Agricultural and Forestry Sciences
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May 14, 2018

Dear Editor Dr. Paolo Tarolli

Thank you for considering our paper for further steps in this revision process. In this iteration we submitted a revised version of our paper with changes accepted, an abstract and in this file the response point by point to the comments, list with the changes to the article, and a revised version with changes that are not accepted.

For the editor comment: “From my side, I suggest justifying the selection of the variables in accordance to people capacity to evacuate. I agree that this is not the main purpose of the manuscript, but the paper would be benefited, and results would be more robust in accordance.”

Response to editor comment: We addressed these points in our response 9 and 10 to reviewer 2. We copied the answer in the next page.

With all the best,

Dr. Marcelo Somos-Valenzuela

Corresponding author

From responses to Reviewer 2:

Comment 9:

The utility of having 22 interviews is not properly set. The four institutions have been not described and the questions are not well explained, as well as the type of those (quantitative, qualitative?). How could respondents define low, medium and high social vulnerability? Why are stakeholders assumed to know the average evacuation time and the percentage of the population that usually evacuates? Was it related to their personal experiences or have the data in support of it? Another critical error is made in creating the social vulnerability index.

Response to comment 9:

The four institutions have been not described and the questions are not well explained, as well as the type of those (quantitative, qualitative?).

We explain in more detail who are the first responders that participated in the survey and how we recollect the data.

The original text from page 7 line 14 after the dots reads as follow:

“Four institutions that work directly to help the population during the evacuation process participated in this study: the navy, the police, firefighters and the municipality of Coquimbo. Each institution selected at least five employees to respond to our questionnaire, these employees work directly during the emergency to help people evacuate their houses. The survey was completed with the help of a research assistant that conducted a personal interview with each participant. We asked first responders to estimate the average evacuation time and the percentage of the population that evacuates their households from 0 to 5 minutes, 0 to 15 minutes, 0 to 30 minutes, 0 to 45 minutes, 0 to 60 minutes in neighbourhoods with low, medium and high social vulnerability in Coquimbo.”

We replace this text with the paragraph below:

“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 to explain the purpose of the study and asked them if they agree to participate in the research, all 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 worked directly during the emergency to help people evacuate their houses. The research assistant conducted a personal interview with each participant. We asked the first responders “In your opinion and based on your experience during the tsunami of 16th of September. Since the evacuation alarm was active, what is the evacuation time of population who live in areas of low/medium/high social vulnerability?” They needed to estimate the average evacuation time in neighborhoods with low, medium and high social vulnerability. Then, we asked “what is the percentage of the population that evacuate in the first X minutes? (X=5, 15, 30, 45, 60)” The first responders write down the percentage of the population that evacuates their households 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 recollected into two scales: percentages and average time (in minutes)

Comment 10: How could respondents define low, medium and high social vulnerability?

Response to comment 10:

We use the National Socio-economic Characterization Survey (CASEN)[1] from 2015, same year that the earthquake/tsunami occurred, to calculate a social vulnerability index at the municipality level, following the same procedure identify 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. We incorporate this information in the survey, so the first responders could identify what neighborhood belongs to each category; all responders generate separate curves for low, medium, or high vulnerability neighborhoods."

[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).

Dear Reviewer 1

We thank you for taking the time to give this exhaustive review that had helped us to improve our document. We have taken your revision very seriously, and in the following pages, we provide answers to all the comments that you gave us, hoping very much that you feel that we have responded thoroughly.

Sincerely,

Marcelo Somos-Valenzuela
Corresponding author

Comments from reviewer 1

Summary: This manuscript describes a promising method of incorporating social vulnerability into evacuation analyses. The review of the social vulnerability literature is relatively strong but the review of research on evacuation analysis is rather weak. Two very extensive reviews of research on hurricane evacuation concluded that sociodemographic variables have weak and inconsistent correlations with evacuation decisions (Baker, 1991; Huang et al., 2016) and the research on evacuation departure times is extremely sparse, even for hurricane evacuations. There is a more directly relevant literature on pedestrian evacuation for tsunamis (see the references cited below) but it does not address social vulnerability to any significant extent. In addition, there are also some unanswered questions about the reliability and validity of the evacuation departure time data reported in this study. Overall, the weak empirical foundation in the existing literature and in this study suggests that the authors should be very cautious about any claims about the contribution that social vulnerability indicators can make in improving evacuation analysis.

Response to Summary:
We appreciate the comments from Referee 1, this methodology is intended to help filling the gap that exists in the combination of Physical and Social vulnerability which is traditionally accomplish by ranking them separately and combining them in a matrix generally of 3 by 3. We agree with most of the comments that Anonymous Referee 1 made, and we addressed them in the following pages. We understand the concern that Referee 1 has regarding the lack of empirical foundations which is also true for previous studies. In this work, what we are proposing is a methodology (ReTSVI) to combine Physical and Social Vulnerability by connecting a series of modules that represent processes that occur in an evacuation due to flood hazards; however, we understand that the outcome of this methodology is highly dependent on the definition of the evacuation rate curves. However, we argue that it has to be part of future studies to explain place to place if social vulnerability is statistically significant to describe differences in the evacuation rate. Although with no statistical significance, our results agree with the literature associated to Hurricanes since we found that social vulnerability has less impact after one hour of warning, which is the case in hurricanes where the warn can be given with days in advance. Therefore, we would restrict this work to floods that occurs in a timescale of an hour or less. What we hope this work will be useful for is to define a framework that helps to raise questions related to specific processes associated to social vulnerability that occur in an evacuation due to flood hazards, improve methodologies and integrate/test this new knowledge as modules in this framework.

- Comment 1: Page, Line, Comment 10 L12. The description of the data from the first responders lacks specificity about the process by which the data were collected. One possibility is that each responder was asked to describe the response curve for a specific neighborhood that she or he assisted in evacuating, after which the authors classified the neighborhoods in terms of their social vulnerability. Alternatively, all responders might have been asked to generate separate curves for low, medium, or high vulnerability neighborhoods. The first procedure is much more likely than the second one to generate reliable data. The description of the data also lacks any measures of interrater agreement for the ratings of the percent evacuated at each point in time. The authors should present some measure of variability such as the standard error of the mean for each point in Figure 5. That information should be accompanied by statistical tests of the differences among the curves for low, medium, or high vulnerability neighborhoods. Given the small sample of responders, it seems quite possible that there are no statistically significant differences among the curves even at 5 minutes. If there are nonsignificant differences among social vulnerability neighborhoods at any given time point, the most appropriate estimate of percentage of evacuees at each point in time would be the median estimate. For example, Figure 5 shows that there is almost certain to be a nonsignificant difference among neighborhoods at 60 minutes. Thus, the median of the three estimates (the estimate of .89 for moderate vulnerability) would be the most appropriate statistical estimate for all three levels of social vulnerability. If there are significant differences at some time points, then those significantly different estimates should be used. However, all time points at which there are nonsignificant differences should have the high and low vulnerability estimates replaced by the median estimate for that time point (the estimate for the moderate vulnerability group).

Response to comment 1:

As the reviewer suggested, there are two possible ways to estimate recollect the data. We tried to use the first procedure (each responder was asked to describe the response curve for a specific neighborhood that she or he assisted in evacuating, after which the authors classified the neighborhoods in terms of their social vulnerability), but it is not possible to do it in Chile due to the lack of data. The most recent data available at household level comes from the census of population conducted in 2002. We checked this dataset, and one of the problems is that many of the new neighborhoods in Coquimbo built after 2002 are not present in the census data. The second option is that all responders might have been asked to generate separate curves for low, medium, or high vulnerability neighborhoods. In the case of Chile, this is the only option available. We use 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 identify 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 incorporate this information in the survey, so the first responders could identify what neighborhood belongs to each category; all responders generate separate curves for low, medium, or high vulnerability neighborhoods. Table 1 shows the variables and levels that we use to define the neighborhoods' social vulnerability in Coquimbo.

Therefore, we added a new Table 1, and the former Table 1 now is 2 and the same happens to the next tables. Also, we added on page 7 line 21 the following paragraph:
"We use the National Socioeconomic Characterization Survey (CASEN)[2] 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 incorporate this information in the survey, so the first responders could identify what neighborhood belongs to each category; all responders generate separate curves for low, medium, or high vulnerability neighborhoods."

Aditionally, we have modified Figure 5 and the section 3.1 and now it reads as follow:

3.1 Survey to first responders

Figure 5 shows the percentage of the population that evacuate after the tsunami alarm was activated in neighborhoods with high, medium and low social vulnerability. Each box presents the 75th percentile (upper hinge), the median (center), the 25th percentile (lower hinge) and the outlier values. Figure 5

[2] 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).

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 term of the percentage of evacuation decrease over time and eventually disappear after an hour since the alarm was activated.

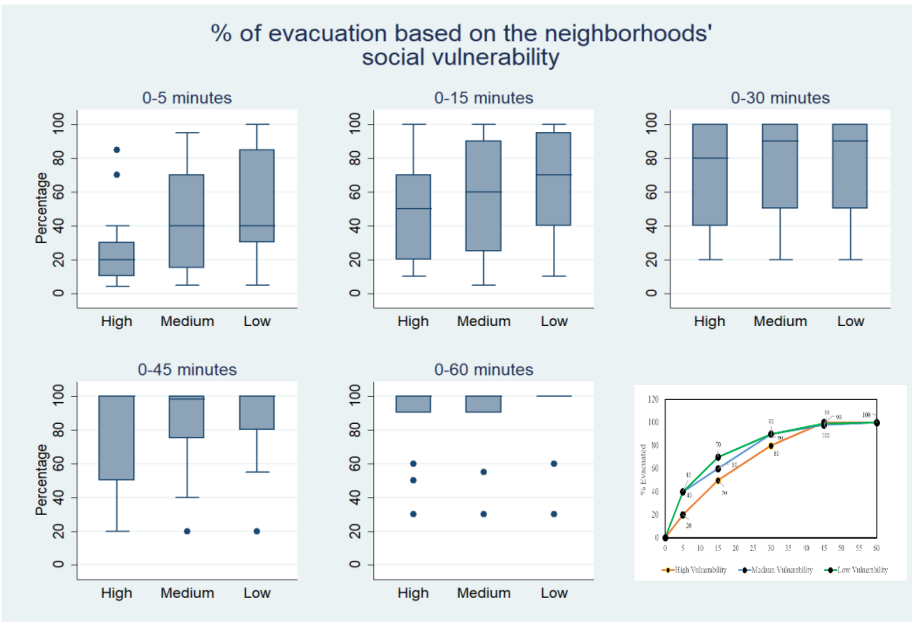

Figure 5: First responder's results by social vulnerability group. Bottom right figure show the median value.

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). Table 1 shows that the differences are not statistically significant between neighborhoods using both methods; this could be due to the limited size of the sample. In consequence, we decide to use the median rather than the mean as the middle point of the distribution of the mean response time.

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

Time	Anova	Kruskal-Wallis
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

- Comment 2: Page 11 L8. If all six components were included in the SVI, what is the justification for believing that all of them are relevant to evacuation vulnerability? This issue of evacuation vulnerability (as distinct from general social vulnerability) is important because most of the Cutter et al. (2003) examples of social vulnerability in their Table 1 refer to disaster recovery rather than evacuation. There are some authors that have addressed evacuation vulnerability but, to the best of my knowledge, only Chakraborty et al. (2005) and Kusenbach et al. (2010) have examined social vulnerability in evacuation. (Cova's papers on evacuation vulnerability examine vulnerability due to evacuation route system geometry and link capacity.) Even the Chakraborty and Kusenbach studies assumed that their measures of social vulnerability would actually make a difference in evacuation rather than demonstrated it empirically. There is a broader literature on household evacuation, but the available data show no evidence that any of the sociodemographic variables measured in these studies is consistently related to evacuation (Baker, 1991; Huang et al., 2016), let alone evacuation departure time distributions. The only evacuation review to cite evidence in support of any relationships of sociodemographic variables with household evacuation only cited positive instances and ignored reports of nonsignificant correlations (Dash & Gladwin, 2007).

Response to comment 2: First of all, we would like to explain why we use 6 components instead of 10 or 11 or any number in between. To determine the number of components that will be part of the social vulnerability index, we selected those components with eigenvalues values greater than one, as the graph below shows. This criterion has been used by previous studies (Schmidtlein et al., 2008) and the methodology to construct the social vulnerability index was added, step by step, in the page 10 after line 9.

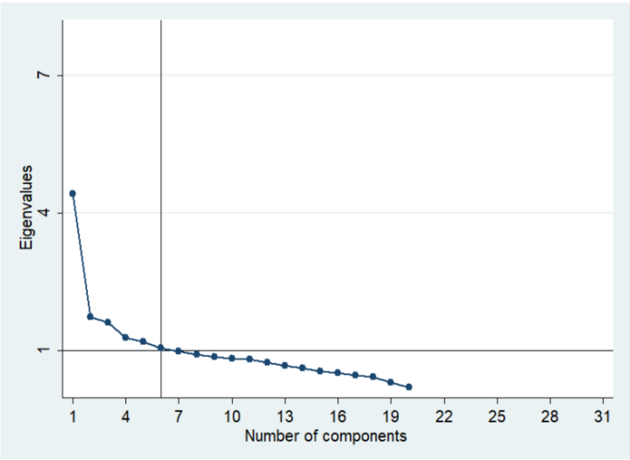

Figure 1 reviewer 1: Eigenvalues calculated using PCA analysis.

As the reviewer mentioned, there is a body of literature that does not find a connection between social vulnerability and evacuation process (i.e. Baker, 1991; Huang, Lindell, & Prater, 2016). However, this literature has been conducted during evacuation process due to Hurricanes, where the population is informed to evacuate their home with hours or days in advance. According to our result, although with no statistical significance, social vulnerability is only relevant during the first 30 minutes after the evacuation alarm is activated, after that, the response time is almost the same among neighborhoods from different levels of social vulnerability. In the case of floods, the literature suggests that social vulnerability is an important element to consider in order to understanding different behaviors during flooding evacuations. In particular, scholars have found that variables such as low household income, poor housing quality, children (Pelling, 1997), women, housewives, students (De Marchi, 2007), elderly, high population density and population with low level of education (Zhang and You, 2014) are key variables to consider to create a social vulnerability index linked to evacuations during disasters. On the other hand, we wanted to use a methodology that make use of census information without major intervention. Therefore, we extend the application of the findings from Fekete (2009) , even though this research was conducted disaster recovery rather than evacuation, who demostrate that "social vulnerability indices are a means for generating information about people potentially affected by disasters that are e.g. triggered by river-floods." Coincidently, the components selected by the criterion used and explained in this work are similar if not the same to what the literature review indicated. Therefore, we felt encouraged to use the 6 components to first explain the responder what we mean by high, medium, and low social vulnerability and to do the exercise of application in Huaraz.

We added this previous paragraph into the discussion section after Page 12 line 29.

- Comment 3: Page 11 L11. Figure 6 does indeed show that there are many blocks of high social vulnerability located close to the river, but there are also blocks of medium and low vulnerability there as well. The authors' argument would be more persuasive if they would overlay the expected inundation zone onto the map and calculate the proportion of high, medium, and low vulnerability blocks within the inundation zone.

Response comment 3:
We agree with this comment and we have change Figure 6

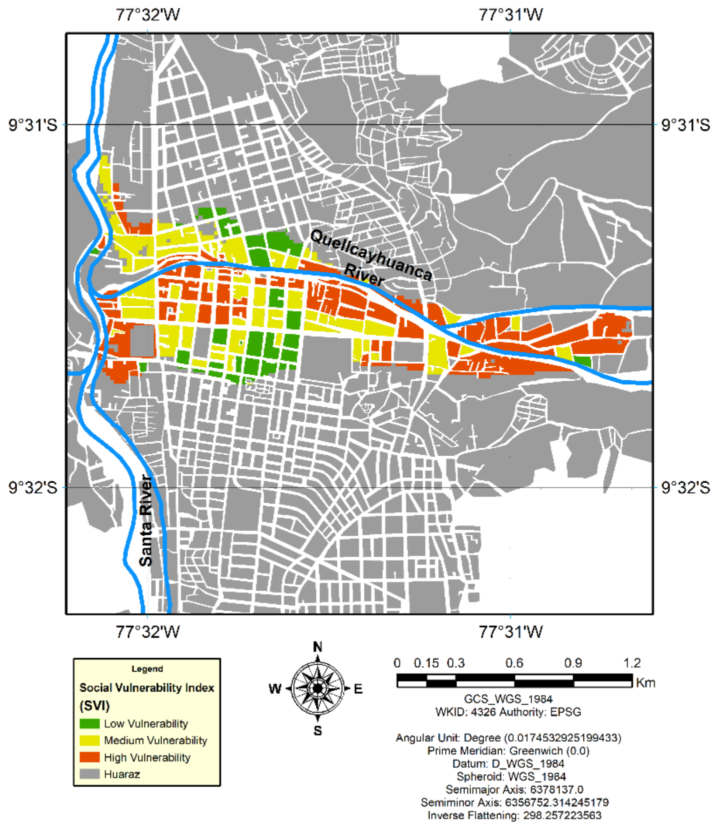

Figure 6: Comparative Vulnerability of Blocks in Huaraz using Social Vulnerability Index (SVI)

And we added in the text after inserting Figure 6: "The proportion of high, medium and low vulnerability blocks within the inundation zone are 15%, 35 %, and 50% respectively."

- Comment 4: Page 11 L27. The differences among the neighborhoods with respect to the outcomes of the evacuation model are necessarily a direct result of the presumed differences among the three evacuation rate curves. If the differences among the three curves are not significantly different from each other, then a single departure time curve should be used and the differences among the neighborhoods with respect to the outcomes of the evacuation model will vanish.

Response comment 4:
The reviewer is right here. If all the curves are not significantly different from each other, at the end the result will be the same to what it is traditionally used, which is a single curve that does not discriminate the population by the social vulnerability. Therefore, this methodology is building from what it is already out there, and it proposes a framework to incorporate information on the evacuation as a function of vulnerability level when it is available.

- Comment 5: Page 11 L29. The finding that evacuations were completed more rapidly with the earth-quake/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 = 1 in Equation 3, which makes the time-consuming contagion process unnecessary.

Response comment 5:

We have included the two references and the paragraph suggested in our text and from Page 11, Line 30 after the dot now it reads “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 = 1 in Equation 3, which makes the time-consuming contagion process unnecessary.”

- Comment 6: Page 12 L7 would be more accurate if restated with the following qualifications. Social vulnerability is thought to be an important factor that needs to be included in evacuation analyses but there are no systematic frameworks to do so. Moreover, although it seems intuitively plausible that people with different levels of social vulnerability would differ in their evacuation rates and departure times, there are no empirical data that support this assumption. One imitation of the available research is that Baker (1991) and Huang et al. (2016) â˘A˘ Tthe two most relevant literature reviewsâ˘A˘Taddressed (primarily vehicular) hurricane evacuation in the Unites States. It is unclear if these results would generalize to pedestrian evacuation in other countries.

Response comment 6:

We modified accordingly to the reviewer suggestion on page 12, from line 7-10. After the dot until the end of the paragraph now it reads: “Social vulnerability is thought to be an important factor that needs to be included in evacuation analyses but there are no systematic frameworks to do so.”

- Comment 7: Page 12 L29. Morss et al. (2011) did not address any studies of evacuation, let alone the effects of social vulnerability on evacuation departure times, so the claim in this sentence about the comparability of the sample size is unsupported.

Response comment 7:

We apologize for this mistake, and we delete the sentence and reference.

- Comment 8: Page 13 L4. This study does not “estimate the percentage of people that evacuate an inundation hazard zone” (my emphasis); it estimates the rate at which people evacuate an inundation zone.

Response comment 8:

The first part of the methodology proposed is to estimate the rate at which people evacuate an inundation hazard zone for three level of social vulnerability (Figure 1). However, when it is combined with the arrival time of the flood and the evacuation mechanism (in our case walking), it is possible to calculate the percentage that departs and reach a safe area before the flood arrives. Therefore, the result of this methodology is the percentage of people that evacuate an inundation hazard zone. Figure 7 and 8 show this, the only difference between the different frames in each figure is that we highlight the effect of delaying the warning, but all of them show the percentage of people evacuated in each scenario according to the assumptions and simplifications we made.

References

Baker, E.J. (1991). Hurricane evacuation behavior. International Journal of Mass Emergencies and Disasters, 9, 287-310.

Chakraborty, J., Tobin, G. A., & Montz, B. E. (2005). Population evacuation: assessing spatial variability in geophysical risk and social vulnerability to natural hazards. Natural Hazards Review, 6(1), 23-33.

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. Social science quarterly, 84(2), 242-261.

Dash, N. & Gladwin, H. (2007). Evacuation decision making and behavioral responses: Individual and household. Natural Hazards Review, 8, 69-77.

Huang, S-K., Lindell, M.K. & Prater, C.S. (2016). Who leaves and who stays? A review and statistical meta-analysis of hurricane evacuation studies. Environment and Behavior, 48, 991-1029.

Kusenbach, M., Simms, J. L., & Tobin, G. A. (2010). Disaster vulnerability and evacuation readiness: coastal mobile home residents in Florida. Natural Hazards, 52(1), 79-95.

Lindell, M.K., Prater, C.S., Gregg, C.E., Apatu, E., Huang, S-K. & Wu, H-C. (2015). Households' immediate responses to the 2009 Samoa earthquake and tsunami. International Journal of Disaster Risk Reduction, 12, 328-340.

Wei, H-L., Wu, H-C., Lindell, M.K., Huang, S-K., Shiroshita, H., Johnston, D.M. &Becker, J.S. (2017). Assessment of households' responses to the tsunami threat: A comparative study of Japan and New Zealand. International Journal of Disaster Risk Reduction, 25, 274-282.

Dear Reviewer 2

We thank you for taking the time to give this exhaustive review that had helped us to improve our document. We have taken your revision very seriously, and in the following pages, we provide answers to all the comments that you gave us, hoping very much that you feel that we have responded thoroughly.

Sincerely,

Marcelo Somos-Valenzuela
Corresponding author

Comments from reviewer 2

The paper entitled “Response Time to Flood Events using a Social Vulnerability Index (ReTSVI)” seeks to explore a new method to convey the social vulnerable indicators together with evacuation response time under flood threat. Although worth of work, there is a need for significant reworking.

- Comment 1:

The introduction section is very general about the framework of social vulnerability (and sometimes only about vulnerability in general, lines 16-25, page 3) and it fails to interpret the studies in relation to floods hazard (for which a rich literature exists, e.g. Koks et al. 2015; Fekete 2009; Rufat et al. 2015; De Marchi and Scolobig 2012; Zhang and You 2014; Pelling 1997; Roder et al. 2017; De Marchi et al. 2007 among others).

Response to comment 1: We appreciate this suggestion and we modify this text from page 2 line 23-26 which originally read:

“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 both vulnerabilities (Cutter & Emrich, 2006; Hegglin & Huggel, 2008)”.

To this: “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 both vulnerabilities to study evacuation (Chakraborty, Tobin, & Montz, 2005)) or recovery process after hazards occur (Cutter & Emrich, 2006; Hegglin & Huggel, 2008)”

Additionally, in page 3 line 25 after the dot we added the following paragraph: “Models of social vulnerability, in this area, have been used to explain the capability of communities to face and recover from disasters (Chakraborty et al., 2005).

Scholars have tried to understand whether socioeconomic and demographic characteristics of the population are relevant to understand why neighborhoods or communities respond differently during an evacuation, why some people evacuate, and others do not evacuate during disasters. The evidence about evacuations during hurricanes shows mixed results. Huang, Lindell, & Prater (2016) analyzed 49 studies linked to evacuations to hurricane warnings conducted since 1991 and concluded that demographics variables have a minor or inconsistent impact on household evacuations. In contrast, others studies show that social vulnerability is a key factor to take into account during emergency management and evacuation planning (Bateman and Edwards, 2002; Chakraborty et al., 2005; Dash and Gladwin, 2007; Kusenbach et al., 2010). In the case of floods, studies suggest that social vulnerability is an important element to consider in order understanding different behaviors during flooding evacuations. In particular, scholars have found that variables such as low household income, poor housing quality, children (Pelling, 1997), women, housewives, students (De Marchi, 2007), elderly, high population density and population with low level of education (Zhang and You, 2014) are key variables to consider to create a social vulnerability index linked to evacuations during disasters.”

- Comment 2: The paper needs extensive restructuring and in its current form fails to analyze the use of mapping social vulnerability for evacuation purposes for emergency management plans. This is a particular application, and the authors were unable to provide a strong bibliography in support of this context.

Response to comment 2: We appreciate this comment and literature suggested by reviewer 1 and 2. We have modified the introduction to narrow our review toward this particular application (see our response above). Regarding restructuring the paper, we have had several native english speaker readers that have helped us to shape this document. Therefore, we feel that, unless the editor thinks otherwise, the paper flow is adequate and it can be easily followed and understood.

- Comment 3: The identification of social vulnerability for effective early warning of disaster-related risks has not been adequately explained. There is no mention of the scale analysis at which mapping social vulnerability can be a usefulness tools for emergency management.

In this work, we do not question if the social vulnerability can be useful for emergency management because it is a normal practice that is widely used. What we identified is that traditionally this process is qualitative where social vulnerability is used to aggregate the population into high, medium and low level of vulnerability. Therefore, we are proposing a methodology to push this use of social vulnerability into a quantifiable unit by including it in the evacuation process. The statistical significance is still an issue that for the number of the first responders we used, we cannot solve in this work and we provide a review for that as well. Please see modified section 3.1 and Table 1.

- Comment 4:

Lines 1-15 page 3 is a repetition of the introduction, and lines 7-1 of the following page bring the reader a bit out of the general content of the manuscript.

Response to comment 4: To avoid redundancy, we deleted page 1 lines 2-5. Regarding page 4 line 7-10, we think that it is important to mention that there are intents to solve the limitation in quantify social vulnerability.

- Comment 5:

Moreover, the evacuation literature is structurally confused (please consider them disasters and not natural disasters that is quite overlooked) for which I suggest a more focused review and the strongest argumentation.

Response to comment 5: We used the term “natural disaster” instead of “disasters” because the nature of the problems analyzed and the spirit of this work are associated with the environment. These disasters may be trigger by human actions, but they are understood as natural events in the literature. Additionally, we extended our literature review to address the evacuation associated with natural disasters. On the other hand, if the editor suggests that we use the word “disaster” instead of “natural disaster” we will change it in the document.

- Comment 6:

The objectives of the study are also not explained adequately.

Response to comment 6: In section 2.1 Conceptual model of ReTSVI, we implicitly explain the objective of the study "The Response Time by Social Vulnerability Index (ReTSVI) methodology allows for the inclusion of social vulnerability into the traditional evacuation/mobilization models. Figure 1 is a chart of ReTSVI, 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 result 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 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 considers their social vulnerability level."

In order to further attend this comment, we modified the paragraph indicate above in the main document and now it reads like this: "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. Figure 1 is a chart of ReTSVI, 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 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 considers their social vulnerability level."

- Comment 7:

The methodology part is a bit confused due to the presence of several small chapters that mix up the methods, data collection and the study area, also lacking a chronological sequence. Please organize the chapter is the simplest format to increase the readability (I suggest to start from the study area, data collection and methods at last).

Response to comment 7: We adressed this question above "Regarding restructuring the paper, we have had several native English speaker readers that have helped us to shape this document. Therefore, we feel that, unless the editor thinks otherwise, the paper flow is adequate and it can be easily followed and understood". Aditionally, we feel like Reviewer 2 suggest that the area of study and Huaraz is the center of this work; however, we used this place as an example of application of the methodology proposed ReSTVI. Therefore, the importance of the “area of study” or “the case study” is secondary and it needs to go after we explain the methodology not to confuse the readers.

- Comment 8:

For the study area selection, there is a need to strongly justify the decision to study GLOF hazards in Peru providing some inundation zone maps and probability of occurrence details.

Response to comment 8: The reason to use this GLOF hazards is that one of the authors did the simulation for a potential inundation in Huaraz as part of a project that was funded by United States Agency for International Development (USAID), Interamerican Development Bank (IBD) and The ministry of environment of Peru. During this work in Peru, we also wanted to evaluate the implication of installing an early warning system. Then, we realized that the population exposed to the potential hazard was completely different in terms of social vulnerability, and we worked with the Ministry of Environment to have access to the Census data, which is not publicly available, to determine the different levels of social vulnerability and which group was going to be affected more or less. This work was published in Somos-Valenzuela (2014). During the work described, we realized that there was not a formal methodology to combine social vulnerability into the evacuation process, which is confirmed from our literature review and the literature recommended for both reviewers, we may still miss publications and examples from others part of the world though. Then we try to generate data on the evacuation rate and the differences in social vulnerability in the evacuation process in Huaraz; however, although there were a couple of evacuation drills organized by the civil defense of Peru in Huaraz, we were not allowed to access the information collected, if there were any information collected. After this, we decided to collect data after a tsunami in Coquimbo knowing that the hazard and the population are different; however, our goal is to provide a methodology and we provide an example of how the methodology should be applied.

For the second part of the question, the inundation maps were published in Somos-Valenzuela et al., (2016), we used the result of that work in this paper (Figure 5). The probability of occurrence is irrelevant for this work because we want to know the evacuation rate given the inundation scenario selected. Therefore, for the sake of this example, the probability of the inundation is 100% since it is the condition that has to happen to have the scenario presented as the application example in this paper. Additionally, calculating the probability of an inundation generated due to GLOF events is not straightforward given the nature of the hazard. There is not enough data to determine the frequency, location, and magnitude of those events. Additionally, the research frontier in GLOF is looking into the calculation of the probability of occurrence of GLOF, which is far from the scope of this paper, although, we are aware of the importance of the frequency of any hazard in a proper risk analysis which is not what we present in this work.

- Comment 9:

The utility of having 22 interviews is not properly set. The four institutions have been not described and the questions are not well explained, as well as the type of those (quantitative, qualitative?). How could respondents define low, medium and high social vulnerability? Why are stakeholders assumed to know the average evacuation time and the percentage of the population that usually evacuates? Was it related to their personal experiences or have the data in support of it? Another critical error is made in creating the social vulnerability index.

Response to comment 9:

The four institutions have been not described and the questions are not well explained, as well as the type of those (quantitative, qualitative?).

We explain in more detail who are the first responders that participated in the survey and how we recollect the data.

The original text from page 7 line 14 after the dots reads as follow:

"Four institutions that work directly to help the population during the evacuation process participated in this study: the navy, the police, firefighters and the municipality of Coquimbo. Each institution selected at least five employees to respond to our questionnaire, these employees work directly during the emergency to help people evacuate their houses. The survey was completed with the help of a research assistant that conducted a personal interview with each participant. We asked first responders to estimate the average evacuation time and the percentage of the population that evacuates their households from 0 to 5 minutes, 0 to 15 minutes, 0 to 30 minutes, 0 to 45 minutes, 0 to 60 minutes in neighbourhoods with low, medium and high social vulnerability in Coquimbo."

We replace this text with the paragraph below:

"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 to explain the purpose of the study and asked them if they agree to participate in the research, all 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 worked directly during the emergency to help people evacuate their houses. The research assistant conducted a personal interview with each participant. We asked the first responders "In your opinion and based on your experience during the tsunami of 16th of September. Since the evacuation alarm was active, what is the evacuation time of population who live in areas of low/medium/high social vulnerability?" They needed to estimate the average evacuation time in neighborhoods with low, medium and high social vulnerability. Then, we asked "what is the percentage of the population that evacuate in the first X minutes? (X=5, 15, 30, 45, 60)" The first responders write down the percentage of the population that evacuates their households 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 recollected into two scales: percentages and average time (in minutes)

- Comment 10: How could respondents define low, medium and high social vulnerability?

Response to comment 10:

We use the National Socio-economic Characterization Survey (CASEN)[3] from 2015, same year that the earthquake/tsunami occurred, to calculate a social vulnerability index at the municipality level, following the same procedure identify 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. We incorporate this information in the survey, so the first responders could identify what neighborhood belongs to each category; all responders generate separate curves for low, medium, or high vulnerability neighborhoods."

- Comment 11: Why are stakeholders assumed to know the average evacuation time and the percentage of the population that usually evacuates? Was it related to their personal experiences or have the data in support of it?

Response to comment 11: Their information provide by first responders is base on their personal experience during the evacuation to the tsunami. This group of first responders participated actively and directly during the evacuation process; we asked them to estimate, based on their experience during the tsunami, what would be the percentage of evacuation, and an average time of the evacuation of the population of Coquimbo.

- Comment 12:

The authors used the receipt of Cutter without acknowledging properly the acronym (SoVI and not SVI as stated), the trademark and the complete receipt.

Response to comment 12: We use the methodology developed by Susan Cutter (2003) to construct the Social Vulnerability Index (SVI). However, we do not use the same variables to run the Principal Component Analysis because the census in Peru has different variables than the US census. Other authors, see Koks et al., (2015), Fekete (2009), also use Cutter's methodology to construct a social vulnerability index calling their indexes SVI. In consequence, we called the name SVI and not SoVI because they are created with a similar process but they are different indexes with different variables.

- Comment 13:

Do the authors transformed the variables to be able to compare them (e.g., z-score normalization)? Do the authors made a multicollinearity analysis to prove that none of the variables was predictive of others? Which threshold for component selection (referring to Eigenvalues.)?

Response to comment 13:

We did not include the methodology in the original text because we considered that the citation was enough. However, we are glad to provide an extensive explanation of what we did. Therefore, in the document in Page 10 line 9 after the dot we included the following paraphaph:

"To construct a Social Vulnerability Index (SVI), we analyzed census data using Principal Component Analysis(PCA). PCA is a multivariate technique "that analyzes a data table in which observations are

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[3] 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).

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 in a new set of orthogonal variables called principal components. For example, PCA "provides an approximation of a data table, a data matrix, X, regarding 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 in social vulnerability over time (Cutter et al., 2003). First, we identify the variables that were linearly correlated using the Variance Inflation Factors (VIF), those variables with VIF higher than 10 points were excluded from the model. Then, we followed Schmidtlein et al. (2008), who list seven steps to calculate the Social Vulnerability Index (SVI): (1) Normalize all variables as a percentage, per capita or density functions. For this paper, we normalized all variables as percentages; for example, the percentage of independent houses per block or the percentage of older adults per block. Then standardize all input (census) variables to z-scores $z = \frac{x-\mu}{\sigma}$. This creates variables with mean 0 and standard deviation 1. (2) Perform the PCA with the standardized input variables (z-scores). Select the number of components based on eigenvalues greater than one. (3) Rotate the initial PCA solution. In our work we used a normal Kaiser varimax rotation for component selection. (4) Calculate the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) and Bartlett's test of sphericity. (5) Interpret the resulting components as to how they may influence (increase or decrease) social vulnerability and allocate signs to the components accordingly. (6) Combine the selected component scores into a univariate score using a predetermined weighting scheme. The factors are named based on variables with significant factor loading, usually greater than .3 or less than -.3. (7) Finally, we standardized the resulting SVI scores to mean 0 and standard deviation 1.
All the steps but step 6 are straightforward. In step 6, we must decide how we want to combine the different components. The first criterion is to use the scores from the PCA, adding them but assuming that all the components have the same contribution to the SVI (Cutter et al., 2003). The second criterion uses the scores from the PCA but assigns different weights to the principal components according to the fraction of variability they explain (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 its explained variance multiplies each component (Schmidtlein et al. 2008). We use the first criterion; we gave the same weight to all components. 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 (2012) page 1167 provide a solid argument that explains the reason of 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) argue that there is no appropriate methodology for the calculation of the index."

- Comment 14: Which the adjusted directionality of the components (Table 1)? The directionality is the most important part in the creation of the equation and thus the resulted index for each block. Also, in this regard, how factors have been weighted? (e.g., equally, Pareto rankings or with the variance each factor explained).

Response to comment 14: For the directionality, we indicate this with the sign in front of the variable name following Table 1 from Fekete (2009). However, for the sake of clarity, we modified Table 1 to clarify the directionality of the component and added a new column with the sign adjustment of the components.

Original Table 1:

Selected Census variables after PCA analysis to estimate Social Vulnerability Index (SVI) + more vulnerable – less vulnerable	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 65 years old		.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 than 1 year 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 %

New version of Table 1

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 65 years old	+		.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 than 1 year 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%

- Comment 15:

The selection of social vulnerability indicators is only based on the work of Cutter et al. (2003) and this step is very reductive in relation to the objective of the research that is focused in evacuation rather than recovery. There is salient need to criticize construction of indicators to flood hazards looking at those variables that really would have an effect on peoples’ capacity to evacuate. It will add important value to the paper and ensure an advancement in understanding social vulnerability for this specific hazard for Peru.

Response to comment 15: Reducing this study just to the work by Cutter (2003) is not accurate, which is demonstrated by the many authors cited in this paper that used social vulnerability indexes. The basic idea is to use census data to shed some light to a very complex process which is understanding social vulnerability interactions. Advancing the research in social vulnerability is by no means an objective of this paper. Therefore we believe that although this is an interesting question it is out of the scope of this work.

- Comment 16: It is not understood how the authors selected the variables (from 245 to 20). This is one of the most critical points in this part of the analysis.

Response to comment 16: The selection of the variables to construct the SVI is explained in our respond to comment 13.

- Comment 17: How the economic status affects people capacity to evacuate? How being divorced? Or renting a house?

Response to comment 17: First of all, the goal of using the methodology selected to construct a social vulnerability index is to generate an index that is driven by Census data and the selection of variables is controlled by the results of the multicollinearity and PCA analyses. The major intervention is the assignment of the contribution sign to the vulnerability, and we support this from the literature revised. According to previous work that link social vulnerability and evacuation process due to disasters, the literature shows that socioeconomic status of families (in particular income and education) (Kusenbach et al., 2010), marital status of the household head and house ownership (Pelling, 1997) affect the ability of people and communities to respond or evacuate during a disaster. In this sense, we use variables to construct our Social Vulnerability Index (SVI). The specificity of the how this variables affect the evacuation is not studied in this paper and we rely on the information provided in previous work to do this selection.

- Comment 18:

In addition, there have not been justified in accordance with the real vulnerability Peruvian people might face in this century.

Response to comment 18: Knowing the real vulnerability of Peruvian people might face in this century is a task that we do not intent to answer. We understand that this is a titanic task that would need a specific project and expertise to be answered and we anticipate that the results of that task would be subjected to scrutiny and qualitative criticism due to the multidimensional nature of human condition and therefore social vulnerability. Therefore, we selected this general methodology, which is well accepted, to estimate social vulnerability and to provide an example of application of the methodology proposed in this study. The advantage of the methodology is that if there is a better alternative to estimate social vulnerability it can be used replacing what we have shown here. We do not intent to claim success nor authorship on the social vulnerability index, we just used a well-known and accepted methodology.

- Comment 19:

Why are women more vulnerable in Peru? Another issue emerges for gender. The impact of gender on social vulnerability to floods hazard is not unambiguous. As mentioned by Rufat et al., (2015) "women are also assigned more coping-capacities, greater commitment to knowledge of risk, and social relations. The case studies reveal that it is difficult to make generalizations about women's social vulnerability and that women's dependency and needs within the context of vulnerable populations might have been overemphasized. Even in developing countries with the most inequitable societies, gender alone is not predictive of social vulnerability because women's everyday living conditions vary across socioeconomic status, household structures, and geographic locations. Within this context, some studies found that gender had no impact on the social vulnerability in the face of floods at all". Some further discussion may seek to explore this factor. This is valid for all the variables. In this regard, Roder et al. 2017 address this specific problem of variables contextualization.

Response to comment 19: This analysis is very important because it is key to identify if the components selected contribute or not to increase social vulnerability. In our study, we select the variables using a multicollinearity test and PCA; and we assign the contribution to the index based on the literature available. In some studies women are identified as more vulnerable to hurricane evacuation than men in Kusenbach et al., 2010. De Marchi (2007) recognizes women and household wives as "the most vulnerable responders in therm of anticipation defined as prior awareness of flood risk, evaluation of personal preparedness, precautionary measures adopted, knowledge of warning systems and codes"

- Comment 20:

Concerning the evacuation curves, are they different statistically? Without this understanding, the related results seem not supported at all.

Response to comment 20:

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). Table 1 shows that the differences are not statistically significant ($p>0.05$) between neighborhoods using both methods; this could be due to the limited size of the sample. In consequence, we decide to use the median rather than the mean as the middle point of the distribution of the mean response time and added Table 1 to the document.

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

Time	Anova	Kruskal-Wallis
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

- Comment 21:

The mapping of the social vulnerability (Figure 6) is meaningless without an understanding of the classification method used to show the three vulnerability classes (e.g. SD, Jenks Natural Breaks), in fact one could conclude that it is quite easy to play with those classes without knowing the distribution curve. Also, which is the minim, maximum and the average value of the index? Again the components have been just mentioned roughly for which is impossible to understand to their contribution to the vulnerability in the evacuation processes during a GLOF and specifically in Peru. I suggest strongly to provide a table with some basic statistics of the number of blocks in the three categories. Also, provide some spatial statistics to relate to the proximity to the river and to analyze the outcome map of social vulnerability overlapped with the flood hazard map.

Response to 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

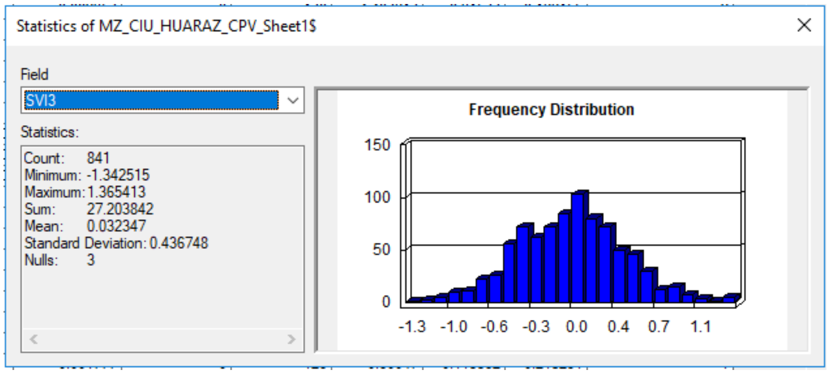

Figure 1 comments: Social Vulnerability Index statistics calculated in ArcGIS

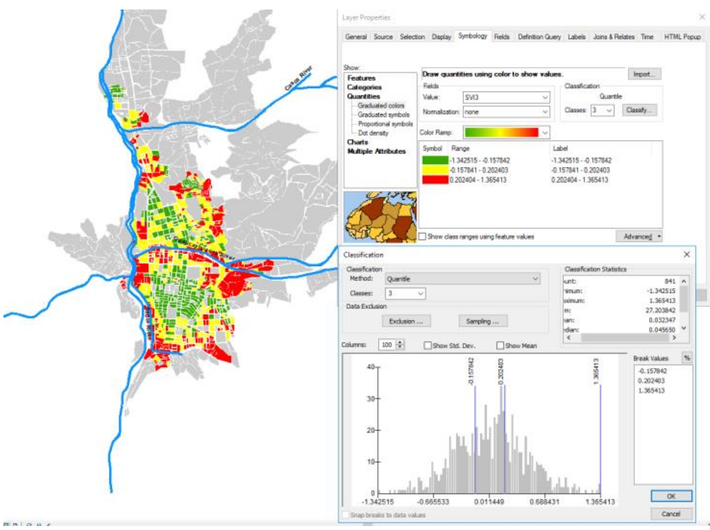

Figure 2 comments: Social Vulnerability Index classification calculated in ArcGIS.

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

- Comment 22: The discussion chapter is not adequately addressed. There is a lengthy introduction that sum up the justification of the research and the methodology undertaken and that present new results never presented before. I suggest entirely rearrange this chapter, enrich it and provide some consideration to flood management and early warning system. I suggest improving the quality of all the figures. All the other comments are made through the file.
- Regarding Result and Discussion, these chapters are very general. I would have expected a more depth analysis.

Response to comment 22:

Figure 9 in the discussion does not provide new information, instead it presents the same results than Figure 5, which is in the result section, but in a different format. We also improved the figures, adding new feature to many of them and improving the resolution.

In the results we rewrite section 3.1 and now it reads as follow: "Figure 5 shows the percentage of population that evacuate after the tsunami alarm was 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 term of the percentage of evacuation decrease over time and eventually disappear after an hour since the alarm was activated.

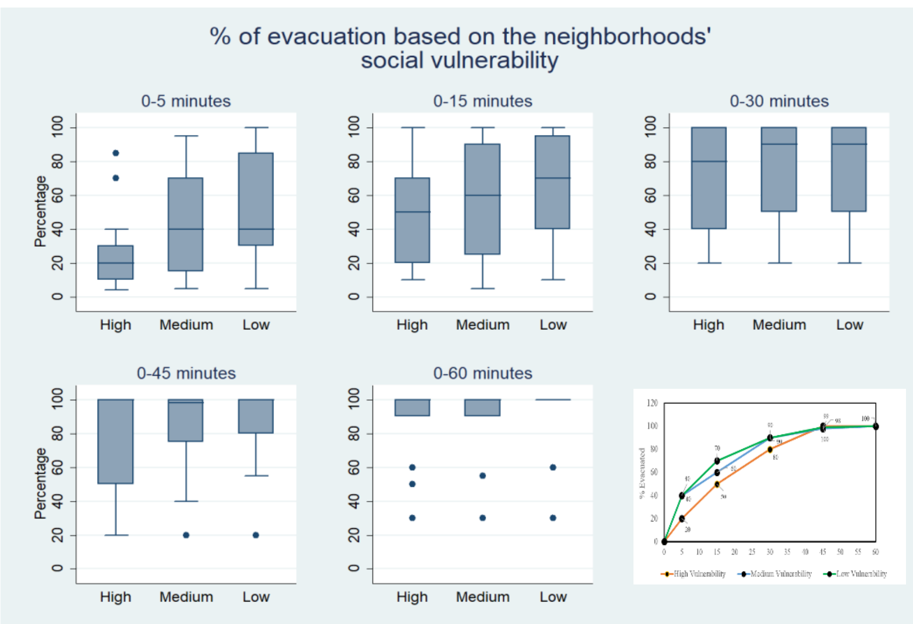

Figure 5: First responder's results by social vulnerability group.

We test if the mean response time to the evacuation alarm between the three types of neighborhoods was statistically significant (p>0.05) using two methods: Anova (parametric method) and Kruskal-Wallis (non-parametric method). Table 1 shows that the differences are not statistically significant between neighborhoods using both methods; this could be due to the limited size of the sample. In consequence, we decide to use the median rather than the mean as the middle point of the distribution of the mean response time.

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

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0-60 minutes	0.87	0.52

”

We also rearrange the Discussion and Conclusions which now read as follow:

“4. Discussion

The literature indicates that social vulnerability has a large influence on how people respond to natural disasters. There is agreement that more vulnerable inhabitants not only suffer the most during a natural disaster but also are less resilient, which affects their ability to recover afterward. Social vulnerability is thought to be an important factor that needs to be included in evacuation analyses but there are no systematic frameworks to do so. This paper deals with this problem by proposing a methodology to integrate social vulnerability into the calculation of how people evacuate after an EWS is activated. We develop 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. For doing this, we used the methods from the LIFESim model and replaced the evacuation curves to reflect the differences in the time response according to social vulnerability level.

The findings from the surveys are in agreement with the theory since the time that people take to respond increases as the vulnerability moves from low to high levels. An interesting result is shown in Figure 9, where we compare the aggregate survey responses with the evacuation responses categorized by social vulnerability level, finding 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. If we extrapolate these results to areas where we just know from first responders the aggregated evacuation rate in time, we can apply the factors indicated in Figure 9 to make a first order approximation of the difference in the evacuation rate by the social vulnerability.

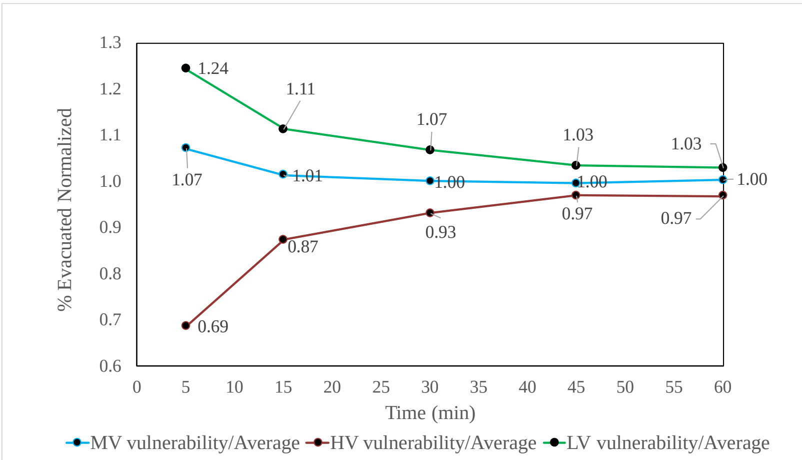

Figure 9: People evacuated per social vulnerability level normalized by the average number of people evacuated.

It is important to keep in mind that the surveys were taken in one location where people are highly trained to deal with tsunamis, which may present limitations applying this model in other locations. Regardless, this is an important advancement in our ability to quantify a process that is normally only addressed with qualitative methodologies. Certainly, we need to collect more data to come up with more general approximations of the importance of social vulnerability in the evacuation.

On the other hand, there is a body of literature that does not find a connection between social vulnerability and evacuation process (i.e. Baker, 1991; Huang, Lindell, & Prater, 2016). However, this literature has been conducted during evacuation process due to Hurricanes, where the population is informed to evacuate their home with hours or days in advance. According to our result, although with no statistical significance, social vulnerability is only relevant during the first 30 minutes after the evacuation alarm is activated, after that, the response time is almost the same among neighborhoods from different levels of social vulnerability. In the case of floods, the literature suggests that social vulnerability is an important element to consider in order to understanding different behaviours during flooding evacuations. In particular, scholars have found that variables such as low household income, poor housing quality, children (Pelling, 1997), women, housewives, students (De Marchi, 2007), elderly, high population density and population with low level of education (Zhang and You, 2014) are key variables to consider to create a social vulnerability index linked to evacuations during disasters. On the other hand, we wanted to use a methodology that make use of census information without major intervention. Therefore, we extend the application of the findings from Fekete (2009) , even though this research was conducted disaster recovery rather than evacuation, who demostrate that "social vulnerability indices are a means for generating information about people potentially affected by disasters that are e.g. triggered by river-floods." Coincidently, the components selected by the criterion used and explained in this work are similar if not the same to what the literature review indicated. Therefore, we felt encouraged to use the 6 components to first explain the responder what we mean by high, medium, and low social vulnerability and to do the exercise of application in Huaraz."

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; however, it fails to connect the physical vulnerability or the characteristics of an inundation event with social vulnerability. Consequently, we propose a three-step methodology to include social vulnerability that we call Response Time by Social Vulnerability Index (ReTSVI).

We provide an example of the application of ReTSVI where we surveyed first responders to estimate the aggregated time of response and the time of response by social vulnerability. Then we used census data to calculate the SVI and applied into the evacuation process to inundation in Huaraz that was estimated in a study by Somos-Valenzuela and colleagues (2016).

The survey shows that in the first five minutes there is the larger difference in time response between social groups. In this initial period 27% of the population living in neighbourhoods with high social vulnerability evacuated, whereas 42% and 49% of people with medium and low vulnerability escape in the same period. This tendency smooths out after 15 minutes where the distances between the different groups get closer. We use the Principal Component Analysis to construct the SVI, six factors explain social vulnerability among all blocks in Huaraz (Perú) and 57% of the variance is captured by these components. Socioeconomic status, age, gender, marital status, labour sector, education level, home-ownership, population density, poverty, and quality of dwelling materials explain the differences in social vulnerability in Huaraz.

The results of the example of ReTSVI in Huaraz highlight the relevance of including social vulnerability in the planning process. 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 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 the influence of SVI. However, we have to mention that although it seems intuitively plausible that people with different levels of social vulnerability would differ in their evacuation rates and departure times, there are no empirical data that support this assumption. Differences in evacuation rate associated 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."

Extra Supplementary Comments (SC)

- SC1: Page 2 line 5, worldwide, where?

Response to comment SC1: yes, worldwide. Now page 2 line 5 reads as follow:

"For example, worldwide natural disasters caused around 3.5 trillion US dollars in damages from 1980 5 to 2011,…"

- SC2: Page 2 line 8, Preparedness of whom? communities? rescue officers? policy makers.

Response to comment SC2: Preparedness of communities. Now page 2 line 8 before the dot, it reads as follow:

"A key strategy to reduce the loss of human life during a disaster is to improve preparedness of communities"

- SC3: Page 2 line 12, repeated work "age" and add "and gender"

Response to comment SC3: Now page 2 line 12 after the dot reads as follow "Individual characteristics such as race, age, gender,…"

- SC4: Page 5 line 3. Can you please explain how class would affect people's decision to evacuate?

Response to comment SC4: we provided an extra reference that support the statement (Kusenbach et al. 2010). Our work is not to study the mechanisms to understand why class, gender or another variable could increase or decrease vulnerability instead we based the selection in the literature available.

- SC5: Page 6 line 6 “2.1 Conceptual model of ReTSVI.” Is this chapter useful at all?

Response to comment SC5:

Yes, this is probably the most important section of this paper. The reason for this is that we are proposing a methodology ReTSVI that combines a series of modules which are pieces of information such us evacuation rate curves, mobilization, inundation models and social vulnerability indexes to create an integrated map of evacuation in a given location. We also provided an application example of this, which is important but it is not as relevant as the methodology proposed.

- SC6: Page 6 line 21 “There is the need for a strong and supported justification of the study area selection.”

Response to comment SC6: We already addressed this point in this document, and we copy our answer here.

“The reason to use this GLOF hazards is that one of the authors did the simulation for a potential inundation in Huaraz as part of a project that was funded by USAID, BID and The ministry of environment of Peru. During this work in Peru, we also wanted to evaluate the implication of installing an early warning system. Then, we realized that the population exposed to the potential hazard was completely different in terms of social vulnerability, and we worked with the Ministry of Environment to have access to the Census data, which is not publicly available, to determine the different levels of social vulnerability and which group was going to be affected more or less. This work was published in Somos-Valenzuela (2014). During the work described, we realized that there was not a formal methodology to combine social vulnerability into the evacuation process, which is confirmed from our literature review and the literature recommended for both reviewers, we may still miss publications and examples from others part of the world though. Then we try to generate data on the evacuation rate and the differences in social vulnerability in the evacuation process in Huaraz; however, although there were a couple of evacuation drills organized by the civil defense of Peru in Huaraz, we were not allowed to access the information collected, if there were any information collected. After this, we decided to collect data after a tsunami in Coquimbo knowing that the hazard and the population are different; however, our goal is to provide a methodology, and we provide an example of how the methodology should be applied.”

- SC7: Page 6 line 22 “I suggest to define what a GLOF is.”

Response to comment SC7: The definition of GLOF is provided on the same line. GLOF stands for Glacier Lakes Outburst Flood.

- SC8: Page 8 line 5-7 “To estimate the percentage of people that evacuate we use the LIFESim model as a base framework. The Army Corps of Engineering incorporated this model into the HEC-Fia model (Lehman and Needham, 2012; USACE, 2012) to evaluate how flood events affect the evacuation during flood events.” This sentence sounds odd. Please revise.

Response to comment SC8:

We modify this sentence and now it reads: "To estimate the percentage of people that evacuate we use the LIFESim model as a base framework. The Army Corps of Engineering incorporated this model into the HEC-Fia model (Lehman and Needham, 2012; USACE, 2012) to evaluate the evacuation during flood events."

- SC9: Page 10 line 2-3 "One of the main critics 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." Already stated

Response to comment SC9:

We intentionally state this again, because it is important to present the information that follows. If the editor considers that it should not be there, we can certainly modify it.

- SC10: Page 10 line 4-5: If you'd followed the methodology of cutter 2003 you should name the index SoVI and acknowledge it properly.

Response to comment SC10: We already addressed this point in this document, and we copy our answer here.

"We use the methodology developed by Susan Cutter (2003) to construct the Social Vulnerability Index (SVI). However, we do not use the same variables to run the Principal Component Analysis because the census in Peru has different variables that the US census. Other authors, see Koks et al., (2015), also use Cutter's methodology to construct a social vulnerability index and also Koks et al., (2015) called their index SVI. In consequence, we called the name SVI and not SOVI because they are different indexes with different variables."

- SC11: Page 11 line 30-33"The explanation for this may be that we took the surveys in Chile after an earthquake struck and produced a tsunami, and the population of Chile is well trained and experienced in knowing what to do in case an alarm is sounded warning of an imminent inundation."

This is true, so why using evacuation curve for a different hazard?

Response to comment SC11:

We have two reasons to do this; the first one is that we do not know any other source of data where the evacuation curves are discriminated by social vulnerability indexes. The second reason is that we wanted to provide an example of the methodology proposed and we used this tsunami hazard with the characteristic of the population similar to Peru (or at least closer than using curves from the US or Europe) as a proxy of flood generated by a GLOF.

- SC12: Page 20 line 6-7 **Figure 1: ReTSVI chart**

Integrated map of..? Why the three classes of the mobilization model have been named as SVI low-medium and high? There should not have anything in common with the social vulnerability outcomes and the inundation model and the evacuation curves.

Response to comment SC12:

The reason to name them like that is that to create those maps, we used the evacuation curves that correspond to the vulnerability level. For example, if the evacuation map is SVI low, it means that we assumed that all the population evacuation rate follows the curve for low social vulnerability index. Then when we have the three maps (because we decided to aggregate the population in three groups), with the result of the SVI from the Census data we determined which evacuation rate should be used in each neighbor.

- SC13: Page 21 line 4 **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).**

What low-medium-high stand for? Any reference to return period? What's the percentage of each level of hazard?

Response to comment SC13:

As the figure indicated it corresponds to flood hazard, for more information on how that was constructed, I would suggest referring to Somos-Valenzuela et al. (2016)

- SC14: Page 23 line 5 **Figure 8: Evacuation using Social Vulnerability Index.**

Spatial reference is missing

Response to comment SC14 :

We modified Figure 6, 7 and 8. Please see below.

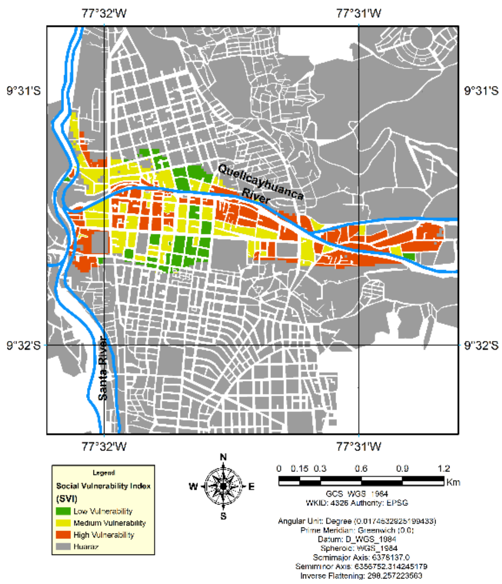

Figure 6: Comparative Vulnerability of Blocks in Huaraz using Social Vulnerability Index (SVI)

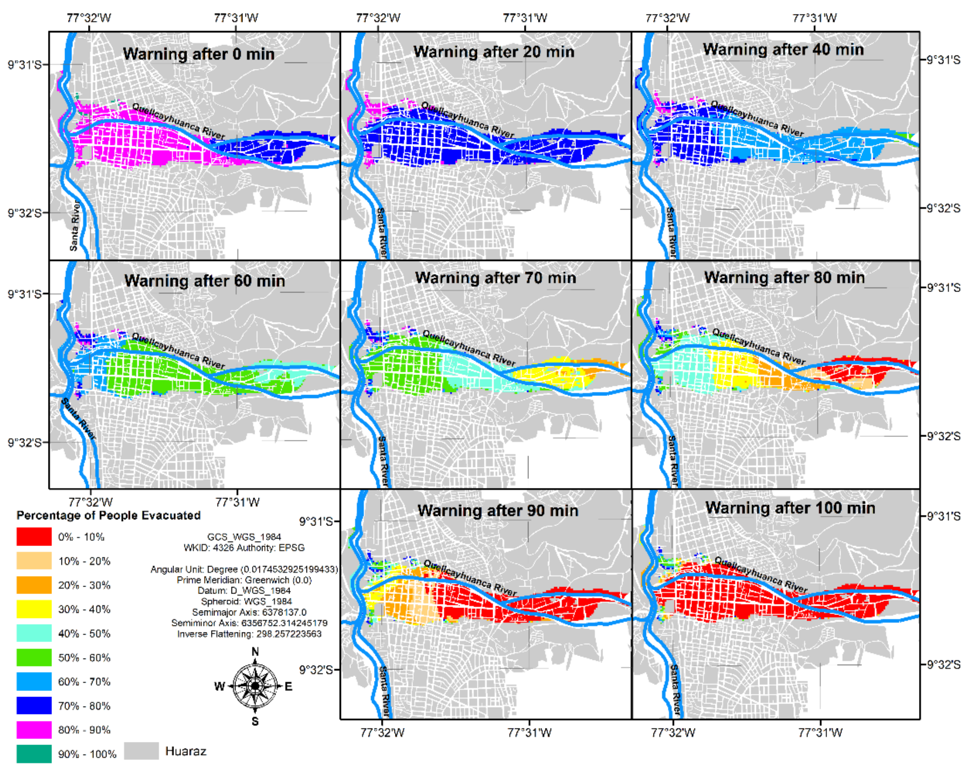

Figure 7: Evacuation using empirical equations.

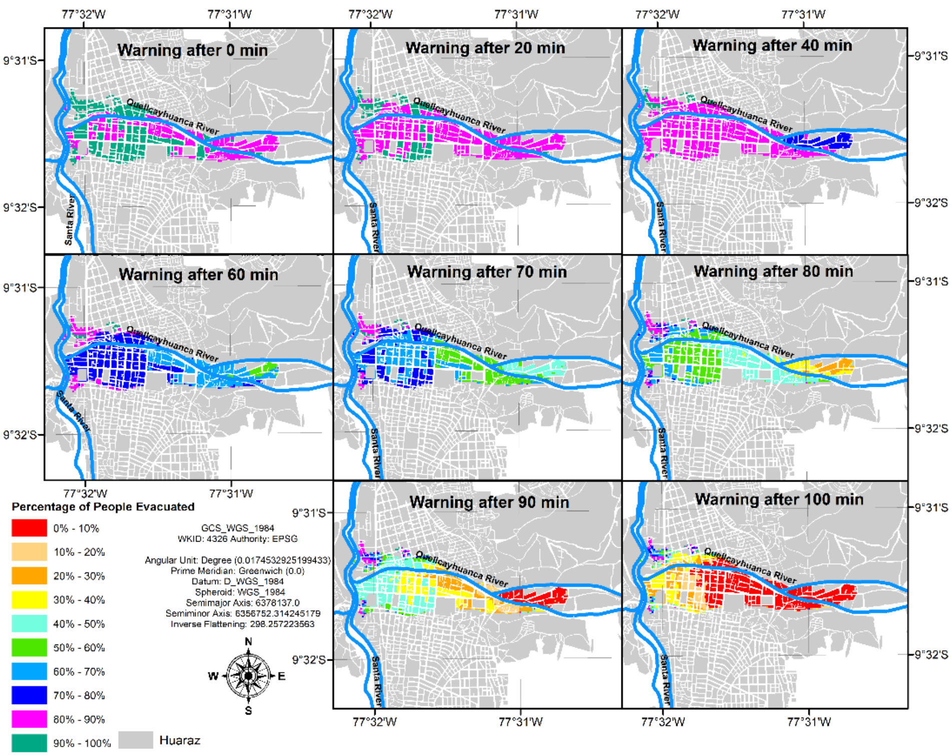

Figure 8: Evacuation using Social Vulnerability Index.

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Somos-Valenzuela, M. A.: PhD Dissertation: Vulnerability and Decision Risk Analysis in Glacier Lake Outburst Floods (GLOF). Case Studies: Quillcay Sub Basin in the Cordillera Blanca in Peru and Dudh Koshi Sub Basin in the Everest Region in Nepal, , 255, 2014.

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List of changes: Response Time to Flood Events using a Social Vulnerability Index (ReTSVI)

R1: Reviewer 1
R2: Reviewer 2

General Changes:
We rewrite the abstract to comply with the words limits of the journal and to reflex the comments from the reviewer and changes to the document.

New Abstract
Current methods to estimate evacuation time during a natural disaster assume that human responses across different social groups are similar. However, individuals respond differently based on their socioeconomic and demographic characteristics. 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 evacuation rate curves, mobilization, inundation models and social vulnerability indexes to create an integrated map of evacuation rate in a given location. Finally, 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 with high social vulnerability evacuate 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, with the data available, with not statistical significance. Using a methodology such as ReTSVI allows first responders to identify areas where the same level of physical vulnerability affects distinct groups differently.

Changes from responses to Reviewer 1:

R1 change 1:
We added a new Table 1, and the former Table 1 now is 2 and the same happens to the next tables. Also, we added on page 7 line 21 the following paragraph:
"We use the National Socioeconomic Characterization Survey (CASEN) 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 incorporate this information in the survey, so the first responders could identify what neighborhood belongs to each category; all responders generate separate curves for low, medium, or high vulnerability neighborhoods."

R1 change 2:
We have modified Figure 5 and the section 3.1 and now it reads as follow:

3.1 Survey to first responders

Figure 5 shows the percentage of the population that evacuate after the tsunami alarm was activated in neighborhoods with high, medium and low social vulnerability. Each box presents the 75th percentile (upper hinge), the median (center), the 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 term of the percentage of evacuation decrease over time and eventually disappear after an hour since the alarm was activated.

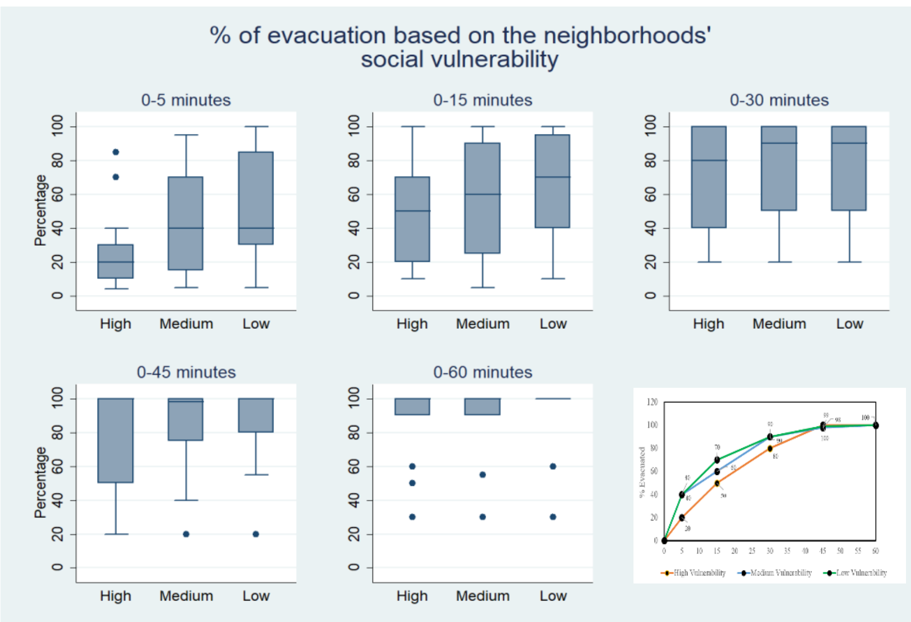


Figure 5: First responder's results by social vulnerability group. Bottom right figure show the median value.

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). Table 1 shows that the differences are not statistically significant between neighborhoods using both methods; this could be due to the limited size of the sample. In consequence, we decide to use the median rather than the mean as the middle point of the distribution of the mean response time.

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

Time	Anova	Kruskal-Wallis

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

R1 change 3:

The methodology to construct the social vulnerability index was added, step by step, in the page 10 after line 9:

“To construct a Social Vulnerability Index (SVI), we analyzed census data using Principal Component Analysis(PCA). This is a multivariate technique “that analyzes a data table in which observations are described by several inter-correlated quantitative dependent variables”(Abdi & 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, 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, Esbensen, & Geladi, 1987). The use of this technique allows for robust and consistent numbers of variables that can be analyzed to estimate changes of social vulnerability over time (Cutter et al., 2003).

We followed Schmidtlein et al. (2008), who list 7steps to calculate the Social Vulnerability Index (SVI): (1) 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 to z-scores $z = \frac{x-\mu}{\sigma}$. This creates variables with mean 0 and standard deviation 1. (2) Perform the PCA with the standardized input variables (z-scores). Select the number of components with eigenvalues greater than one. (3) Rotate the initial PCA solution. In our work we used a normal Kaiser varimax rotation for component selection. (4) Calculate the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) and Bartlett's test of sphericity. (5) Interpret the resulting components as to how they may influence (increase or decrease) social vulnerability and allocate signs to the components accordingly. (6) Combine the selected component scores into a univariate score using a predetermined weighting scheme. The factors are 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 straightforward. In step 5, we must decide how we want to combine the different components. The first criterion is to use the scores from the PCA, adding them but assuming that all the components have the same contribution to the SVI (Cutter et al., 2003). The second criterion uses the scores from the PCA, but assigns different weights to the principal components according to the fraction of variability they explain (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 use the first criterion, in other words, we gave the same weight to all components.”

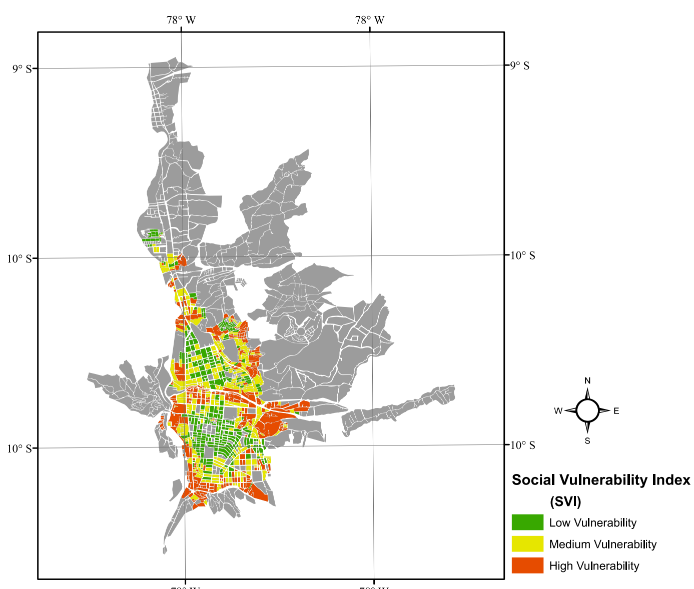
R1 change 4:

We added the following paragraph into the discussion section after Page 12 line 28

“On the other hand, there is a body of literature that does not find a connection between social vulnerability and evacuation process (i.e. Baker, 1991; Huang, Lindell, & Prater, 2016). However, this literature has been conducted during evacuation process due to Hurricanes, where the population is informed to evacuate their home with hours or days in advance. According to our result, although with no statistical significance, social vulnerability is only relevant during the first 30 minutes after the evacuation alarm is activated, after that, the response time is almost the same among neighborhoods from different levels of social vulnerability. In the case of floods, the literature suggests that social vulnerability is an important element to consider in order to understanding different behaviours during flooding evacuations. In particular, scholars have found that variables such as low household income, poor housing quality, children (Pelling, 1997), women, housewives, students (De Marchi, 2007), elderly, high population density and population with low level of education (Zhang & You, 2014) are key variables to consider to create a social vulnerability index linked to evacuations during disasters. On the other hand, we wanted to use a methodology that make use of census information without major intervention. Therefore, we extend the application of the findings from Fekete (2009) , even though this research was conducted disaster recovery rather than evacuation, who demostrate that “social vulnerability indices are a means for generating information about people potentially affected by disasters that are e.g. triggered by river-floods.” Coincidently, the components selected by the criterion used and explained in this work are similar if not the same to what the literature review indicated. Therefore, we felt encouraged to use the 6 components to first explain the responder what we mean by high, medium, and low social vulnerability and to do the exercise of application in Huaraz.”

R1 change 5:

We replaced figure 6



For this new Figure 6:

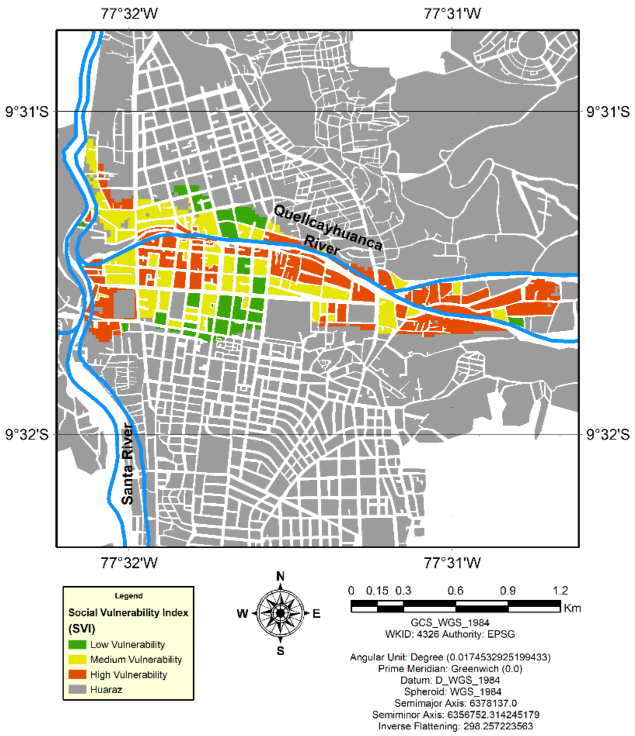


Figure 6: Comparative Vulnerability of Blocks in Huaraz using Social Vulnerability Index (SVI)

And we added in the text after inserting Figure 6: “The proportion of high, medium and low vulnerability blocks within the inundation zone are 15%, 35 %, and 50% respectively.”

R1 change 6:
We have included the two references and the paragraph suggested in our text and from Page 11, Line 30 after the dot now it reads “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 = 1 in Equation 3, which makes the time-consuming contagion process unnecessary.”

R1 change 7:

We modified accordingly to the reviewer suggestion on page 12, from line 7-10. After the dot until the end of the paragraph now it reads: “Social vulnerability is thought to be an important factor that needs to be included in evacuation analyses but there are no systematic frameworks to do so.”

R1 change 8: in page 12 L29, we delete “However, the literature available shows that previous studies have used similar sample size (Morss et al., 2011)”

References added:

Baker, E.J. (1991). Hurricane evacuation behavior. International Journal of Mass Emergencies and Disasters, 9, 287-310.

Chakraborty, J., Tobin, G. A., & Montz, B. E. (2005). Population evacuation: assessing spatial variability in geophysical risk and social vulnerability to natural hazards. Natural Hazards Review, 6(1), 23-33.

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. Social science quarterly, 84(2), 242-261.

Dash, N. & Gladwin, H. (2007). Evacuation decision making and behavioral responses: Individual and household. Natural Hazards Review, 8, 69-77.

Huang, S-K., Lindell, M.K. & Prater, C.S. (2016). Who leaves and who stays? A review and statistical meta-analysis of hurricane evacuation studies. Environment and Behavior, 48, 991-1029.

Kusenbach, M., Simms, J. L., & Tobin, G. A. (2010). Disaster vulnerability and evacuation readiness: coastal mobile home residents in Florida. Natural Hazards, 52(1), 79-95.

Lindell, M.K., Prater, C.S., Gregg, C.E., Apatu, E., Huang, S-K. & Wu, H-C. (2015). Households' immediate responses to the 2009 Samoa earthquake and tsunami. International Journal of Disaster Risk Reduction, 12, 328-340.

Wei, H-L., Wu, H-C., Lindell, M.K., Huang, S-K., Shiroshita, H., Johnston, D.M. &Becker, J.S. (2017). Assessment of households' responses to the tsunami threat: A comparative study of Japan and New Zealand. International Journal of Disaster Risk Reduction, 25, 274-282.

Changes from responses to Reviewer 2:

R2 Change 1: we modify from page 2 line 29-34 which originally read: “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 both vulnerabilities (Cutter & Emrich, 2006; Hegglin & Huggel, 2008)”.

To this: “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 both vulnerabilities to study evacuation (Chakraborty, Tobin, & Montz, 2005)) or recovery process after hazards occur (Cutter & Emrich, 2006; Hegglin & Huggel, 2008)”

Additionally, after page 3 line 25 we added the following paragraph: “Models of social vulnerability, in this area, have been used to explain the capability of communities to face and recover from disasters (Chakraborty et al., 2005).

Scholars have tried to understand whether socioeconomic and demographic characteristics of the population are relevant to understand why neighborhoods or communities respond differently during an evacuation, why some people evacuate, and others do not evacuate during disasters. The evidence about evacuations during hurricanes shows mixed results. Huang, Lindell, & Prater (2016) analyzed 49 studies linked to evacuations to hurricane warnings conducted since 1991 and concluded that demographics variables have a minor or inconsistent impact on household evacuations. In contrast, others studies show that social vulnerability is a key factor to take into account during emergency management and evacuation planning (Bateman and Edwards, 2002; Chakraborty et al., 2005; Dash and Gladwin, 2007; Kusenbach et al., 2010). In the case of floods, studies suggest that social vulnerability is an important element to consider in order understanding different behaviors during flooding evacuations. In particular, scholars have found that variables such as low household income, poor housing quality, children (Pelling, 1997), women, housewives, students (De Marchi, 2007), elderly, high population density and population with low level of education (Zhang and You, 2014) are key variables to consider to create a social vulnerability index linked to evacuations during disasters.”

R2 Change 2:

To avoid redundancy, we deleted page 1 lines 2-5

R2 Change 3: We rewrite the paragraph in section 2.1 as follows:

“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. Figure 1 is a chart of ReTSVI, 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 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 considers their social vulnerability level."

R2 Change 4:

The original text from page 7 line 14 after the dots reads as follow:

"Four institutions that work directly to help the population during the evacuation process participated in this study: the navy, the police, firefighters and the municipality of Coquimbo. Each institution selected at least five employees to respond to our questionnaire, these employees work directly during the emergency to help people evacuate their houses. The survey was completed with the help of a research assistant that conducted a personal interview with each participant. We asked first responders to estimate the average evacuation time and the percentage of the population that evacuates their households from 0 to 5 minutes, 0 to 15 minutes, 0 to 30 minutes, 0 to 45 minutes, 0 to 60 minutes in neighbourhoods with low, medium and high social vulnerability in Coquimbo."

We replace this text with the paragraph below:

"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 to explain the purpose of the study and asked them if they agree to participate in the research, all 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 worked directly during the emergency to help people evacuate their houses. The research assistant conducted a personal interview with each participant. We asked the first responders "In your opinion and based on your experience during the tsunami of 16th of September. Since the evacuation alarm was active, what is the evacuation time of population who live in areas of low/medium/high social vulnerability?" They needed to estimate the average evacuation time in neighborhoods with low, medium and high social vulnerability. Then, we asked "what is the percentage of the population that evacuate in the first X minutes? (X=5, 15, 30, 45, 60)" The first responders write down the percentage of the population that evacuates their households 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 recollected into two scales: percentages and average time (in minutes)

R2 Change 5:

We added the following paragraph in Page 10 line 9 after the dot:

"To construct a Social Vulnerability Index (SVI), we analyzed census data using Principal Component Analysis(PCA). PCA 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 in a new set of orthogonal variables called principal components. For example, PCA "provides an approximation of a data table, a data matrix, X, regarding 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 in social vulnerability over time (Cutter et al., 2003). First, we identify the variables that were linearly correlated using the Variance Inflation Factors (VIF), those variables with VIF higher than 10 points were excluded from the model. Then, we followed Schmidtlein et al. (2008), who list seven steps to calculate the Social Vulnerability Index (SVI): (1) Normalize all variables as a percentage, per capita or density functions. For this paper, we normalized all variables as percentages; for example, the percentage of independent houses per block or the percentage of older adults per block. Then standardize all input (census) variables to z-scores $z = \frac{x-\mu}{\sigma}$. This creates variables with mean 0 and standard deviation 1. (2) Perform the PCA with the standardized input variables (z-scores). Select the number of components based on eigenvalues greater than one. (3) Rotate the initial PCA solution. In our work we used a normal Kaiser varimax rotation for component selection. (4) Calculate the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) and Bartlett's test of sphericity. (5) Interpret the resulting components as to how they may influence (increase or decrease) social vulnerability and allocate signs to the components accordingly. (6) Combine the selected component scores into a univariate score using a predetermined weighting scheme. The factors are named based on variables with significant factor loading, usually greater than .3 or less than -.3. (7) Finally, we standardized the resulting SVI scores to mean 0 and standard deviation 1.
All the steps but step 6 are straightforward. In step 6, we must decide how we want to combine the different components. The first criterion is to use the scores from the PCA, adding them but assuming that all the components have the same contribution to the SVI (Cutter et al., 2003). The second criterion uses the scores from the PCA but assigns different weights to the principal components according to the fraction of variability they explain (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 its explained variance multiplies each component (Schmidtlein et al. 2008). We use the first criterion; we gave the same weight to all components. 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 (2012) page 1167 provide a solid argument that explains the reason of 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) argue that there is no appropriate methodology for the calculation of the index."

R2 Change 6:

We modified Table 1 to clarify the directionality of the component and added a new column with the sign adjustment of the components.

Original Table 1:

Selected Census variables after PCA analysis to estimate Social Vulnerability Index (SVI)	Components					
	1	2	3	4	5	6

+ more vulnerable – less vulnerable						
- 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 65 years old		.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 than 1 year 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 %

New version of Table 1 that now it corresponds to Table 2

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 65 years old			.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 than 1 year 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 %

R2 Change 7: We added Table 1 to the document.

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

Time	Anova	Kruskal-Wallis
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

R2 Change 8: After Figure 6 we added "The proportion of high, medium and low vulnerability blocks within the inundation zone are 15%, 35 %, and 50% respectively."

R2 Change 9: In the results we rewrite section 3.1 and now it reads as follow: "Figure 5 shows the percentage of population that evacuate after the tsunami alarm was 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 term of the percentage of evacuation decrease over time and eventually disappear after an hour since the alarm was activated.

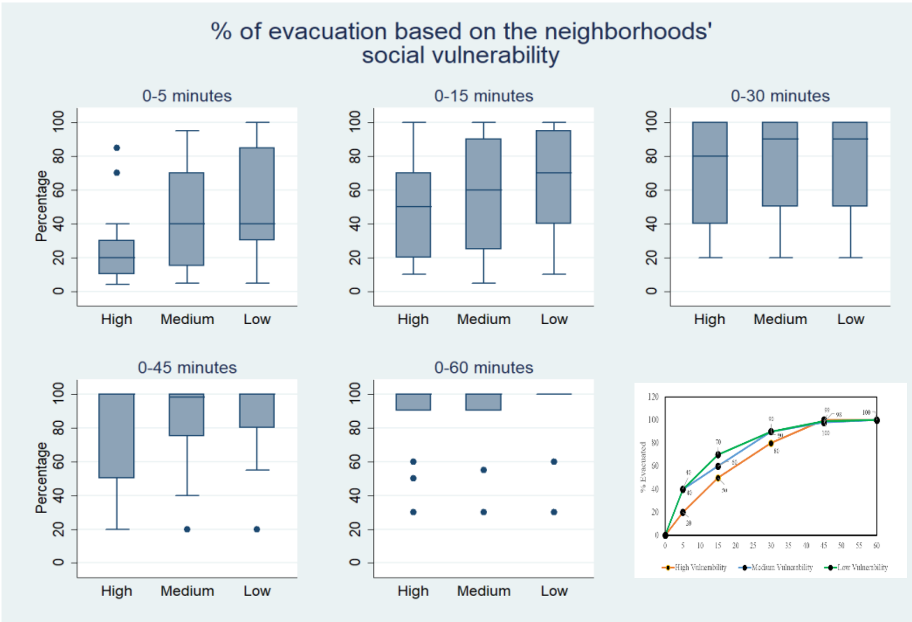


Figure 5: First responder's results by social vulnerability group.

We test if the mean response time to the evacuation alarm between the three types of neighborhoods was statistically significant (p>0.05) using two methods: Anova (parametric method) and Kruskal-Wallis (non-parametric method). Table 1 shows that the differences are not statistically significant between neighborhoods using both methods; this could be due to the limited size of the sample. In consequence, we decide to use the median rather than the mean as the middle point of the distribution of the mean response time.

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

Time	Anova	Kruskal-Wallis
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

"

R2 Change 10:

We also rearrange the Discussion and Conclusions which now read as follow:

"4. Discussion

The literature indicates that social vulnerability has a large influence on how people respond to natural disasters. There is agreement that more vulnerable inhabitants not only suffer the most during a natural disaster but also are less resilient, which affects their ability to recover afterward. Social vulnerability is thought to be an important factor that needs to be included in evacuation analyses but there are no systematic frameworks to do so. This paper deals with this problem by proposing a methodology to integrate social vulnerability into the calculation of how people evacuate after an EWS is activated. We develop 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. For doing this, we used the methods from the LIFESim model and replaced the evacuation curves to reflect the differences in the time response according to social vulnerability level.

The findings from the surveys are in agreement with the theory since the time that people take to respond increases as the vulnerability moves from low to high levels. An interesting result is shown in Figure 9, where we compare the aggregate survey responses with the evacuation responses categorized by social vulnerability level, finding 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. If we extrapolate these results to areas where we just know from first responders the aggregated evacuation rate in time, we can apply the factors indicated in Figure 9 to make a first order approximation of the difference in the evacuation rate by the social vulnerability.

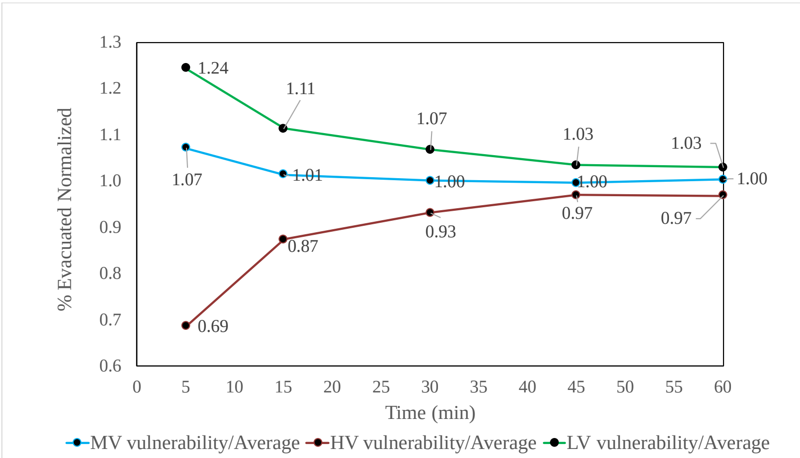


Figure 9: People evacuated per social vulnerability level normalized by the average number of people evacuated.

It is important to keep in mind that the surveys were taken in one location where people are highly trained to deal with tsunamis, which may present limitations applying this model in other locations. Regardless, this is an important advancement in our ability to quantify a process that is normally only addressed with qualitative methodologies. Certainly, we need to collect more data to come up with more general approximations of the importance of social vulnerability in the evacuation.

On the other hand, there is a body of literature that does not find a connection between social vulnerability and evacuation process (i.e. Baker, 1991; Huang, Lindell, & Prater, 2016). However, this literature has been conducted during evacuation process due to Hurricanes, where the population is informed to evacuate their home with hours or days in advance. According to our result, although with no statistical significance, social vulnerability is only relevant during the first 30 minutes after the evacuation alarm is activated, after that, the response time is almost the same among neighborhoods from different levels of social vulnerability. In the case of floods, the literature suggests that social vulnerability is an important element to consider in order to understanding different behaviours during flooding evacuations. In particular, scholars have found that variables such as low household income, poor housing quality, children (Pelling, 1997), women, housewives, students (De Marchi, 2007), elderly, high population density and population with low level of education (Zhang and You, 2014) are key variables to consider to create a social vulnerability index linked to evacuations during disasters. On the other hand, we wanted to use a methodology that make use of census information without major intervention. Therefore, we extend the application of the findings from Fekete (2009) , even though this research was conducted disaster recovery rather than evacuation, who demostrate that "social vulnerability indices are a means for generating information about people potentially affected by disasters that are e.g. triggered by river-floods." Coincidently, the components selected by the criterion used and explained in this work are similar if not the same to what the literature review indicated. Therefore, we felt encouraged to use the 6 components to first explain the responder what we mean by high, medium, and low social vulnerability and to do the exercise of application in Huaraz."

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; however, it fails to connect the physical vulnerability or the characteristics of an inundation event with social vulnerability. Consequently, we propose a three-step methodology to include social vulnerability that we call Response Time by Social Vulnerability Index (ReTSVI).

We provide an example of the application of ReTSVI where we surveyed first responders to estimate the aggregated time of response and the time of response by social vulnerability. Then we used census data to calculate the SVI and applied into the evacuation process to inundation in Huaraz that was estimated in a study by Somos-Valenzuela and colleagues (2016).

The survey shows that in the first five minutes there is the larger difference in time response between social groups. In this initial period 27% of the population living in neighbourhoods with high social vulnerability evacuated, whereas 42% and 49% of people with medium and low vulnerability escape in the same period. This tendency smooths out after 15 minutes where the distances between the different groups get closer. We use the Principal Component Analysis to construct the SVI, six factors explain social vulnerability among all blocks in Huaraz (Perú) and 57% of the variance is captured by these components. Socioeconomic status, age, gender, marital status, labour sector, education level, home-ownership, population density, poverty, and quality of dwelling materials explain the differences in social vulnerability in Huaraz.

The results of the example of ReTSVI in Huaraz highlight the relevance of including social vulnerability in the planning process. 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 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 the influence of SVI. However, we have to mention that although it seems intuitively plausible that people with different levels of social vulnerability would differ in their evacuation rates and departure times, there are no empirical data that support this assumption. Differences in evacuation rate associated 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."

R2 Change 11:

Now page 2 line 5 reads as follow:

"For example, worldwide natural disasters caused around 3.5 trillion US dollars in damages from 1980 5 to 2011,…"

R2 Change 12: Now page 2 line 8 before the dot, it reads as follow:

"A key strategy to reduce the loss of human life during a disaster is to improve preparedness of communities"

R2 Change 13:

Now page 2 line 12 after the dot reads as follow "Individual characteristics such as race, age, gender,…"

R2 Change 14: Page 8 line 5-7 now reads: "To estimate the percentage of people that evacuate we use the LIFESim model as a base framework. The Army Corps of Engineering incorporated this model into the HEC-Fia model (Lehman and Needham, 2012; USACE, 2012) to evaluate the evacuation during flood events."

R2 Change 15: We modified Figure 6, 7 and 8. Please see below.

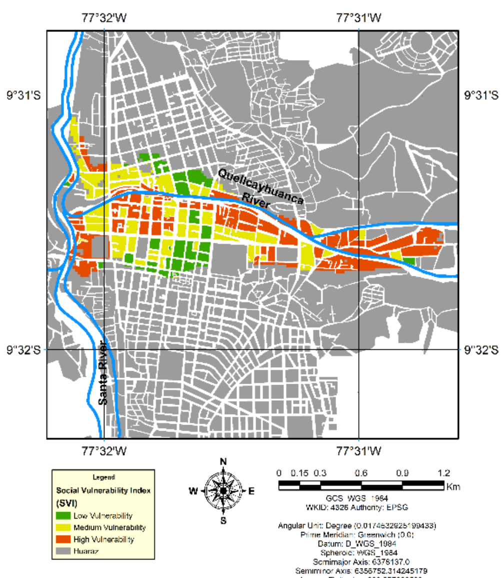


Figure 6: Comparative Vulnerability of Blocks in Huaraz using Social Vulnerability Index (SVI)

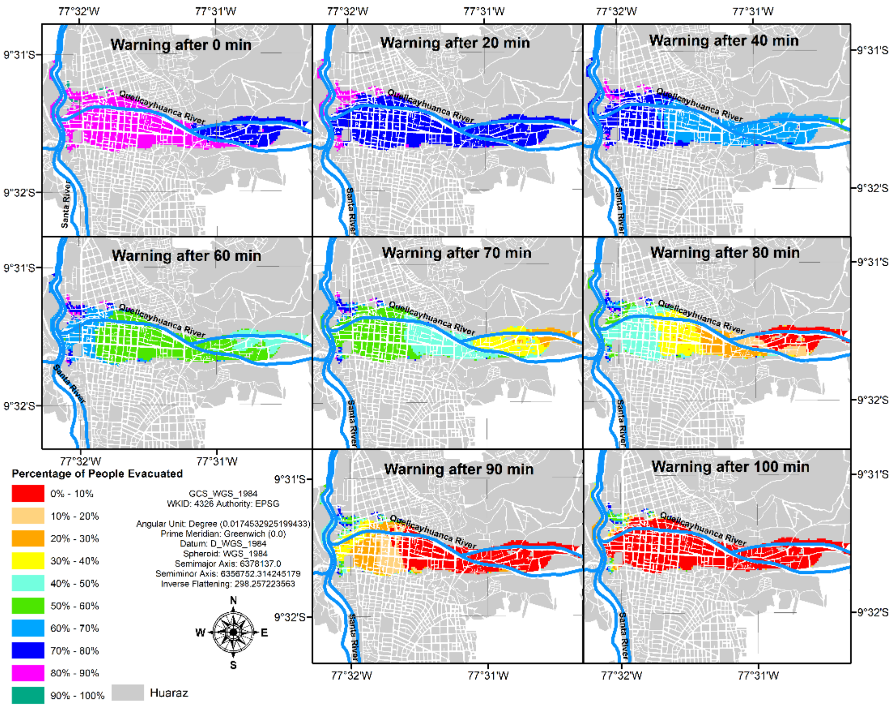


Figure 7: Evacuation using empirical equations.

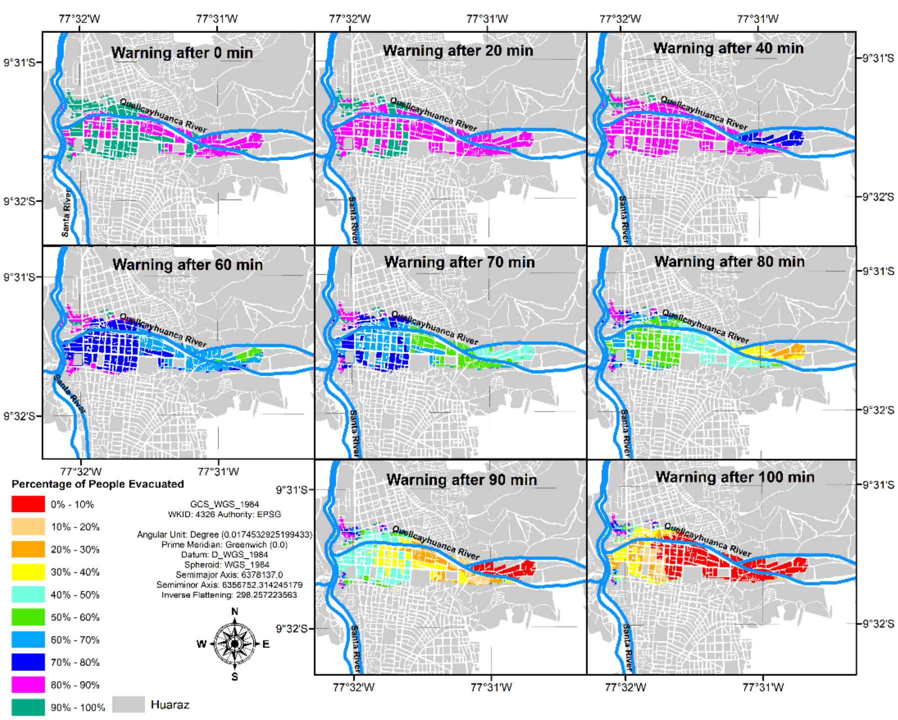


Figure 8: Evacuation using Social Vulnerability Index.

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Marked-up manuscript version

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 assume that human responses across different social groups are similar. However, individuals respond differently based on their socioeconomic and demographic characteristics. 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 evacuation rate curves, mobilization, inundation models and social vulnerability indexes to create an integrated map of 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 with high social vulnerability evacuate 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, with the data available, with not statistical significance. Using a methodology such as ReTSVI allows first responders to identify areas where the same level of physical vulnerability affects distinct groups differently.~~Current methods used to estimate people's evacuation times during a natural disaster assume that human responses across different social groups are similar. However, individuals respond differently based on their socioeconomic and demographic characteristics and previous knowledge. This article develops the Response Time by Social Vulnerability Index (ReTSVI), which is a methodology to estimate how human response time to evacuation warnings during a natural hazard is affected by considering characteristics related to both physical and social vulnerability. ReTSVI is a three-step methodology: first we calculate a population's evacuation curves considering social vulnerability level, certain demographic information and a model that describes an inundation hazard. Then, we use a mobilization model to generate evacuation maps per level of vulnerability and we also estimate the social vulnerability index for the area of study. In the third step, we combine the results from the second step to generate a map that indicates the percentage of people that could evacuate a hazard zone according to their social vulnerability level. Finally, 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 with high social vulnerability evacuate 15% and 22% fewer people than the neighbourhoods 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. Using a methodology such as ReTSVI~~

~~allows first responders to identify areas where the same level of physical vulnerability affects distinct groups differently, providing them with a tool to quantify the differences in time to evacuate and where the resources before and during an evacuation should be preferentially allocated.~~

Keywords: ReTSVI, Social Vulnerability, Early Warning Systems, 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 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 3.5 trillion US dollars in damages from 1980 5 to 2011~~natural disasters caused around 3.5 trillion US dollars in damages from 1980 to 2011~~, one-third took place in low or middle-income countries, and the number of people affected by natural disasters increased 1.5 times, economic damage by 1.8 times and total deaths by two times (Basher, 2006; Hallegatte, 2014).

A key strategy to reduce the loss of human life during a disaster is to improve preparedness of communities. ~~A key strategy to reduce the loss of human life during a disaster is to improve preparedness.~~ A common means to achieve this is to develop Early Warning 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, Shaw, & Albores, 2012; Nicholls & Klein, 1999). Individual characteristics such as ~~age,~~ race, age, gender, education, income, and employment influence the susceptibility to which certain groups or communities might be exposed and also define their ability to respond to a natural hazard (Cutter, Boruff, & Shirley, 2003; Gaillard & 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 & Finch, 2008; Ionescu, Klein, Hinkel, Kavi Kumar, & Klein, 2005; ISDR, 2004; Santos & Aguirre, 2004). Despite the evidence, the literature focuses mainly on the physical dimension of natural hazards and disregards human aspects. A real improvement in our understanding of emergency evacuations will depend on the integration of both (Basher, 2006; Couling, 2014; Santos & Aguirre, 2004).

The problem that arises is how we can incorporate social and physical vulnerability in a comprehensive matter to improve our understanding of an evacuation process. Both concepts have been developed independently in the social sciences and engineering; therefore, it is not a straightforward process to link them. In fact, there is little data on how social vulnerability influences the evacuation process and how it is linked to the number of human casualties (Bolin, 2007; Morss, Wilhelmi, Meehl, & Dilling, 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 both vulnerabilities to study evacuation (Chakraborty, Tobin, & Montz, 2005)) or recovery process after hazards occur (Cutter & Emrich, 2006; Hegglin & Huggel, 2008)~~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 both vulnerabilities (Cutter & Emrich, 2006; Hegglin & Huggel, 2008)~~. This information is still descriptive and provides qualitative information to policy makers, government institutions or local governments to understand how a population would react in an evacuation process. Therefore, questions such us: 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? are not possible to answer with the current methods developed in social sciences nor engineering.

1.1 Social Vulnerability and Natural Disasters

~~The need to adapt to climate change is widely recognized, and, there is a critical need to understand how people or communities will adapt to global environmental change. It is clear that the consequences associated with natural disasters cannot be understood without information about the community that will be affected (Adger, 1999; UN, 2009; Urwin & Jordan, 2008).~~

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, Gregory, Hallisey, Heitgerd, & Lewis, 2011). This integration refers to identifying which and where problems exist before natural disaster strikes, making it possible to take steps to prevent possible damage (Schmidtlein, Deutsch, Piegorsch, & Cutter, 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 the recovery of communities (Cutter & 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, Mitchell, & Scott, 2000).

The study of vulnerability can be traced back to the early 1950s and 1960s in the field of behavioural 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, Siegel, Jørgensen, & Tech, 2001; Balica, 2012; Birkmann, 2007). For example, in the economic literature, vulnerability includes food security and sustainable development (Fekete, 2011; Rygel, O'sullivan, & Yarnal, 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). Models of social vulnerability, in this area, have been used to explain the capability of communities to face and recover from disasters (Chakraborty et al., 2005).

Scholars have tried to understand whether socioeconomic and demographic characteristics of the population are relevant to understand why neighborhoods or communities respond differently during an evacuation, why some people evacuate, and others do not evacuate during disasters. The evidence about evacuations during hurricanes shows mixed results. Huang, Lindell, & Prater (2016) analyzed 49 studies linked to evacuations to hurricane warnings conducted since 1991 and concluded that demographics variables have a minor or inconsistent impact on household evacuations. In contrast, others studies show that social vulnerability is a key factor to take into account during emergency management and evacuation planning (Bateman & Edwards, 2002; Chakraborty et al., 2005; Dash & Gladwin, 2007; Kusenbach, Simms, & Tobin, 2010). In the case of floods, studies suggest that social vulnerability is an important element to consider in order understanding different behaviors during flooding evacuations. In particular, scholars have found that variables such as low household income, poor housing quality, children (Pelling, 1997), women, housewives, students (De Marchi, 2007), elderly, high population density and population with low level of education (Zhang & You, 2014) are key variables to consider to create a social vulnerability index linked to evacuations during disasters.

Research in social vulnerability linked to natural hazards can be divided into two groups. The first group, "post-disaster cases studies," tries to understand how natural disasters impact differently communities based on their level of social vulnerability (Rufat, Tate, Burton, & Maroof, 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, Biernacki, Fiedeń, Listwan-Franczak, & Franczak, 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 studies." Scholars in this subfield use primarily 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, 2011). 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, the capability of communities to cope with and recover from disaster seem to depend also from other factors such as vigor, vitality, energy, strength, etc., which are usually excluded from studies about social vulnerability (De Marchi, 2007; De Marchi & Scolobig, 2012).

Despite these limitations, scholars have developed indices to quantify social vulnerability based on their interests. Some researchers use the percentage of women, racial groups or age average as indexes to estimate different levels of social vulnerability (Harvey, Kato, & Passidomo, 2016; Sebastiaan N Jonkman, Maaskant, Boyd, & Levitan, 2009; Sadia, Iqbal, Ahmad, Ali, & Ahmad, 2016). Other scholars use variables linked with 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 & 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, researchers have employed strategies such as including a higher number of variables to construct social vulnerability indexes or estimating the connection among variables that are linked theoretically with social vulnerability. In this area, one of the most recognized indices to have been applied both in the US and abroad is the Social Vulnerability Index (SoVI) (Cutter, 1996). SoVI has been used in California, Colorado and South Carolina in the USA, 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 SoVI is relevant because the method makes it possible to compare the spatial variability in socioeconomic vulnerability using a single index value. SoVI can also be linked spatially to physical aspects to calculate the overall vulnerability of a specific place (Boruff, Emrich, & Cutter, 2005).

Social vulnerability indexes are useful to detect 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 data from the 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, 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, 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. In the case of evacuation process during hurricanes and floods, variables such as number of housing units, mobile homes, poverty, age, people with disabilities (Chakraborty et al., 2005), education, household income, pet ownership (Kusenbach et al., 2010), household size, elderly, children (Dash & Gladwin, 2007), household quality, community organization (Pelling, 1997), communities' immaterial characteristics as energy, vigour, vitality (De Marchi, 2007; De Marchi & Scolobig, 2012), average number of people per house, population density (person/km2), illiterate population and urban population ration (Zhang & You, 2014)

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1.2 Response Time, Evacuation and Flood Impacts

Multiple factors seem to affect people's decision-making process to evacuate, such as risk perception, beliefs, demographic characteristics, previous knowledge, social networks, gender, age and class, among others (Elliott & Pais, 2006; Lindell, Lu, & Prater, 2005; Mileti & 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, 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 just a few of them consider social vulnerability as an explanatory variable in their models (S. N. Jonkman, Vrijling, & Vrouwenvelder, 2008).

In ocean and river floods, variables such as the percentage of buildings collapsed, the proportion of evacuated people seem to influence the number of human fatalities (Vrouwenvelder & Steenhuis, 1997).

Other scholars take into account the level of water 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 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, 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 HEC-FIA. Models, in general, 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. Few authors consider the characteristics of the population to estimate human causalities during a flood event. 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 and colleagues (2005) consider "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 Ramsbottom and colleagues (2004) include levels of population vulnerability, and this category is based on expert judgment. Consequently, even though there is an upward trend of research that endeavours to understand how social characteristics of population influence human response to natural disasters, academics have failed to incorporate social vulnerability into estimations of loss of life (Elliott & Pais, 2006; Rodriguez, Quarentelli, & Dynes, 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, 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 with low vulnerability will evacuate versus those who live in neighbourhoods with high vulnerability or how much time people who live in neighbourhoods with medium vulnerability will take to evacuate versus those who live in highly vulnerable areas, etc. To fill this gap in the literature, 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

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)' 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

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assessment. Figure 1 is a chart of ReTSVI, 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 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 considers their social vulnerability level."

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Insert Figure 1

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

In 1941, the city of Huaraz was affected by a Glacier Lake Outburst Flood (GLOF) generated at Lake Palcacocha, in the Cordillera Blanca, Peru (Figure 2). The GLOF killed in the order of 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 in a state of emergency several times, and currently, there are 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 not been studied except for qualitative 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, the evacuation curves that we used are generated in the area of study, however, there is no data that describes how people in Huaraz evacuate after an EWS is released; 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 data provided by the Ministry of Environment of Peru to create a social vulnerability map of Huaraz.

Surveys in Coquimbo, Chile

We conducted 22 surveys with first responders to 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 to explain the purpose of the study and asked them if they agree to participate in the research, all 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 worked directly during the emergency to help people evacuate their houses. The research assistant conducted a personal interview with each participant. We asked the first responders “In your opinion and based on your experience during the tsunami of 16th of September. Since the evacuation alarm was active, what is the evacuation time of population who live in areas of low/medium/high social vulnerability?” They needed to estimate the average evacuation time in neighborhoods with low, medium and high social vulnerability. Then, we asked “what is the percentage of the population that evacuate in the first X minutes? (X=5, 15, 30, 45, 60)”. The first responders write down the percentage of the population that evacuates their households 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 recollected into two scales: percentages and average time (in minutes). ~~Four institutions that work directly to help the population during the evacuation process participated in this study: the navy, the police, firefighters and the municipality of Coquimbo. Each institution selected at least five employees to respond to our questionnaire, these employees work directly during the emergency to help people evacuate their houses. The survey was completed with the help of a research assistant that conducted a personal interview with each participant.~~

~~We asked first responders to estimate the average evacuation time and the percentage of the population that evacuates their households from 0 to 5 minutes, 0 to 15 minutes, 0 to 30 minutes, 0 to 45 minutes, 0 to 60 minutes in neighbourhoods with low, medium and high social vulnerability in Coquimbo.~~

We use 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 incorporate this information in the survey, so the first responders could identify what neighborhood belongs to each category; all responders generate 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 divided into three main categories: (a) location of household (blocks), (b) household characteristics: number of rooms, ownership, type of house, etc. 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 use the inundation results obtained by Somos-Valenzuela et al. (2016) that considers 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, in this study, we will use 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 incorporated this model into the HEC-Fia model (Lehman & Needham, 2012; USACE, 2012) to evaluate the evacuation during flood events~~to evaluate how flood events affect 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) 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}).

[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).

Second, we need to calculate the percentage from N_{exp} 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 to quantify. In the literature 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; S. N. Jonkman et al., 2008; McClelland & 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)

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

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

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

The model LIFESim provides a methodology for how to calculate FE (Aboelata & 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 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 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.

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

Where:

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

k = percentage of people alert 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 & Sorensen, 1991))

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

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

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

Mobilization Process

After people understand that there is a treat, they start to evacuate to a safe zone. Figure 35 from Aboelata & Bowles (2005) defines mobilization curves, below 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 impacts 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, with a Monte Carlo simulation with 1000 samples shows that the activity, as it is described in LIFESim, that people are doing when the alarm is released does not affect the penetration of the warning.

Although the emphasis of this work is to include Social 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 fits into state of the art evacuation process assessments. In Figure 4 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 Social Vulnerability. Additionally, at the moment of the survey, we did not 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 speed that ranges from 80-187 meter 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 critics 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 face these limitations, we construct a Social Vulnerability Index (SVI) by analysing census data using Principal Component 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, Esbensen, & Geladi, 1987). The use of this technique allows for robust and consistent numbers of variables that can be analysed to estimate changes in social vulnerability over time (Cutter et al., 2003). We followed Schmidtlein et al. (2008), who list seven steps to calculate the Social Vulnerability Index (SVI).
To construct a Social Vulnerability Index (SVI), we analyzed census data using Principal Component Analysis(PCA). This is a multivariate technique "that analyzes a data table in which observations are described by several inter-correlated quantitative dependent variables"(Abdi & 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, 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 social vulnerability over time (Cutter et al., 2003).

We followed Schmidtlein et al. (2008), who list 7steps to calculate the Social Vulnerability Index (SVI): (1) 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 to z-scores $z = \frac{x-\mu}{\sigma}$. This creates variables with mean 0 and standard deviation 1. (2) Perform the PCA with the standardized input variables (z-scores). Select the number of components with eigenvalues ~~highe~~greater~~r~~ than one~~to be used~~. (3) Rotate the initial PCA solution. In our work we used a normal Kaiser varimax rotation for component selection. (4) Calculate the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) and Bartlett's test of sphericity. (5) Interpret the resulting components as to how they may influence (increase or decrease) social vulnerability and allocate signs to the components accordingly. (6) Combine the selected component scores into a univariate score using a predetermined weighting scheme. The factors are 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 straightforward. In step 5, we must decide how we want to combine the different components. The first criterion is to use the scores from the PCA, adding them but assuming that all the components have the same contribution to the SVI (Cutter et al., 2003). The second criterion uses the scores from the PCA, but assigns different weights to the principal components according to the fraction of variability they explain (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 use the first criterion, in other words, we gave the same weight to all components. 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~~2~~) provide a solid argument that explains the reason of 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) argue 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 evacuate after the tsunami alarm was 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 term of the percentage of evacuation decrease over time and eventually disappear after an hour since the alarm 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 ($p>0.05$) using two methods: Anova (parametric method) and Kruskal-Wallis (non-parametric method). Table 1 shows that the differences are not statistically significant between neighborhoods using both methods; this could be due to the limited size of the sample. In consequence, we decide to use the median rather than the mean as the middle point of the distribution of the mean response time.

Insert Table1

~~The survey responses plotted in Figure 5 indicate that the population of high social vulnerability takes on average 22 minutes to evacuate after an alarm is activated, while neighbourhoods with medium and low vulnerability take 19 and 16 minutes on average. Figure 5 illustrates that areas of high social vulnerability systematically evacuate fewer people than areas with medium or low social vulnerability. The first five minutes are key regarding differences among the three groups. For example, the answers from the first responders indicate that blocks with high social vulnerability evacuate 15% and 22% fewer people than the blocks with medium and low social vulnerability. These differences gradually decrease over time; for example, between 0-30 minutes, groups with high social vulnerability evacuate 5% and 10% fewer people than groups with medium and low social vulnerability, and between 0-60 minutes the differences are 3% and 6% between these three groups.~~

~~Insert Figure 5~~

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 floods (for more details see Carey, 2010; Hegglin & Huggel, 2008; Somos-Valenzuela et al., 2016).

Using the population census of Peru and PCA, we were able to identify 20 census variables grouped into six components that explained social vulnerability among all the neighbourhoods in Huaraz (Table 1). The first component explains 20% of the variance and identifies 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. The groups most affected by natural disasters— the elderly, women, and people with disabilities— are grouped in the second component, which explains 9% of the variance. The third component describes variables linked with poverty such as illiteracy rates, the existence of informal settlements, and households without electricity. 8% of the variation in blocks is captured by this component. The fourth component identifies home-ownership and marital status; this factor explains 7% of the variance. The fifth component groups neighbourhoods with high population density and workers in blue collar jobs that are usually linked with low-income payment, insecure and more precarious work conditions. This component captures 7% of the variation in blocks. Finally, the sixth component identifies children (<1 years old) and population working in the manufacturing sector; this component explains 6% of the variance

Insert Table 1

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, present 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 an alarm as soon as the hazard is detected. However, the protocols normally require checking multiple sensors 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 use two methodologies to estimate the proportion of inhabitants that can leave their household before the hazard strikes. First, we use the empirical equations described in the methodology, where we assumed that different groups react and evacuate homogeneously (Figure 7). Second, we use 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 estimate the percentage of people that evacuate if the alarm 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 not 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 impact when the warning alarm is delayed. After 60 minutes, Figure 8 gets patchier, which indicates that the population has different 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)~~(see Lindell et al., 2015; Wei et al., 2017). In

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those situations, k = 1 in Equation 3, which makes the time-consuming contagion process unnecessary. ~~The explanation for this may be that we took the surveys in Chile after an earthquake struck and produced a tsunami, and the population of Chile is well-trained and experienced in knowing what to do in case an alarm is sounded warning of an imminent inundation.~~

Insert Figure 7

Insert Figure 8

4 Discussion

The literature indicates that social vulnerability has a large influence on how people respond to natural disasters. There is agreement that more vulnerable inhabitants not only suffer the most during a natural disaster but also are less resilient, which affects their ability to recover afterward. Social vulnerability is thought to be an important factor that needs to be included in evacuation analyses but there are no systematic frameworks to do so. ~~However, when we review the literature that deals with evacuation processes, social vulnerability, in the best cases, is acknowledged as an important factor that needs to be included but there are no systematic frameworks to do so. Therefore, it is assumed that people with different social vulnerability behave similarly in an evacuation process.~~

This paper deals with this problem by proposing a methodology to integrate social vulnerability into the calculation of how people evacuate after an EWS is activated. We develop 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. For doing this, we used the methods from the LIFESim model and replaced the evacuation curves to reflect the differences in the time response according to social vulnerability level.

The findings from the surveys are in agreement with the theory since the time that people take to respond increases as the vulnerability moves from low to high levels. An interesting result is shown in Figure 9, where we compare the aggregate survey responses with the evacuation responses categorized by social vulnerability level, finding 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. If we extrapolate these results to areas where we just know from first responders the aggregated evacuation rate in time, we can apply the factors indicated in Figure 9 to make a first order approximation of the difference in the evacuation rate by the social vulnerability.

Insert Figure 9

It is important to keep in mind that the surveys were taken in one location where people are highly trained to deal with tsunamis, which may present limitations applying this model in other locations. Regardless, this is an important advancement in our ability to quantify a process that is normally only addressed with qualitative methodologies. Certainly, we need to collect more data to come up with more general approximations of the importance of social vulnerability in the evacuation. ~~However, the literature available shows that previous studies have used similar sample size (Morss et al., 2011)~~

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On the other hand, there is a body of literature that does not find a connection between social vulnerability and evacuation process (i.e. Baker, 1991; Huang, Lindell, & Prater, 2016). However, this literature has been conducted during evacuation process due to Hurricanes, where the population is informed to evacuate their home with hours or days in advance. According to our result, although with no statistical significance, social vulnerability is only relevant during the first 30 minutes after the evacuation alarm is activated, after that, the response time is almost the same among neighborhoods from different levels of social vulnerability. In the case of floods, the literature suggests that social vulnerability is an important element to consider in order to understanding different behaviours during flooding evacuations. In particular, scholars have found that variables such as low household income, poor housing quality, children (Pelling, 1997), women, housewives, students (De Marchi, 2007), elderly, high population density and population with low level of education (Zhang & You, 2014) are key variables to consider to create a social vulnerability index linked to evacuations during disasters. On the other hand, we wanted to use a methodology that make use of census information without major intervention. Therefore, we extend the application of the findings from Fekete (2009) , even though this research was conducted disaster recovery rather than evacuation, who demostrate that "social vulnerability indices are a means for generating information about people potentially affected by disasters that are e.g. triggered by river-floods." Coincidently, the components selected by the criterion used and explained in this work are similar if not the same to what the literature review indicated. Therefore, we felt encouraged to use the 6 components to first explain the responder what we mean by high, medium, and low social vulnerability and to do the exercise of application in Huaraz.

~~The results of the example of ReTSVI in Huaraz highlight the relevance of including social vulnerability in the planning process. There are distinct differences in the percentage of people evacuated in Huaraz for blocks that are close to each other, which is only explained by 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 the influence of SVI.~~

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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; however, it fails to connect the physical vulnerability or the characteristics of an inundation event with social vulnerability. Consequently, we propose a three-step methodology to include social vulnerability that we call Response Time by Social Vulnerability Index (ReTSVI).

We provide an example of the application of ReTSVI where we surveyed first responders to estimate the aggregated time of response and the time of response by social vulnerability. Then we used census data to calculate the SVI and applied into the evacuation process to inundation in Huaraz that was estimated in a study by Somos-Valenzuela and colleagues (2016).

The survey shows that in the first five minutes there is the larger difference in time response between social groups. In this initial period 27% of the population living in neighbourhoods with high social vulnerability evacuated, whereas 42% and 49% of people with medium and low vulnerability escape in the same period. This tendency smooths out after 15 minutes where the distances between the different groups get closer. We use the Principal Component Analysis to construct the SVI, six factors explain social vulnerability among all blocks in Huaraz (Perú) and 57% of the variance is captured by these components. Socioeconomic status, age, gender, marital status, labour sector, education level, home-ownership, population density, poverty, and quality of dwelling materials explain the differences in social vulnerability in Huaraz.

~~When we incorporate social vulnerability in the evacuation models, we can identify areas where people need not only more time but also how much time to evacuate. This result is even more relevant when there is less time to react. The application of ReTSVI allows for the identification of groups that need more support at the block level. This allows policy makers to allocate resources properly, particularly in countries with limited budgets or less resilience.~~

The results of the example of ReTSVI in Huaraz highlight the relevance of including social vulnerability in the planning process. 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 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 the influence of SVI. However, we have to mention that although it seems intuitively plausible that people with different levels of social vulnerability would differ in their evacuation rates and departure times, there are no empirical data that support this assumption. Differences in evacuation rate associated 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.

Acknowledgements

We would like to acknowledge the Ministry of Environment of Peru for providing the 2007 Census of Peru. We also thank Cesar Portocarrero for inspiring us to develop new methodologies to help the 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 feedbacks and English review that help us to improve this study.

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List of Tables

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

Time	Anova	Kruskal-Wallis
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~~1~~: Summary of PCA Results

~~Selected Census variables after PCA analysis to estimate Social Vulnerability Index (SVI)~~	~~Components~~					
~~+ more vulnerable – less vulnerable~~	~~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 65 years old~~		~~.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 than 1 year 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~~

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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 65 years old	+		.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 than 1 year 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

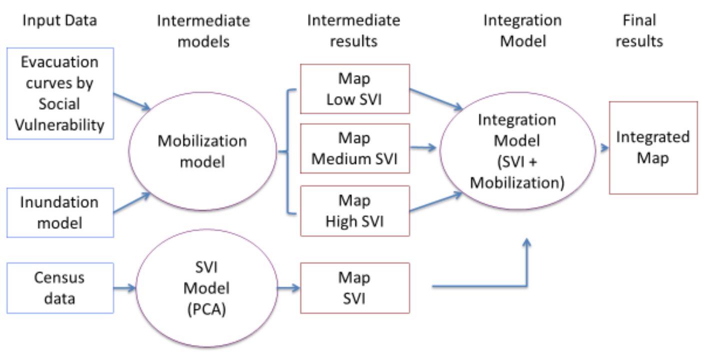


Figure 1: ReTSVI chart

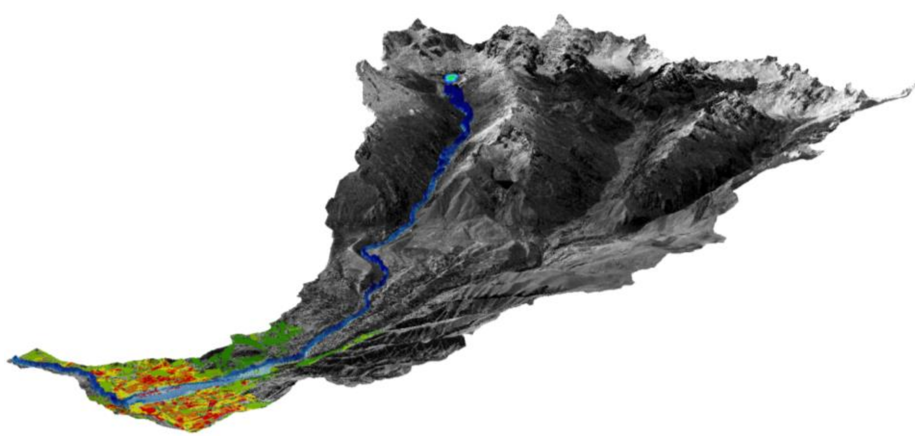


Figure 2: Huaraz City in Peru at the bottom of the Cojup River. Palcacocha Lake, a potential source of a GLOF, is located at the head of the river.

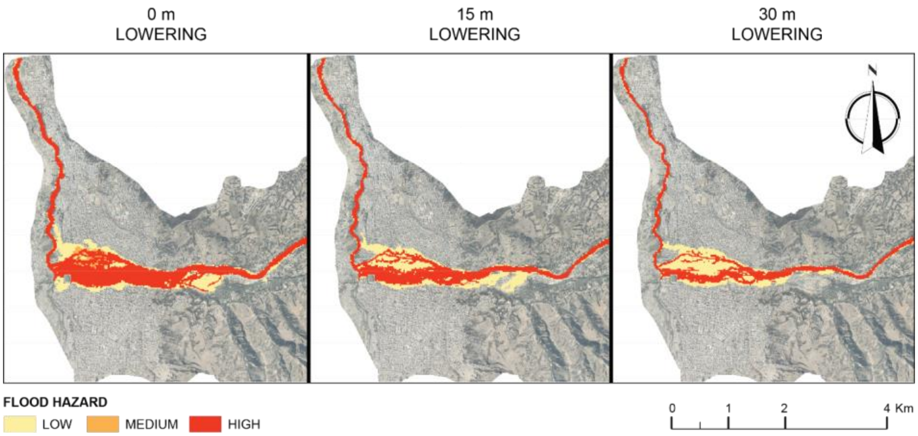


Figure 3: This image corresponds to Figure 9 from (Somos-Valenzuela et al., 2016). Preliminary hazard map of Huaraz due to a potential GLOF originating from Lake Palcacocha with the lake at its current level (0 m lowering) and for the two mitigation scenarios (15 m lowering, and 30 m lowering).

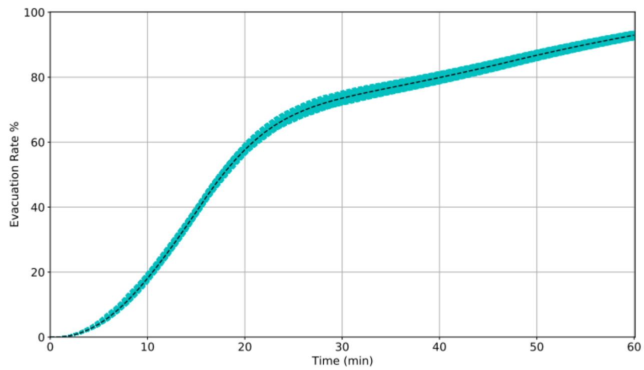
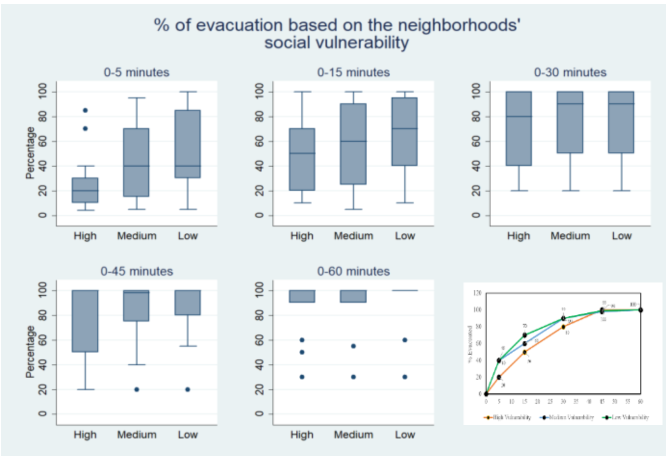
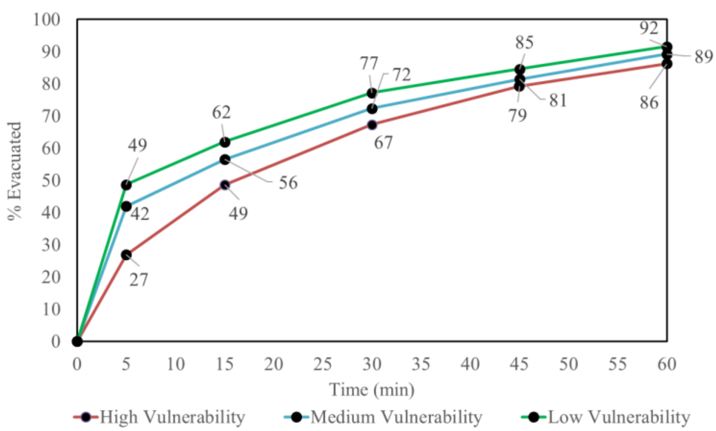


Figure 4: Evacuation rate during the first hour calculated using 1000 samples in a Monte Carlo Simulation



<ins>**Figure 5: First responder's results by social vulnerability group.**</ins>



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

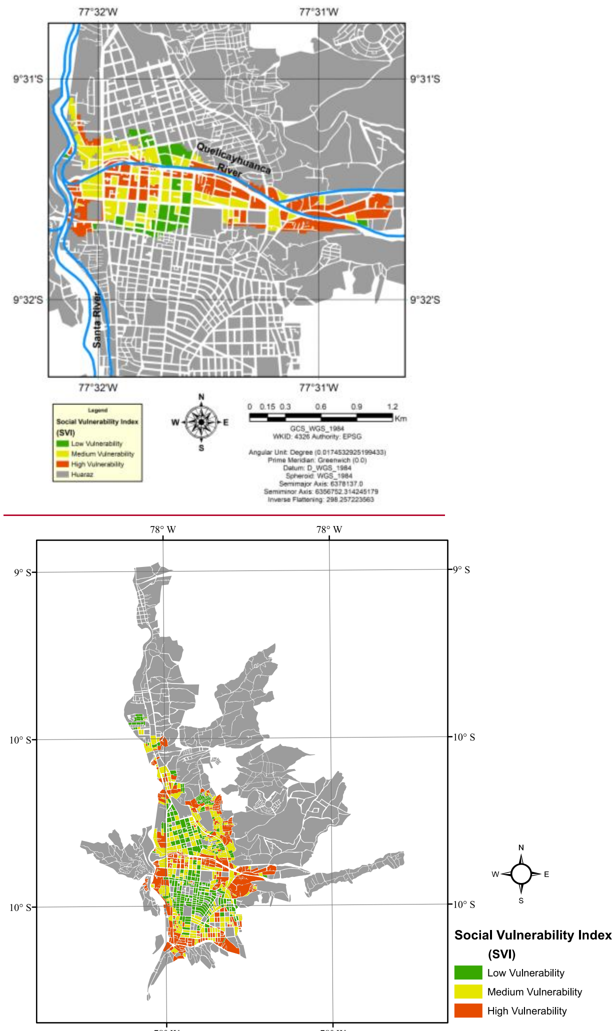


Figure 6: Comparative Vulnerability of Blocks in Huaraz using Social Vulnerability Index (SVI)

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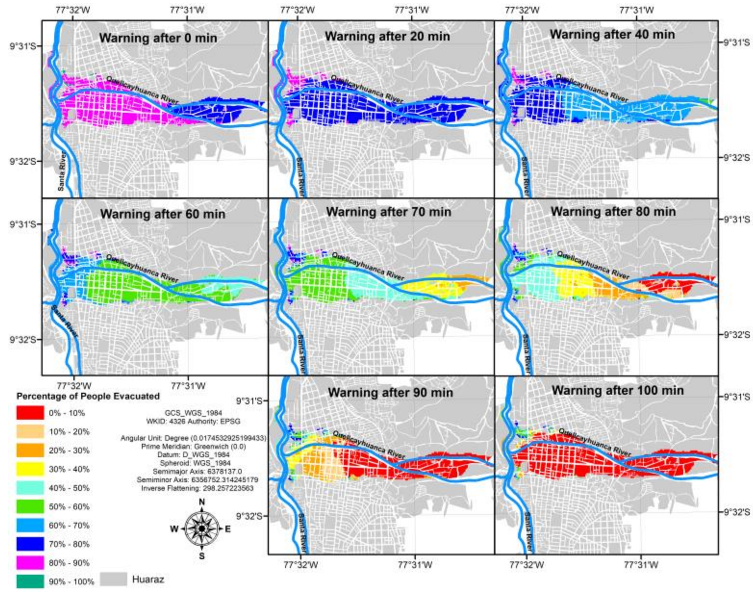

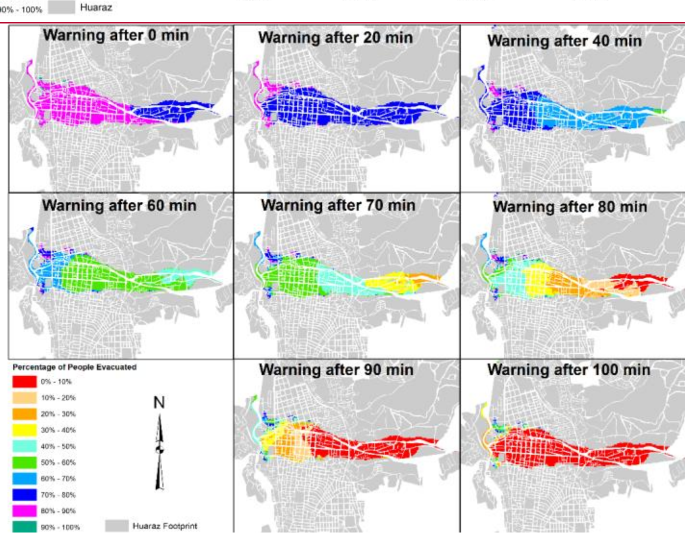

Figure 7: Evacuation using empirical equations.

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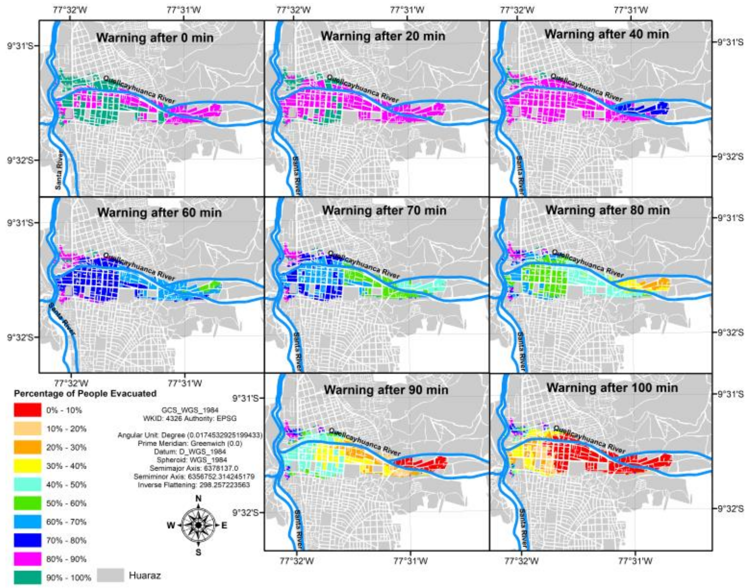

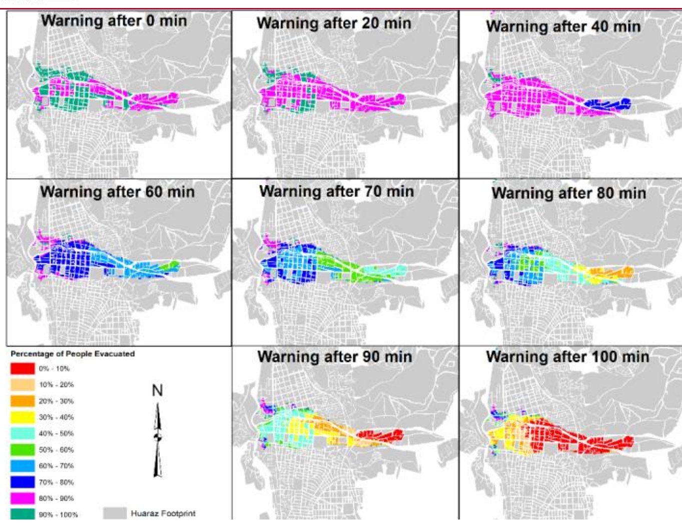

Figure 8: Evacuation using Social Vulnerability Index.

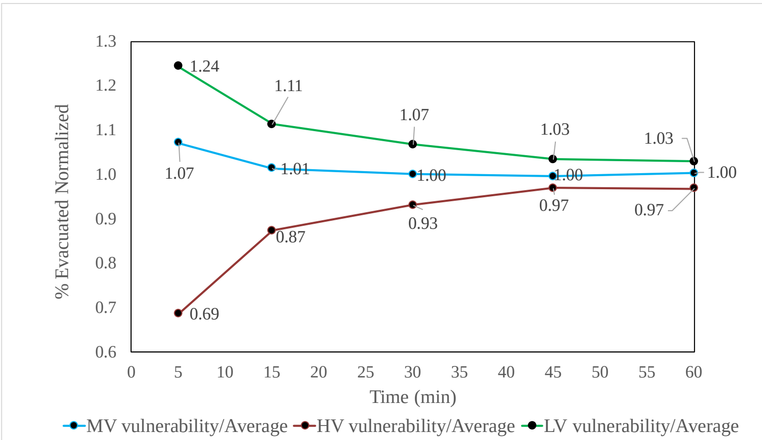

Figure 9: People evacuated per social vulnerability level normalized by the average number of people evacuated.