4: We sent the document for a professional proofreader (native speaker) to review and address the problems with the language.

Minor issue 5: Can you please add the total variance obtained from the PCA (that I feel is quite low)? What about the minimum value, the maximum one of the SVI? Can you please add them to the text?

Response minor issue 5: We already included the explained variance from the PCA, 57 %, in Table 3 which was Table 2 in the previous versions of this paper.

For the SVI values we repeated here our answer from Revision 1, reviewer 2 comment 21:

For the classification, we used three quantiles as it is shown in the figure below. The maximum value is 1.365, the minimum is -1.3425, the mean is 0.03, and the standard deviation is 0.4367

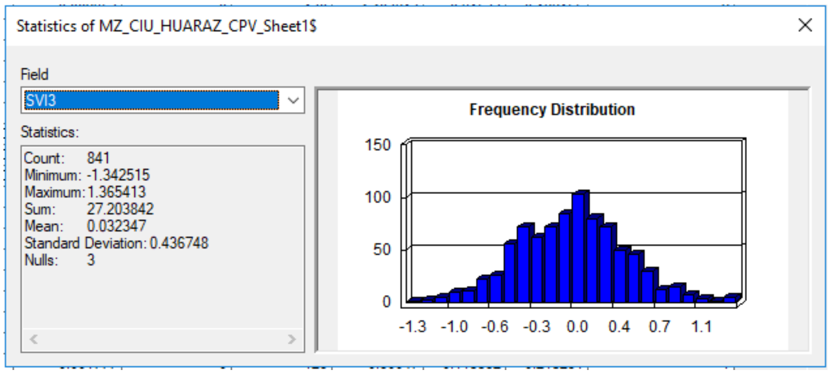

Figure 1 comments: Social Vulnerability Index statistics calculated in ArcGIS

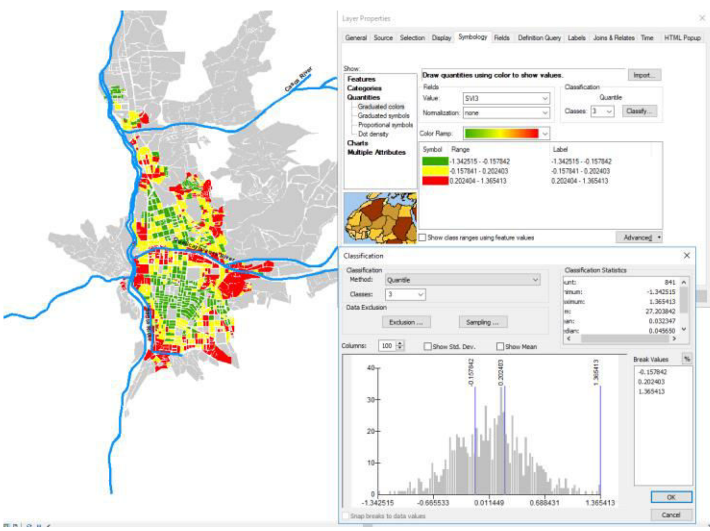

Figure comment 21, revision 1, reviewer 2: Social Vulnerability Index classification calculated in ArcGIS.

The proportion of high, medium and low vulnerability blocks within the inundation zone is 15%, 35 %, and 50% respectively.

Therefore, to answer the reviewer comment we added the percentage of the variance explained by the PCA components selected in the second paragraph of section 3.2.1. And we added, “The resulted SVI ranges from -1.3424 to 1.365 with a mean of 0.03 and a standard deviation is 0.4367.” After Table 2 and 3.

Minor issue 6: In addressing the limitations of the study, the authors said that there is a need for more data. Can you please define which ones and for which purposes?

Response minor issue 6: The limitation is explained in the same paragraph which relates to the lack of statically significance in the differences found. However, we added again this information, so this is even clearer for the readers.

Page 13 Line 26 it originally said: “To overcome the limitation of the no-significance in the difference between the evacuation curves more data need to be collected.”

Now it says: “To overcome the limitation of the no-significance in the difference between the evacuation curves more data related to the evacuation process, specifically when people decided to evacuate, need to be collected.”

Response Time to Flood Events using a Social Vulnerability Index (ReTSVI)

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Abstract. Current methods to estimate evacuation time during a natural disaster do not consider the socioeconomic and demographic characteristics of the population. This article develops the Response Time by Social Vulnerability Index (ReTSVI). ReTSVI combines a series of modules which are pieces of information that interact during an evacuation, such ~~us~~ as evacuation rate curves, mobilization, inundation models and social vulnerability indexes, to create an integrated map of the evacuation rate in a given location. We provide an example of the application of ReTSVI in a potential case of a severe flood event in Huaraz, Peru. The results show that during the first 5 minutes of the evacuation, the population that lives in ~~neighbourhoods~~neighborhoods with a high social vulnerability ~~evacuate~~evacuates 15% and 22% fewer people than the blocks with medium and low social vulnerability. These differences gradually decrease over time after the evacuation warning, and social vulnerability becomes less relevant after 30 minutes ~~although~~. The results of the application example ~~of application~~ ha~~ve~~ves no statistical significance, which should be ~~considere~~considered in a real case of application. Using a methodology such as ReTSVI could make it possible ~~allow~~ to combine social and physical vulnerability in a qualitative framework for evacuation, although~~,~~ ~~first~~ more research is needed ~~needs to be done~~ to understand the socioeconomic variables that explain the differences in evacuation rate.

Keywords: ReTSVI, Social Vulnerability, Flood Hazard Evacuation

1 INTRODUCTION

The costs associated with health, food security and the physical environment produced by climate change are expected to reach between USD 2 and 4 trillion ~~US dollars~~ by 2030 (Hallegatte, 2014). The United Nations has indicated that the frequency and severity of climate change-related natural disasters are expected to increase faster than risk reduction can be achieved (UN, 2009). For example, worldwide natural disasters caused around USD 3.5 trillion ~~US dollars~~ in damages from 1980~~-5~~ to 2011, with a ~~one~~ third taking ~~took~~ place in low or middle-income countries, and the number of people affected by natural disasters ~~increased~~ increasing 1.5 times, economic damage by 1.8 times and total deaths doubling~~by two times~~ (Basher, 2006; Hallegatte, 2014).

A key strategy to reduce the loss of human life during a disaster is to improve community preparedness ~~of communities~~. A common means to achieve this is to develop ~~Early~~ early ~~Warning~~ warning ~~Systems~~ systems (EWS) to alert the population to evacuate before disaster strikes. Ideally, EWS should consider not only the so-~~-~~called physical dimensions such as exposure and intensity, but also the human or social dimensions that help us ~~to~~ understand differences in response to similar stresses (Basher, 2006; Bouwer, 2011; Nagarajan et al., 2012; Nicholls and Klein, 1999). Individual characteristics such as race, age, gender, education, income~~,~~ and ~~employment~~ type of job influence the susceptibility to which certain groups or communities might be exposed and also define their ability to respond to a natural hazard (Cutter et al., 2003; Gaillard and Dibben, 2008). For example, women and men or those people with different levels of physical and cognitive ability, experience and respond to disasters differently (Cutter and Finch, 2008; Ionescu et al., 2005; ISDR, 2004; Santos and Aguirre, 2004). Despite the evidence, the literature focuses mainly on the physical dimension of natural hazards and disregards the human aspects. A real improvement in our understanding of emergency evacuations will depend on the integration of both (Basher, 2006; Couling, 2014; Santos and Aguirre, 2004).

The real issue ~~problem that arises~~ is how ~~we can~~ to incorporate social and physical vulnerability ~~in a~~ comprehensively ~~matter~~ to improve our understanding of an evacuation process. Both concepts have been developed independently in the social sciences and engineering; therefore, ~~it~~ linking them is not a straightforward process ~~to link them~~. In fact, there ~~is~~ are few~~little~~ data on how social vulnerability influences the evacuation process and how it is linked to the number of human casualties (Bolin, 2007; Morss et al., 2011). To address this problem, some scholars have mapped physical and social vulnerability to visualize how they overlap. They have also combined them using arithmetic operations such as multiplication or addition of social and physical vulnerability indexes to create a unique indicator that ~~considers~~ includes both vulnerabilities to study evacuation (Chakraborty, Tobin, & Montz, 2005)~~)~~ or the recovery process after hazards occur (Cutter & Emrich, 2006; Hegglin & Huggel, 2008). This information is still descriptive and provides ~~qualitative information to~~ policy makers, government institutions or local governments with qualitative information to understand how a population would react in an evacuation process. Therefore, questions such ~~us~~as: what it means to live in a neighborhood with high physical and social vulnerability~~?~~ and, how much time will the population need to evacuate neighborhoods with high social vulnerability and low physical vulnerability cannot be answered ~~? are~~

~~not possible to answer~~ with the ~~current~~ methods currently available ~~developed~~ in either social sciences ~~n~~or engineering.

1.1 Social Vulnerability and Natural Disasters

Recent major natural disasters such as Hurricane Katrina and the 2010 earthquake in Haiti have shown the relevance of integrating social vulnerability into risk management and decision-making (Flanagan et al., 2011). This integration refers to identifying which ~~and where~~ problems exist where before a natural disaster strikes, making it possible to take steps to prevent possible damage (Schmidtlein et al., 2008). In this context, a better understanding of how problems like segregation, socioeconomic deprivation and inequalities affect the type of response and the degree of resiliency of communities affected by natural disasters is crucial. With this information, federal and local governments could be more effective in mitigating losses or improving community ~~the~~ recovery ~~of communities~~ (Cutter and Emrich, 2006; Heinz Center, 2002). The degree to which communities and people are vulnerable to hazards is explained not only by proximity to potential natural disasters, but also social characteristics such as socioeconomic and demographic features that could exacerbate or lessen the impact of a disaster (Chakraborty et al., 2005; Cutter et al., 2000).

The study of vulnerability can be traced back to the early 1950s and 1960s in the field of ~~behavioural~~behavioral sciences, the main objective of which was to understand the features of areas that make them ~~either~~ suitable to inhabit. During the 1970s, the US federal government was interested in the relationship between social well-being and progress indicators; consequently, the connection between socioeconomic inequalities and social problems became clearer at that time (Cutter & Emrich, 2006). Today, the concept has broadened to include a more comprehensive approach that combines different areas, such as social, demographic, economic~~,~~ and geographic vulnerability, but each discipline defines the concept differently (Alwang et al., 2001; Balica, 2012; Birkmann, 2007). For example, in the economic literature, vulnerability includes food security and sustainable development (Fekete, 2012; Rygel et al., 2006). In the disaster risk community, vulnerability is defined as the physical, social~~,~~ and environmental factors that increase the likelihood of a community being impacted by hazards (Zhou et al, 2014)~~.~~; social vulnerability m~~ Models~~odels ~~of social vulnerability,~~ in this area~~,~~ have been used to explain a community's ability ~~the capability of communities~~ to face and recover from disasters (Chakraborty et al., 2005).

Scholars have tried to understand whether a population's socioeconomic and demographic characteristics ~~of the population~~ are relevant to understanding why neighborhoods or communities respond differently during an evacuation, why some people evacuate~~,~~ and others do not ~~evacuate~~ during disasters. Huang, Lindell, & Prater (2016) analyzed 49 studies conducted since 1991 linking ~~ed to~~ evacuations to hurricane warnings ~~conducted since 1991~~ and they concluded that demographic~~s~~ variables have a minor or inconsistent impact on household evacuations.~~.~~

In the case of floods, however, we found few studies that seek to understand the relationship between evacuation and socioeconomic variables. For example, Henry et al., (2017) analyzed the relationship between income disparity and disaster information collection, and the resulting impacts on peoples' vulnerability after the 2011 Chao Phraya River Flood in Thailand. They found that among different demographic and socioeconomic variables, income was the strongest predictor of the population's decision to evacuate during the flood ($p<0.01$). They concluded that "…among those respondents affected by the flood, it could be seen that lower-income respondents had a higher tendency not to

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Formatted: Font: (Default) Times New Roman, 12 pt, Font color: Auto, English (United States) evacuate their homes." Furthermore, Medina & Moraca (2016) conducted a study to identify factors that influence the decision to evacuate upon flood warning by authorities in the province of Bukidnon, Philippines. They found that household income, measured as poverty, was a significant factor to explain whether families will evacuate upon advice by local authorities. ~~In the case of floods; , however, we have not found any studies that link demographic and socio economic variables to the evacuation process.~~

Research ~~in~~ on social vulnerability linked to natural hazards can be divided into two groups. The first group, "post-disaster case~~s~~ studies," tries to understand how natural disasters impact ~~differently~~ communities differently based on their level of social vulnerability (Rufat et al., 2015). Most of the research in this area uses qualitative methods, such as semi-~~-~~structured interviews, focus groups, key informant interviews and participant observation (Działek et al., 2016). One of the main limitations of these studies is that their findings cannot be generalized to aggregated levels such as regions or countries. The second group ~~of research~~ is ~~in~~ "geospatial ~~modelling~~modeling studies." Scholars in this subfield ~~use~~ primarily use quantitative methods and focus on creating maps or developing indexes to compare the different levels of social vulnerability among communities, regions or countries (Rufat et al., 2015). A central aim of developing techniques to quantify vulnerability is to reduce gaps between theoretical concepts of vulnerability and the decision-making process (Birkmann, 2007).

There are multiple challenges in constructing an index to measure the social vulnerability of a certain population. The most evident is the degree of subjectivity in the selection of variables as well as the application and operationalization of vulnerability as a concept (Fekete, 2012). Furthermore, an index does not indicate the structure and causes of social vulnerability; therefore, using a single factor to measure vulnerability might disregard the importance of particular variables that are relevant to explaining social vulnerability in a particular area (Rygel et al., 2006). In fact, a community's ability ~~the capability of communities~~ to cope with and recover from disaster seems to also depend ~~also~~ on~~from~~ other factors such as vigor, vitality, energy, strength, etc., which are usually excluded from studies ~~about~~ on social vulnerability (De Marchi, 2007; De Marchi and Scolobig, 2012). Despite these limitations, scholars have developed ~~indices~~ indexes to quantify social vulnerability based on their interests. Some researchers use the percentage of women, racial groups or ~~age~~ average age as indexes to estimate different levels of social vulnerability (Harvey et al., 2016; Jonkman et al., 2009; Sadia et al., 2016). Other scholars use variables linked ~~with~~ to social vulnerability as independent variables in regression models (Działek et al., 2016); variables are simply ranked from lowest to highest values (Flanagan et al., 2011) or using the weighted average to estimate social vulnerability (Adger and Vincent, 2005). However, these indexes have some limitations;~~,~~ namely, they use a limited number of variables and do not consider the interrelationship among variables to quantify social vulnerability. To address this ~~problem~~issue, researchers have employed strategies such as including a higher number of variables to construct social vulnerability indexes or estimating the connection among variables theoretically ~~that are~~ linked ~~theoretically with~~to social vulnerability. In this area, one of the most recognized ~~indices~~ indexes that has been applied ~~both~~ in both the US and abroad is the Social Vulnerability Index (SoVI) (Cutter, 1996). The SoVI has been used in California, Colorado and South Carolina in the US~~A~~, and in countries such as England, Australia, Germany~~,~~ and Norway (Zhou et al., 2014). The SoVI approach has been replicated in different geographical settings~~,~~ and on different spatial and temporal scales (Schmidtlein et al., 2008). The use of the SoVI is relevant because the method

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Formatted: Default Paragraph Font, Font: (Default) Times New Roman, English (United States) makes it possible to compare the spatial variability in socioeconomic vulnerability using a single index value. The SoVI can also be linked spatially to physical aspects to calculate the overall vulnerability of a specific place (Boruff et al., 2005).

Social vulnerability indexes are useful ~~to~~ for detecting differences in social vulnerability to flood events (Fekete, 2009). In particular, the ~~Social Vulnerability Index (~~SoVI~~)~~ (Cutter, 1996) is adaptable to developing countries since it can be constructed using ~~Census~~ census data from the study area ~~of study~~. The literature identifies several variables that contribute to social vulnerability (post-~~-~~disaster). At the individual level, social vulnerability is related to poverty and health ~~indices~~indexes, age and education level. At the community level, social vulnerability is affected by income distribution, access to economic assets~~,~~ and qualitative indicators of institutional arrangements (Adger, 1999). Furthermore, Fekete (2010) identified key variables that may explain the different levels of social vulnerability such as age group, gender, income, education, home ownership~~whether one owns a home~~, social capital~~,~~ and household size. Cutter, Boruff, & Shirley (2003) also included race and ethnicity, commercial and industrial development, unemployment, rural/urban residency, residential property, infrastructure and lifelines, occupation, family structure, population growth, medical services, social dependence and special needs populations as fundamental variables to quantify social vulnerability.~~.~~

1.2 Response Time, Evacuation and Flood Impacts

Multiple factors seem to affect people's decision-making process to evacuate, including but not limited to ~~such as~~ risk perception, beliefs, demographic characteristics, previous knowledge, social networks, gender, age and class~~, among others~~ (Elliott and Pais, 2006; Lindell et al., 2005; Mileti and O'Brien, 1992; Whitehead et al., 2000). -Understanding what factors influence people's decisions in an evacuation is relevant because this information could help ~~to~~ improve the evacuation process, for example, reducing the ~~time of~~ evacuation response time, and consequently decreasing the percentage of human casualties.

The most sensitive cost of disaster is the loss of life; nonetheless, a limited number of methods estimate the loss of life due to natural disasters and only ~~just~~ a few ~~of them consider~~ include social vulnerability as an explanatory variable in their models (Jonkman et al., 2008).

In ocean and river floods, variables such as the percentage of buildings collapsed~~,~~ and the proportion of people evacuated ~~people~~ seem to influence the number of human fatalities (Vrouwenvelder and Steenhuis, 1997). Other scholars take into account the ~~level of~~ water level~~depth~~, flow velocity, ~~the~~ possibilities for evacuation, flood hazard and area vulnerability (Boyd, Levitan, & van Heerden, 2005; Jonkman, 2001). In the case of dam break floods, Brown & Graham (1988) ~~analysed~~analyzed 24 major dam failures and flash floods to estimate the number of lives lost as a function of time available for evacuation and the number of people at risk, they found that time available for evacuation and population size are critical, similar results were found by DeKay & McClelland (1993). Graham (1999) proposed that fatality rates are functions of the severity of the flood, the amount of warning time and the population's understanding of the hazard. In another example, to estimate human casualties due to flood events, the US Army Corps of Engineers developed the Hydrologic Engineering Center's Flood Impact Analysis (HEC-FIA). Models~~, in~~ general~~,~~ly assume that people react the same way during an evacuation process, and do not consider that people can respond differently based on their social vulnerability. -Reiter (2001) incorporated some variables linked to social vulnerability such as the number of children and elderly to estimate the loss of life during a flood event. ~~(~~Penning-Rowsell et al.~~,~~ (2005) ~~Penning-~~

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~~Rowsell and colleagues (2005)~~ considered "people vulnerability" defined by age, disability or illness using census data. A general conclusion from the literature explored is that only a few of the methods studied have systematically included social vulnerability as an explanatory variable of human fatalities during natural disasters. In fact, Jonkman et al. (2008) reviewed 20 methods to quantify the loss of life during different types of flood events and ~~only~~ found that only (Ramsbottom et al.~~,~~ (2004) ~~Ramsbottom and colleagues (2004)~~ included levels of population vulnerability, and this category is based on expert judgment. Consequently, even though there is an upward trend of research that ~~endeavours~~endeavors to understand how a population's social characteristics ~~of population~~ influence human response to natural disasters, academics have failed to incorporate social vulnerability into ~~estimations of~~ loss of life estimations (Elliott and Pais, 2006; Rodriguez et al., 2007). We argue that this is due to the lack of understanding of how social vulnerability influences the evacuation process and human casualties (Bolin, 2007; Morss et al., 2011). In fact, current methods to quantify social vulnerability allow for the classification of ~~neighbourhoods~~neighborhoods, counties or regions from the lowest to highest levels of vulnerability. However, using these classifications scholars or policy makers cannot predict how many people from ~~neighbourhoods~~neighborhoods with low vulnerability will evacuate versus those who live in ~~neighbourhoods~~neighborhoods with high vulnerability or how much time people who live in ~~neighbourhoods~~neighborhoods with medium vulnerability will take to evacuate versus those who live in highly vulnerable areas, etc.

In order to have a methodology that enables researchers and practitioners to include social vulnerability and test if it has any impact on the evacuation process during a flood event, we propose the Response Time by Social Vulnerability Index (ReTSVI), a methodology that incorporates the demographic and socioeconomic characteristics of population into ~~the~~ current evacuation models.

2.METHODS AND DATA TO ESTIMATE ReTSVI

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2.1 Conceptual model of ReTSVI

The objective of this work is to propose a conceptual model – 'The Response Time by Social Vulnerability Index (ReTSVI)' – a methodology that allows for the inclusion of social vulnerability into the traditional evacuation/mobilization models and ~~it~~ moves away from traditional methods that combine~~d~~ social vulnerability and hazard magnitude by ranking in a matrix system ~~that~~ result~~s~~ing in a qualitative assessment. Figure 1 is a chart of ReTSVI~~,~~. ~~w~~We use three types of input data~~, which are~~: 1) ~~the~~ evacuation curves, one for each level of vulnerability (high, medium and low ~~vulnerability~~); 2) a model that describes the physical hazard that the population may be exposed to, for example, the time that a flood takes to reach a populated area; and 3) demographic information such as a census data that allows us to categorize the population into different levels of social vulnerability. Then we have two intermediate models. The first ~~one~~ corresponds to the mobilization model that combines the evacuation curves and the inundation model. The results of this step are three maps (one for each level of vulnerability) of the percentage of people that evacuate before the flood strikes a place. The second intermediate model is the calculation of the social vulnerability index (SVI) using the census data, which produces a map of the city ~~in which~~where we can classify each block by social vulnerability. Finally, we combined the results (Integration Model Figure 1) from the mobilization model and the SVI calculations to generate a map with the percentage of people that can evacuate, which includes~~considers~~ their social vulnerability level.

Insert Figure 1

2.2 Application of ReTSVI in a potential flood in Huaraz, Peru.

In 1941, the city of Huaraz was affected by a ~~Glacier~~ glacial ~~L~~lake ~~O~~outburst ~~F~~flood (GLOF) generated at Lake Palcacocha~~,~~ in the Cordillera Blanca, Peru (Figure 2). The GLOF killed ~~in the order of~~approximately 2000 people and damaged infrastructure all the way from the lake ~~, located in the Cordillera Blanca,~~ to the Pacific Ocean (Carey, 2010; Carey, 2005; Wegner, 2014). According to new observations and data, a new GLOF could occur at this location. In fact, Lake Palcacocha has been declared to be in a state of emergency several times, and ~~currently,~~ there are currently initiatives to mitigate the risk by lowering the water level and installing early warning systems (EWS) to protect the population in case a GLOF occurs (HiMAP, 2014). The physical aspects of a potential GLOF have been studied extensively with the support of international agencies such as USAID, the IDB~~,~~ and the government of Peru (Rivas et al. , 2015; Somos-Valenzuela, 2014; Somos-Valenzuela et al., 2016). However, the social aspects of a flood hazard have only ~~not~~ been studied ~~except for~~ qualitatively ~~studies~~ (Hegglin & Huggel, 2008; Somos-Valenzuela, 2014).

Insert Figure 2

2.2.1 Input Data

To produce the ReTSVI we use three types of input data (Figure 1). First, we need the evacuation curves, one for each level of social vulnerability. ~~Ideally,~~ T~~t~~he evacuation curves that we used are ideally generated in the study area ~~of study,~~; however, there ~~is~~ are no data that describe~~s~~ how people in Huaraz evacuate after an EWS is released~~;~~. ~~t~~Therefore, we had to generate this information. Our closest available event was the tsunami triggered by an 8.3 magnitude earthquake on 16 September 2015 in Coquimbo, Chile. Second, a model describing a potential hazard is also needed, thus we use the model of a potential GLOF in Huaraz developed by Somos-Valenzuela et al. (2016). This model provides the time that people have to react before the inundation arrives. Finally, we have the 2007 ~~Census~~ census data provided by the Peruvian Ministry of the Environment ~~of Peru~~ to create a social vulnerability map of Huaraz.

Surveys in Coquimbo, Chile

We conducted 22 surveys with first responders ~~to~~ regarding the 8.3 magnitude earthquake and tsunami that occurred on September 16, 2015, in Coquimbo, Chile. Four institutions that work directly to help the population during the evacuation process participated in this study: the navy, the police, firefighters and the emergency office from the municipality of Coquimbo. First, we contacted ~~by phone with~~ each institution by phone to explain the purpose of the study and asked them if they would agree to participate in the study~~research~~, all did so~~of them agree~~. Then, a research assistant visited each institution and asked them to select at least five emergency experts to respond to our questionnaire. The main requirement was that the participants had to have worked directly during the emergency to help people evacuate their houses. ~~The~~ A research assistant conducted a survey with each participant. ~~-~~We asked the first responders: "In your opinion and based on your experience during the tsunami of ~~16th of~~ September 16, ~~. S~~when ~~ince~~ the evacuation alarm was activated, how long did it take ~~what is the evacuation time of~~ the population ~~who~~ liv~~e~~ing in areas of low/medium/high social vulnerability to evacuate?" They needed to estimate the average evacuation time in neighborhoods with low, medium and high social vulnerability. Then~~,~~ we asked: "~~w~~What is the percentage of the population that evacuated in the first X minutes? (X=5, 15, 30, 45, 60)". The first responders wr~~i~~ote down the percentage of the population that ~~evacuates~~ evacuated their homes~~useholds~~ from 0 to 5 minutes, 0 to 15 minutes, 0 to 30 minutes, 0 to 45 minutes, 0 to 60 minutes in neighborhoods with low, medium and high social vulnerability in Coquimbo. The answers were ~~re~~collected on ~~into~~ two scales: percentages and average time (in minutes).

We used the National Socioeconomic Characterization Survey (CASEN)[1] from 2015, the same year that the earthquake/tsunami occurred, to calculate a social vulnerability index at the municipality level~~,~~ following the same procedure identified in ~~the~~ section 2.2.3. This way we were able to identify the socioeconomic and demographic characteristics of the neighborhoods with high, medium and low social vulnerability in Chile. We incorporated this information in the survey~~,~~ so the first responders could identify ~~what~~ which neighborhood belong~~s~~ed to which~~each~~ category; all responders generated separate curves for low, medium ~~,~~or high vulnerability neighborhoods.

Census Data from Peru

We used the 2007 national population census to quantify the social vulnerability of Huaraz, Peru. The census has 53 questions that describe the main socio-demographic characteristics of the population of Peru (INE, 2015). The census data is aggregated at ~~the~~ block level, and in the case of Huaraz provides full information on 1,404 blocks. The census data ~~is~~ are divided into three main categories: (a) location of household (blocks), (b) household characteristics: number of rooms, ownership, type of house, etc.

[1] CASEN is a tool to describe and analyze the socio-economic situation of Chilean families, including housing, education, and labour characteristics. This is a cross-sectorial survey, whose periodicity yields a time based picture of the evolution of individual/household welfare (Contreras 2001).

and (c) population characteristics by block: age, religion, marital status, education, occupation, etc. There are 245 variables available in these three categories. Blocks without population are excluded from the analysis.

Flood Model

In this study, we ~~will~~ used the inundation results obtained by Somos-Valenzuela et al. (2016) that consider~~s~~ that an avalanche of rocks and ice could potentially fall into Palcacocha Lake and produce a chain of events that would lead to flooding in Huaraz. From all the scenarios ~~analysed~~analyzed~~,~~ in this study, we ~~will~~ used the scenario in which an avalanche of 3 million cubic meters falls into Palcacocha Lake producing a wave that overtops the moraine dike and inundates Huaraz. In Figure 3 (0 m Lowering), we show the physical hazard map for that scenario with no mitigation.

Insert Figure 3

2.2.2 Evacuation Model

To estimate the percentage of people that evacuate we use the LIFESim model as a base framework. The Army Corps of ~~Engineering~~ Engineers incorporated this model into the HEC-Fia model (Lehman and Needham, 2012; USACE, 2012) to ~~evaluate~~ assess ~~the~~ evacuation during flood events. LIFESim has three modules: 1) Warning and Evacuation, 2) Loss of Shelter, including prediction of building performance, and 3) Loss of Life calculation.

To estimate the number of people that can perish during a flood event, we need to divide the calculation into two main processes. First, we need to estimate the number of people at risk (Npar) who cannot ~~that are not able to~~ escape before a flood arrives, or what it is known as the number of people exposed to risk (N_{exp}). Second, we need to calculate the percentage ~~from~~ of N_{exp} who~~that~~ can survive once they are in the inundation zone. This paper deals with the first process, the calculation of N_{exp} by including social vulnerability.

Explaining why people evacuate faster, slower~~,~~ or not at all is a process with many layers that is ~~not easy~~difficult to quantify. ~~In t~~The literature describes ~~it is possible to recognize~~ marked processes that can be generalized in Equation 1. First, we need to know the fraction of people that can escape (FE), for which we need to know how much time people have to escape (TE) and how feasible it is that in TE people can reach a safe area. For example, in a sudden dam breach, the maximum TE is the time that a flood has to travel from the dam to the area of interest (Graham, 2009; Jonkman et al., 2008; McClelland and Bowles, 2002). Then, we have the fraction of people that can find shelter (FS) within the inundated area, and finally the number of people that can be rescued (NRES)

$$N_{EXP} = (1 - FE) \cdot (1 - FS) \cdot (NPAR) - NRES \qquad (1)$$

Since we are interested in the impact of social vulnerability in the evacuation process, we reduce Equation 1 to Equation 2

$$N_{EXP} = (1 - FE) \cdot (NPAR) \qquad (2)$$

The model LIFESim provides a methodology for how to calculate the FE (Aboelata and Bowles, 2005). We use LIFESim to illustrate how to apply our findings, but the accuracy of the methodology is beyond the scope of this paper and ~~needs~~ requires further analysis. To calculate the proportion of people that escape we consider three processes: warning, mobilization~~,~~ and evacuation-transportation.

Warning

Time is a key component of the evacuation process; therefore, an efficient EWS is crucial to saving lives. However, understanding the presence of ~~that there is~~ an imminent threat is not a direct process. Equation 3 from Rogers and Sorensen (1991) is used to estimate the proportion of people that understand the alarm when they hear it or learn from others' behavior that there is an imminent hazard and they need to evacuate.

$$\frac{dn}{dt} = k \cdot (a1 \cdot a1f \cdot (N - n)) + (1 - k) \cdot (a2n \cdot (N - n)) \quad (3)$$

Where:

$\frac{dn}{dt}$ = is the proportion of people that understand that there is imminent hazard

k = percentage of people alerted as a function of the broadcast system (Rogers & Sorensen, 1991)

(1-k) = proportion of people left to be warned (Rogers & Sorensen, 1991)

a_1=effectiveness of the warning system (Table 1 from (Rogers and Sorensen, 1991))

a_1f = adjustment factor by location and activity (Table 2 from (Rogers and Sorensen, 1991))

a_2= effectiveness of the contagion warning process (Table 1 from (Rogers and Sorensen, 1991))

N = fraction that the system is designed to warn~~ed~~ in the first 30 minutes after issuance of the warning, also referred to in Table 1 from (Rogers and Sorensen, 1991), as the 30-min limit, and n = proportion of people warned.

Mobilization Process

After people understand that there is a ~~treat~~threat, they start to evacuate to a safe zone. Figure 35 from Aboelata & Bowles (2005) defines mobilization curves, below which we show the "improved" curves from the cited reference.

HEC-Fia, which applies a version of LIFESim, includes the activities in which people are involved at the moment of a flood. To understand the impact~~s~~ of engaging in daily activities on the evacuation, we combined the warning penetration (using sirens and tone alert radios) and the mobilization process, including the uncertainty bounds for both processes~~,~~. In addition, ~~with~~ a Monte Carlo simulation with 1000 samples shows that the activity~~,~~ as ~~it is~~ described in LIFESim~~,~~ that people are engaged in ~~doing~~ when the alarm is ~~released~~ triggered does not keep ~~affect the penetration of~~ the warning from penetrating.

Although the emphasis of this work is to include ~~Social~~ social ~~Vulnerability~~vulnerability, it is pertinent to show a current methodology ~~that is~~ adapted by the U.S. Army Corps of Engineers to provide context on how our data fit~~s~~ into state-of-the-art evacuation process assessments. ~~In~~ Figure 4 illustrates ~~we demonstrated~~ that according to the LifeSIM/HecFIA models the activity that people are doing when the alarm is released does not cause significant changes in the percentage of people mobilized. Therefore, we will not include activities in our calculations when we ~~include~~consider ~~Social~~ social ~~Vulnerability~~vulnerability. Additionally, at the moment of the survey, we did not ask ~~specify to~~ the first responder to quantify the time ~~that~~ people take to understand the alarm (warning penetration) nor the time ~~that~~ it took them to get ready to evacuate (mobilization). Therefore, the answers from the first responders correspond to the penetration and mobilization processes aggregated, which is equivalent to Figure 4.

Insert Figure 4

Escape

In the example of the application of this methodology, we assumed that people would walk at ~~a~~ speeds ~~that~~ rang~~es~~ing from 80-187 meters per minute with an average of 107 meters per minute (Aboelata and Bowles 2005). The shortest path was calculated using ArcGIS.

2.2.3 Social Vulnerability Index

One of the main ~~critique~~ criticisms of the use of indexes to quantify social vulnerability is the limited number of variables and the lack of connection and interrelationship among variables used by the indexes. To address~~face~~ these limitations, we constructed a Social Vulnerability Index (SVI) by ~~analysing~~analyzing census data using a ~~Principal~~ principal ~~Component~~ component ~~Analysis~~ analysis (PCA) following the ~~-~~methodology developed by Cutter et al., (2003). The main objective of a PCA is to extract information from the variables and represent this information as a set of new orthogonal variables called principal components ~~-~~(Wold et al., 1987). This ~~e use of this~~ technique allows for robust and consistent numbers of variables that can be ~~analysed~~analyzed to estimate changes in social vulnerability over time (Cutter et al., 2003). To construct a ~~Social~~ social ~~Vulnerability~~ vulnerability ~~Index~~ index (SVI), we analyzed census data using ~~Principal Component Analysis~~a ~~(~~PCA~~)~~. This is a multivariate technique “that analyzes a data table in which observations are described by several inter-correlated quantitative dependent variables”(Abdi and Williams, 2010). The main objective of a PCA is to extract information from the variables and represent this information as a set of new orthogonal variables called principal components. For example, a PCA “provides an approximation of a data table, a data matrix, X, in terms of the product of two small matrices T and P’, These matrices, T and P’, capture the essential data pattern of X” (Wold et al., 1987). The use of this technique allows for robust and consistent numbers of variables that can be analyzed to estimate changes ~~of~~ in social vulnerability over time (Cutter et al., 2003).

We followed Schmidtlein et al. (2008), who listed 7 steps to calculate the ~~Social Vulnerability Index~~ ~~(~~SVI~~)~~: (1) First, we performed a multicollinearity test called the ~~V~~variance ~~I~~inflation ~~F~~factor (VIF). Variables with a VIF>10 were excluded. Then, we normalize all variables as percentage, per capita or density functions. For the purposes of this paper, we normalized all variables as percentages; for example, the percentage of independent houses per block or the percentage of elderly people per block. Then ~~standardize~~ all input (census) variables were standardized to z-scores $z = \frac{x-\mu}{\sigma}$. This creates variables with mean 0 and standard deviation 1. Finally, we used the Bartlett's test of sphericity to determine if the variables ~~are~~ were suitable for structure detection. (2) ~~Perform t~~The PCA was performed with the standardized input variables (z-scores). ~~Select t~~The number of components with eigenvalues greater than one were selected and ~~corroborate~~ the selection corroborated with a scree test. (3) ~~Rotate t~~The initial PCA solution was rotated. In our work we used a normal Kaiser varimax rotation for component selection. (4) ~~Calculate t~~The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) was calculated. (5) ~~Interpret t~~The resulting components were interpreted as to how they may influence (increase or decrease) social vulnerability and ~~allocate~~ signs were allocated to the components accordingly. (6) ~~Combine t~~The selected component scores were combined into a univariate score using a predetermined weighting scheme. The factors ~~a~~were named based on variables with significant factor loading, usually greater than .3 or less than -.3. (7) Finally, we standardized the resulting scores to mean 0 and standard deviation 1.

All the steps but step 7 ~~are~~ were straightforward. In step 5, we had to ~~must~~ decide how we wanted to combine the different components. The first criterion ~~is~~ was to use the scores from the PCA, adding them but assuming that all the components ~~have~~ had the same contribution to the SVI (Cutter et al., 2003). The second criterion ~~uses~~ used the scores from the PCA, but ~~assigns~~ assigned different weights to the principal components according to the fraction of variability they explained (Schmidtlein et al. 2008). The third method also does not assume that each component contributes equally to social vulnerability, but in contrast to the second method, it multiplies each z-score by the factor load and then each component is multiplied by its explained variance. We used the first criterion, in other words, we gave ~~the same weight to~~ all the components the same weight. The same was done by Chakraborty et al.~~,~~ (2005); Chen et al.~~,~~ (2013); Cutter et al.~~,~~ (2003); Fekete~~,~~ (2009) and Zhang and You~~,~~ (2014). Fekete (2011) provided a solid argument ~~that explains the reason of~~for using equal weighting, which avoids adding assumptions that are qualitative and mostly not empirically supported, although it may sound intuitive to use the loading factor or the variance explained by the factor to combine the variables selected. Moreover, Roder et al.~~,~~ (2017) argued that there is no appropriate methodology for the calculation of the index.

3 RESULTS

3.1 Survey to first responders

Figure 5 shows the percentage of population that evacuates after the tsunami alarm ~~was~~has been activated in neighborhoods with high, medium and low social vulnerability. Each box presents the 75th percentile (upper hinge), the median (center), 25th percentile (lower hinge) and the outlier values. Figure 5 indicates that neighborhoods with high social vulnerability systematically evacuate fewer people than areas with medium or low social vulnerability~~,~~ ; for example, the first 5 minutes after the alarm is activated, the median (percentage of evacuation) for neighborhoods with high social vulnerability is ~~the~~ 20%, and 40% for medium and low social vulnerability. Figure 5 also shows that the differences in terms of the ~~percentage of~~ evacuation percentage decrease over time and eventually disappear after an hour after ~~since~~ the alarm has been ~~was~~ activated.

Insert Figure 5

We test if the mean response time to the evacuation alarm between the three types of neighborhoods was statistically significant using two methods: Anova (parametric method) and Kruskal-Wallis (non-parametric method). ~~The t~~Table 1 shows that the p-values between the response time ~~of response~~ and level of social vulnerability (low, medium and high) are not statistically significant. All the p-values are higher ~~that~~ than 0.05 (alpha level), and therefore we accept the null hypothesis that the response times ~~of responses~~ between the three groups of social vulnerability are not statistically significant (p-value >.05). This could be due to the limited sample size ~~of the sample~~. ~~In c~~Consequently~~e~~, we opted for ~~decide to use~~ the median rather than the mean as the middle point of the distribution of the mean response time.

Insert Table1

3.2 Case Study: Hypothetical Application Case of ReTSVI in Huaraz, Peru.

3.2.1 Social Vulnerability Index

Peru has a long history of mudflows generated from glacial lakes in the Cordillera Blanca. As global warming progresses and glaciers start shrinking at a higher rate, this problem is growing. In some cases, glaciers leave behind a weak moraine that holds a large amount of water that can suddenly release and ~~generate~~ cause floods (for more details see Carey, 2010; Hegglin & Huggel, 2008; Somos-Valenzuela et al., 2016).

Using the population census of Peru, Bartlett's test of sphericity (Table 2) and a PCA, we identified 20 census variables grouped into six components that explained 57 % of the total variance of the variable in which we applied the PCA to construct the social vulnerability index among all the neighborhoods in Huaraz (Table 3).

~~Using the population census of Peru and a PCA, we were able to identify~~ied ~~20 census variables grouped into six components that explained 57 % of the total variance of the variable in which we applied the PCA to construct the social vulnerability index among all the neighbourhoods~~neighborhoods ~~in Huaraz (Table 1).~~ The first component ~~explains~~ explained 20% of the variance and ~~identifies~~ identified the wealth of each block measured by population with primary and college education, with health insurance, indigenous population, white collar jobs and households with five or more rooms. ~~Elderly~~The elderly, women~~,~~ and people with disabilities ~~are~~ were grouped in the second component, which explains 9% of the variance. The third component ~~describes~~ described variables linked ~~with~~ to poverty such as illiteracy rates, the existence of informal settlements, and households without electricity. 8% of the variation in blocks ~~is~~ was captured by this component. The fourth component ~~identifies~~ identified home ~~-~~ownership and marital status; this factor ~~explains~~ explained 7% of the variance. The fifth component ~~groups~~ grouped ~~neighbourhoods~~neighborhoods with high population density and workers in blue collar jobs that are usually linked with a low- income~~income payment~~, insecure and more precarious working conditions. This component ~~captures~~ captured 7% of the variation in blocks. Finally, the sixth component ~~identifies~~ identified children (<1 years old) and the population working in the manufacturing sector; this component ~~explains~~ explained 6% of the variance.

Insert Table 2~~1~~

Insert Table 3

The resulted SVI ranges from -1.3424 to 1.365 with a mean of 0.03 and a standard deviation is 0.4367. As Figure 6 illustrates, most of the blocks located close to the Quilcay River exhibit a higher level of social vulnerability. Conversely, those blocks concentrated in the south of the city (away from the Quilcay River) are less vulnerable. Finally, the population who lives upriver, north of Huaraz, presents a middle level of vulnerability with a combination of medium-low and low levels of social vulnerability.

Insert Figure 6

The proportion of high, medium and low vulnerability blocks within the inundation zone are 15%, 35 %~~,~~ and 50% respectively.

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3.2.2 Evacuation process

We calculated the percentage of people that could evacuate after a GLOF from Palcacocha Lake, Peru. An ideal EWS would ~~release~~ trigger an alarm as soon as the hazard is detected. However, the protocols normally require that ~~checking~~ multiple sensors be checked in order to avoid a false positive error. This process delays the alarm's release, consuming important time that could otherwise be used for the population to begin evacuating. We used two methodologies to estimate the proportion of inhabitants that can leave their household before the hazard strikes. First, we used the empirical equations described in the methodology, where we assumed that different groups react and evacuate homogeneously (Figure 7). Second, we used the information provided by the first responders, census data and SVI to include social vulnerability in the evacuation process (Figure 8). In both cases, we estimated the percentage of people that would evacuate if the alarm were ~~is~~ sounded at 0, 20, 40, 60, 70, 80, 90 and 100 minutes after the inundation starts traveling from Palcacocha Lake toward Huaraz.

An obvious~~,~~ but no~~t~~ less important finding is that as the alarm is delayed the population has less time to escape. The results also suggest that social vulnerability has a ~~larger~~ greater impact when the warning alarm is delayed. After 60 minutes, Figure 8 gets patchier, which indicates that the population has different evacuation rates ~~of evacuation~~, even though they have a similar amount of time to respond. Also, when we use information from the first responders, the evacuation is faster than when we use empirical equations from LIFESim. The finding that evacuations were completed more rapidly with the earthquake/tsunami response data than with the LIFESim equations is due to the fact that, as long as the local population recognizes earthquake shaking as a tsunami warning cue, the shaking is an instantaneous broadcast mechanism (see Lindell et al., 2015; Wei et al., 2017). In those situations, k tends to 1 in Equation 3, which makes the time-consuming contagion process less important.

Insert Figure 7

Insert Figure 8

4 Discussion

This paper proposes a methodology to integrate social vulnerability into the calculation of the ~~people~~ evacuation rate after an EWS is activated. We developed the Response Time by Social Vulnerability Index (ReTSVI) methodology, which is a three-step process to determine the percentage of people that would leave an area that could be potentially inundated.

We found that the aggregated evacuation rate curve for the 2015 tsunami in Coquimbo has similarities with the evacuation curve for the 2009 tsunami in American Samoa after ~~a~~the 8.1 earthquake described in Lindell et al. (2015). This similarity is notable considering the distance as well as~~, and~~ socioeconomic and cultural differences. The evacuation results in both studies show that in the first 15 minutes the aggregated evacuation rate falls between 50-70%, in 30 minutes from 80-90% and after an hour is close to 100%. These aggregated evacuation curves for tsunamis are faster than the results from Equation 1 (Figure 4)~~,~~ and the results from Abolaeta et al. (2003) that deal with rivers and dam break floods,

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suggesting that the process is understood earlier by the population. This could be due to awareness/training or to the shaking ~~that is~~ felt by most ~~of the~~ people immediately.
When we separate the results by social vulnerability, the results suggest that people with a higher level of vulnerability need~~s~~ more time to evacuate than people with a lower level of vulnerability. However, in our results, the differences between the evacuation curves are not statistically significant. In Figure 9, where we compare the aggregate survey responses with the evacuation responses categorized by social vulnerability level, we find that people at a medium level of vulnerability respond similarly to the aggregated values. Then, people with low and high vulnerability behave almost symmetrically around the average~~.~~, ~~W~~which in a more general application could be used to generate boundaries for the evacuation curves.

Insert Figure 9

To overcome the limitation of the no-significance in the difference between the evacuation curves more data related to the evacuation process, specifically when people decided to evacuate, need to be collected.
One of the primary variables that are linked to social vulnerability is the household income (Cutter et al. 2003), but in the case of Peru, this variable is not surveyed in the census. Consequently, we used proxy variables of income such us job types, marital status, renters and house without electricity. The relationship between income distribution and the job type has been established worldwide (Galbraith, 2001) as well as in literature linked to social vulnerability (post disaster) “Some occupations, especially those involving resource extraction, may be severely impacted by a hazard event” (Cutter, 2003 page 248). In relation to renters, they are considered to be more vulnerable to disaster “People that rent do so because they are either transient or do not have the financial resources for home ownership. They often lack access to information about financial aid during recovery. In the most extreme cases, renters lack sufficient shelter options when lodging becomes uninhabitable or too costly to afford”. (Cutter 2003, page 247). Regarding to “houses without electricity,” we assumed that it indicates more precarious conditions and the same is true for many other variables in the Census such as houses without restroom and tab water which were disregard in the collinearity test. Finally, “adult population divorced” as proxies to household income, for example Schoeni (1995) found that “In most cases, both separated and divorced men earn more than men who are never married but less than those who are currently married”. We recalculate the SVI excluding marital status (adult population divorced) and gender, and we found differences between the former and the recalculated SVI. However, after a lengthy discussion, we do not have strong arguments to support such changes specially because the variables initially selected are easily found in the literature to influence the level of Social Vulnerability.
~~More data are needed T~~t~~o overcome the limitation of the no~~n~~-significance in the difference between the evacuation curves more data need to be collected.~~
A limitation that arises when we apply a methodology such ~~us~~ as ReTSVI, which relies on the construction of a social vulnerability index, is that we could not find any studies that relate evacuation rates with social vulnerability for inundations that take less than an hour from the triggering to the flooding. In this study, we used a~~n~~ PCA-based SVI ~~based on PCA~~ to select the variables as proxy; however, this index was created and validated for post~~-~~event assessments. Therefore, this is a limitation that needs to be addressed before applying this framework.

Traditionally, the evacuation rate is calculated using one evacuation rate curve; therefore, ReTSVI seeks to overcome~~s~~ this limitation by allowing the user to include social vulnerability. The user decides which social vulnerability index to use and which ~~the~~ evacuation curves for the levels of vulnerability. Here we have provided an example using as a proxy a social vulnerability index for post-~~-~~disaster and evacuation curves that have no~~t~~ statistical significance. However, it still provides valuable information (Figure 8) ~~of~~ with respect to the implications of including social vulnerability that need~~s~~ to be validated. For example, more vulnerable people, according to the PCA-based SVI ~~based on PCA~~ and census data, live closer to the river where the inundation strikes earlier and harder, having less time to evacuate while at the same time they evacuate later. ~~Aditionally~~Additionally, social vulnerability seems to be less important as the EWS i~~get~~s delayed.

5 Conclusion

This article proposes a methodology to incorporate social vulnerability into current methodologies to estimate the percentage of people that evacuate an inundation hazard zone. Previous research recognizes the relevance of social vulnerability in risk assessments; however, in general the methodologies available fail to connect the physical vulnerability or the characteristics of an inundation event with social vulnerability in a quantitative framework. The results of the example of the ReTSVI in Huaraz show how a social vulnerability index could be used in the evacuation planning process. For example, such an analysis might show that there are distinct differences in the percentage of people evacuated in Huaraz for blocks that are close to each other, which could be explained by the SVI since their exposure to the physical hazard and the distance to escape are similar. The same is true when the alarm is delayed~~,~~; the longer it takes for the authorities to warn people, the ~~larger~~ greater the influence of the SVI. However, although it seems intuitively probable that people with different levels of social vulnerability would differ in their evacuation rates and departure times, there is no empirical data ~~that~~ to support this assumption. Differences in evacuation rates associated with~~to~~ level of social vulnerability needs further study because with the current state of the art and the data collected in this study, we cannot answer this question with statistical significance. We faced a similar situation when constructing a pre-inundation social vulnerability index. It is unclear which variables explain the differences in departure time, which is critical to applying the ReTSVI framework~~,~~; therefore, it also ~~needs~~ requires further study.

Acknowledgements

We would like to acknowledge the Ministry of the Environment of Peru for providing the 2007 Census of Peru. We also wish to thank Cesar Portocarrero for inspiring us to develop new methodologies to help those ~~ones~~ in need. Finally, we would like to thank Luis Rios-Cerda for his help applying the survey to first responders and Lindsey Carte for all her feedback~~s~~ and English review that helped us ~~to~~ improve this study.

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List of Tables

Table 1: Parametric and non-parametric statistical difference test between ~~level~~levels of social vulnerability.

Time	Anova (p-value)	Kruskal-Wallis (p-value)
0-5 minutes	0.13	0.09
0-15 minutes	0.44	0.39
0-30 minutes	0.67	0.60
0-45 minutes	0.85	0.87
0-60 minutes	0.87	0.52

Table 2: Bartlett test of sphericity

Chi-square	4014.63
Degrees of freedom	190
p-value	0.00
H0: variables are not intercorrelated	

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Table ~~2~~3: Summary of PCA Results

Selected Census variables after PCA analysis to estimate Social Vulnerability Index (SVI)	Sign Adjustment	Components					
		1	2	3	4	5	6
Household with 5 or more rooms	-	.31					
Population with health insurance		.40					
Population with primary education		-.37					
Population with college education		.43					
Population with “white collar jobs”		.40					
Indigenous population		-.35					
Population with disabilities	+		.53				
Population ~~older than~~over 65 years ~~old~~of age			.53				
Women			.44				
Informal settlement	+			.74			
Household without electricity				.41			
Illiterate population				.33			
Independent houses	-				.56		
House rented					.53		

Adult population divorced					-.57		
Jobs in the commerce sector						.61	
Jobs in the construction sector	+					-.33	
Number of people per square kilometer						.52	
Children ~~less~~ under ~~than~~ 1 year of age~~old~~	+						.59
Jobs in the manufacturing sector							.66
% of variance explained by component		20%	9%	8%	7%	7%	6%
Cumulative explained variance		20%	29%	37%	44%	51%	57%

List of Figures

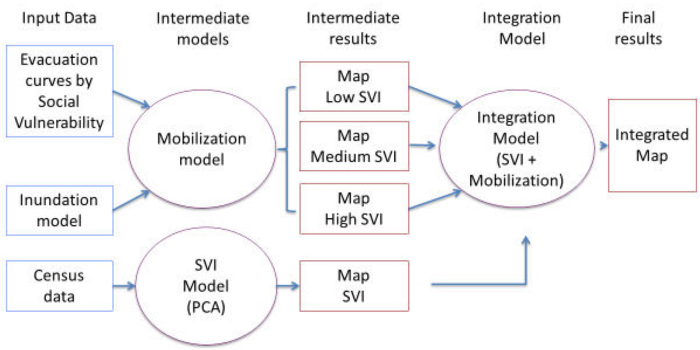


Figure 1: ReTSVI chart

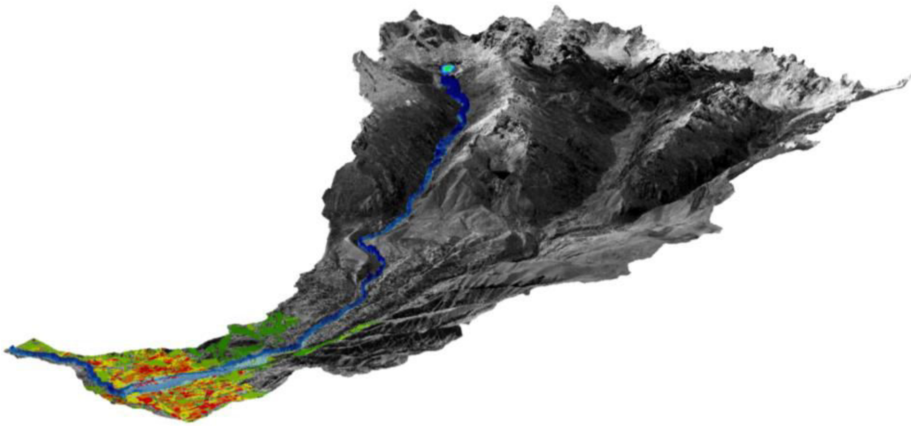
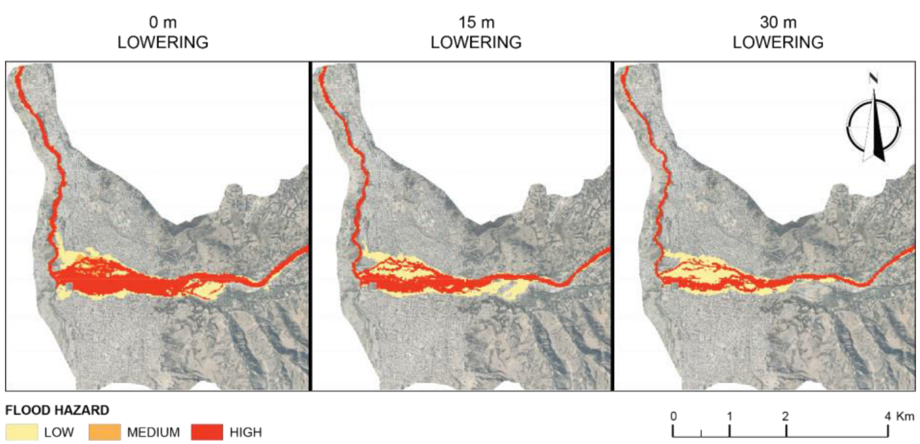


Figure 2: Huaraz, ~~City in~~ Peru at the bottom of the Cojup River. Lake Palcacocha ~~Lake~~, a potential source of a GLOF, is located at the head of the river.



5 **Figure 3: This image corresponds to Figure 9 from (Somos-Valenzuela et al., 2016). Preliminary hazard map of Huaraz due to a potential GLOF originating from Lake Palcacocha with the lake at its current level (0 m lowering) and for the two mitigation scenarios (15 m lowering, and 30 m lowering).**

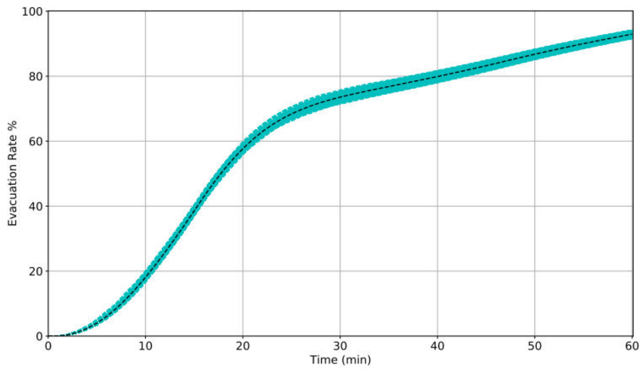


Figure 4: Evacuation rate during the first hour calculated using 1000 samples in a Monte Carlo ~~Simulation~~simulation

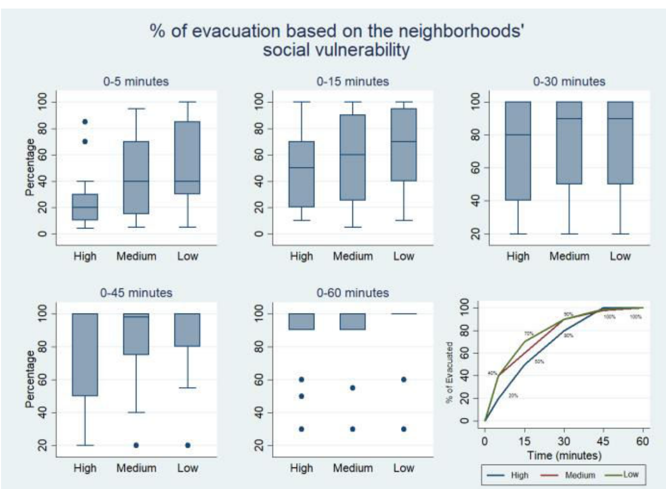


Figure 5: First responder~~'~~s results by social vulnerability group.

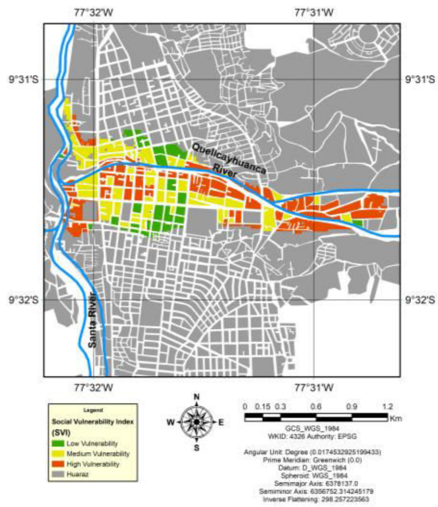


Figure 6: Comparative Vulnerability of Blocks in Huaraz using the Social Vulnerability Index (SVI)

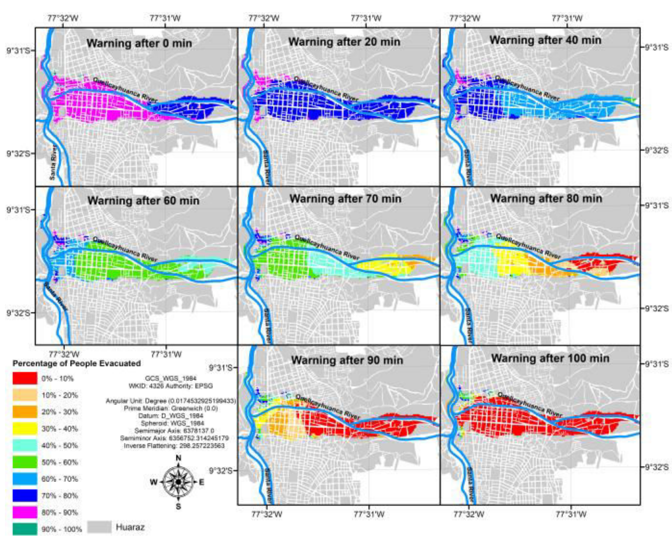


Figure 7: Evacuation using empirical equations.

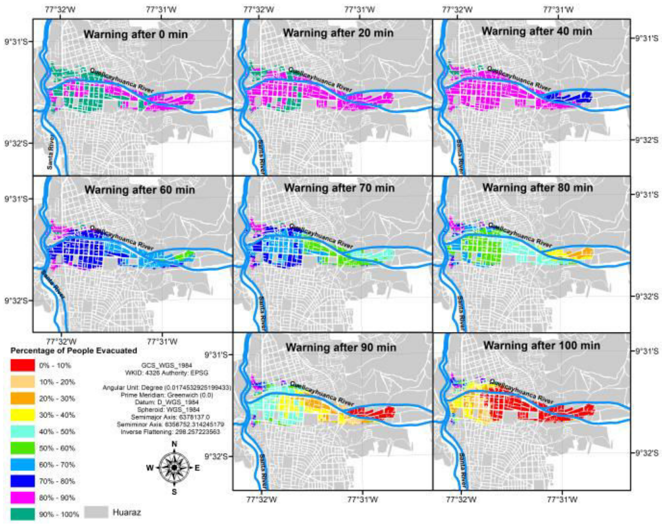


Figure 8: Evacuation using the Social Vulnerability Index.

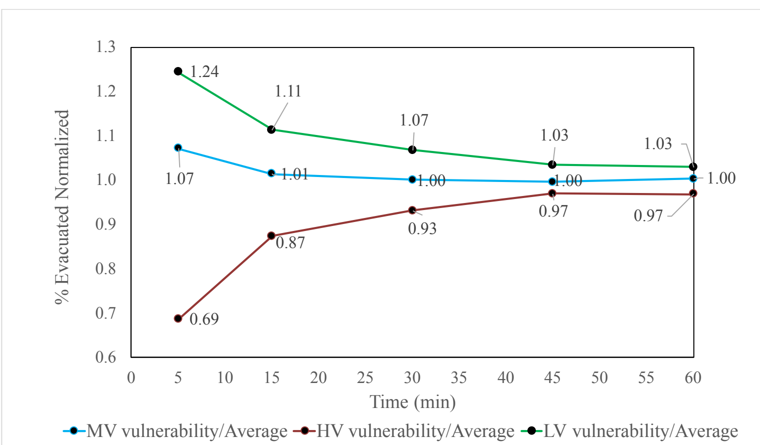


Figure 9: People evacuated per social vulnerability level normalized by the average number of people evacuated.