Agricultural and Forestry Sciences

UNIVERSIDAD DE LA FRONTERA

Avda. Francisco Salazar 01145, Casilla 54-D, 56-45-2325000, Temuco, Chile

August 23, 2018

Dear Editor Dr. Paolo Tarolli

Thank you for considering our paper for further steps in this revision process. In this second 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.

With all the best,

Dr. Marcelo Somos-Valenzuela

Corresponding author

Reviewer 1

Comment 1 R1:

Summary: This manuscript continues to have significant problems that make it unacceptable for publication. These problems could be avoided if the authors would acknowledge that they have not identified any studies that provide empirical evidence that any of their census variables, let alone their overall social vulnerability index, is related to evacuation departure time. Consequently, their analysis doesn't show anything other than how a social vulnerability index *might be used if an empirically valid social vulnerability index were available*. For example, line 8 on page 15 would be acceptable if stated "The results of the example of ReTSVI in Huaraz show how a social vulnerability index could be used in the evacuation planning process. For example, such an analysis might show that there are distinct differences in the percentage of people evacuated in Huaraz for blocks that are close to each other". In the absence of any empirical evidence that their social vulnerability index is related to evacuation departure times, the current manuscript's conclusions are completely unsupported.

Response to comment 1 R1

We agree with you and we tried, unsuccessfully, to indicate this in the first revision. Therefore, we include the paragraph suggested by you in the conclusion section.

Where originally reads:

"The results of the example of ReTSVI in Huaraz highlight the relevance of including social vulnerability in the planning process."

Now it reads:

"The results of the example of ReTSVI in Huaraz show how a social vulnerability index could be used in the evacuation planning process. For example, such an analysis might show that there are distinct differences in the percentage of people evacuated in Huaraz for blocks that are close to each other".

For "the absence of any empirical evidence that their social vulnerability index is related to evacuation departure times, the current manuscript's conclusions are completely unsupported", we reviewed the document and modified in several places to avoid this claim.

Comment 2 R1:

P 3 L29. This sentence attempts to support the authors' conclusion by contrasting the conclusions of a statistical meta analysis (Huang et al., 2016) with the results from 1) one of the studies in that SMA (Bateman and Edwards, 2002), 2) a woefully inadequate narrative review that only reported confirming evidence and disregarded disconfirming evidence (Dash & Gladwin, 2007), and 3) two studies that did not in fact test whether "social vulnerability is a key factor to take into account during emergency management and evacuation planning (Chakraborty et al., 2005; Kusenbach et al., 2010). Thus, the cited studies do not support the authors' conclusion. Indeed, the authors have ignored an important aspect of the Chakraborty et al. (2005) and Kusenbach et al. (2010) studies; both of them used a small set of rationally selected indicators of evacuation vulnerability rather than this study's index of unknown relevance to evacuation that was constructed by factor analyzing an arbitrary set of census variables.

The inadequacy of the supposed support for a vulnerability index can also be seen in the claim "women, housewives, students (De Marchi, 2007) … are key variables to consider to create a social vulnerability index linked to evacuations during disasters." The report by De Marchi and her colleagues (2007)—which should actually be cited as De Marchi, Scolobig, Delli Zotti, & Del Zotto (2007)—did conclude on p. 190 that these demographic groups were vulnerable with respect to anticipation of hazards. However, they qualified this finding in the following paragraph by noting "[a]s to the phase of resistance and coping, the most vulnerable appear to be those with a low level of community embedding and with a low trust in local authorities. *The latter finding is just the opposite of that commented above pertaining to the anticipation phase, which proves that the same group may be more vulnerable at certain points in time and less vulnerable in others*" (my emphasis). More emphatically, De Marchi and Scolobig (2012, p. 317) state "[w]e maintain that one of the main problems with the operationalisation of the concept of vulnerability through indicators (see, for example, Blaikie et al., 1994; Hewitt, 1997; Anderson, 2000; Cutter, Boruff and Shirley, 2003) lies in a certain circularity of reasoning, whereby the relation between the property to be investigated and its indicators is not clarified adequately. For instance, what is the justification for the greater vulnerability assigned a priori to women (gender being a commonly accepted vulnerability indicator)?"

Response to comment 2 R1

We modified the paragraph to consider the comments

Before it reads:

"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."

Now it reads:

"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) analysed 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 the case of floods, we have not found studies that link demographic and socio economic variables to the evacuation process."

Comment 3 R1:

Ultimately, as skeptical as I am about the value of a social vulnerability index derived from factor analysis of census data, I do not object to the authors using such an index in this paper as long as they make it clear that they are providing an example of how such an analysis would be done if they had a measure of social vulnerability that had demonstrated validity in predicting evacuation departure times. However, I do insist that they avoid claiming support of such an index from studies that do not provide such support.

Response to Comment 3 R1: We clarify this point through the document, particularly we addressed this concern in the discussion section.

Comment 4 R1: P5 L8. Lines 8-14 have two problems. First, this is a list of variables rather than a sentence. Second, this passage seems to be intended to repeat the claim of support for a census variable-based social vulnerability index. As noted above, none of these studies shows a reliable predictive relationship between the listed variables and any measure of people's "capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard" (Blaikie et al. 1994, 9), let alone evacuation departure times.

Response to Comment 4 R1:

We agree with you, this was a repetition of what was already said, and we deleted the paragraph.

Comment 5 R1:

P7 L16. The authors seem to be committed to a policy of citing the results of individual studies even if those studies conflict with the evidence from a statistical meta analysis (e.g., Huang et al., 2016). If they really believe that these individual studies provide more conclusive evidence than a statistical meta-analysis, they should explain their reasoning.

Response to Comment 5 R1: We can say that there was no a policy, instead of an involuntary slip. So, we delete the individual studies that contradict the general finding of the meta-analysis as it was pointed in the previous responses.

Comment 6 R1:

P7 L26. The context suggests that the authors conducted 22 "interviews"; the entire process of selecting and contacting prospective respondents is a single "survey".

Response to Comment 6 R1:

We change the word "interview" for "survey".

Comment 7 R1:

P 10 L20. A "critic" is a person who criticizes something; a "critique" is the content of the criticism.

Response to Comment 7 R1:

We change the word "critic" for "critique".

Comment 8 R1:

L29-37. PCA is a well-known and noncontroversial technique; it is only necessary to report the authors' choices of how they handled missing data (pairwise, listwise, mean substitution,), what they analyzed (correlations or covariances), which factor extraction they used, how they determined the number of factors, and which factor rotation procedure they used.

Response to Comment 8 R1:

Census data from Huaraz does not have missing values. For the factor extraction, first we perform PCA, then we selected the factors with eigenvalues greater than one (we extracted 6 components) which was corroborated with a screen test that we did not include in the paper due to the large extend of it (see next response). Finally, we used the Kaiser varimax rotation.

Comment 9 R1:

P11 L1. Kaiser's criterion for the number of factors (eigenvalues greater than one) tends to extract too many factors; Cattell's scree test tends to be better (e.g., Costello & Osborne, 2005; Zwick & Velicer, 1986).

Response to Comment 9 R1:

We used the scree test to verify whether the extraction of the components with eigenvalues greater than 1 is adequate, which we did not included it in the previous version of the manuscript. The figure below shows that the appropriate number of components should be between 5 and 6 components. Therefore, we feel confident in our original selection of 6 components using the original criteria.

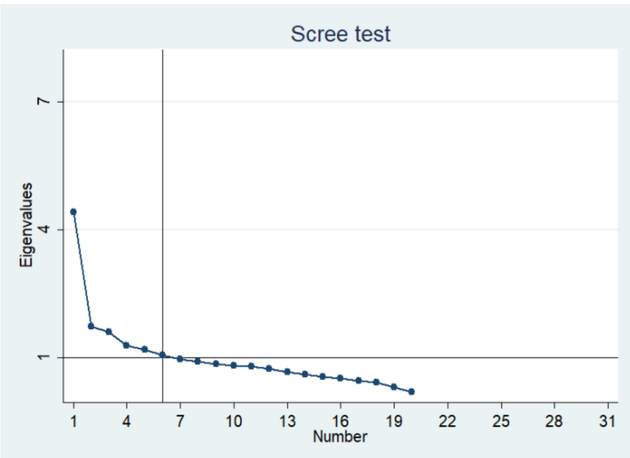

Figure 1 responses: Scree test

Comment 10 R1:

L3. Bartlett's test is performed on the correlation matrix, so this step should be listed *before* the current step (2)

Response to Comment 10 R1:

We delete the test from step 2 and moved it to step 1 that now reads as follows:

"(1) First we perform a multicollinearity test call Variance Inflation Factor (VIF). Variables with VIF>10 were excluded. Then, we normalize all variables as percentage, per capita or density functions. For the purposes of this paper, we normalized all variables as percentages; for example, the percentage of independent houses per block or the percentage of elderly people per block. Then standardize all input (census) variables to z-scores $z =$

$\frac{x-\mu}{\sigma}$. This creates variables with mean 0 and standard deviation 1. Finally, we use the Bartlett's test of sphericity to determine if the variables are suitable for structure detection."

Comment 11 R1:

P13 L13. Shaking is an instantaneous broadcast mechanism only if the entire population recognizes it as a warning cue. However, many people in the Lindell et al. (2015) and Wei et al. (2017) studies were warned by the social contagion process because some people were unaware of the connection between earthquake shaking and tsunamigenesis.

Response to Comment 11 R1:

Before the earthquake/tsunami in Coquimbo described in this paper, there was 8.9 earthquake in Chile were people were unaware of the connection between earthquake shaking and tsunami genesis and many of them did not evacuate and perish. There was also confusing information from the authorities. Because of that, in Coquimbo as well as most of the coast of Chile, people were more alert and readier to evacuate even when the authorities said differently.

Comment 12 R1:

L21. The literature, especially the literature cited in this study, mostly *speculates* that "social vulnerability has a large influence on how people respond to natural disasters." This is especially true for the relationship between measures of social vulnerability and evacuation departure times.

Response to Comment 12 R1:

We modified the paragraph.

Before it read:

"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."

Now it reads:

"The literature indicates that social vulnerability has a large influence on how people are affected by 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 and there is not strong evidence that proves that demographic and socio economic variables can explain the evacuation process”

Comment 13 R1:

L31. The findings from the interviews (not surveys) are *not* “in agreement with the theory” because there were no statistically significant differences among the evacuation curves for low, medium, and high social vulnerability.

Response to Comment 13 R1:

“The findings from the interviews (not surveys)” in a previous comment you mentioned that we should use survey and not interview so we changed accordingly, and we are using survey to refer to our data collection process.

Additionally, we modified the sentence and now it reads: “The findings from the surveys look somewhat similar with the theory, even though there were no statistically significant differences among the evacuation curves for low, medium, and high social vulnerability”

Comment 14 R1:

L38. Although there is no justification for discussing differences among the vulnerability groups with respect to their evacuation departure time curves, it is interesting to note that the aggregate curve is somewhat similar to the evacuation departure time curves reported in Lindell et al. (2015).

Response to Comment 14 R1:

Yes, this is very interesting considering the distance, and socioeconomic and cultural differences that the evacuation results in both studies show that in the first 15 minutes the aggregated evacuation rate falls between 50-65%, in 30 minutes from 80-90% and after an hour is close to 100%. It would be interesting to see what explains the differences between the inland and the coastal evacuation curves in Lindell et al (2015) considering that the differences are statistically significant (p<0.05).

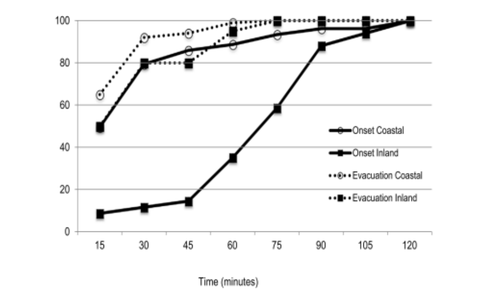

Fig. 2. Percent of repondents reporting expected time of tsunami arrival and actual time of evacuation departure, by Location.

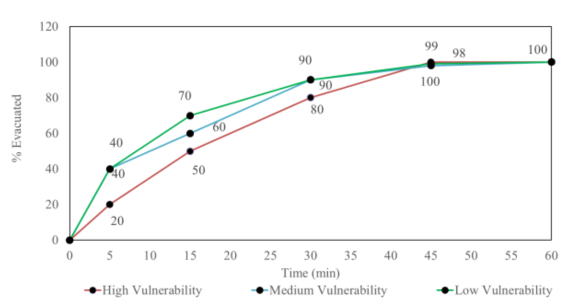

Figure 2 responses: Left, Aggregated evacuation rate from Lindell et al. (2015). Right, Figure 5 of this paper.

As a result, both evacuation process is considerably faster than the results for dam breaks from Aboelata et al. (2003) that was incorporated in the model LifeSIM and HEC-FIA model from the corp of engineering as it was pointed out in the paper.

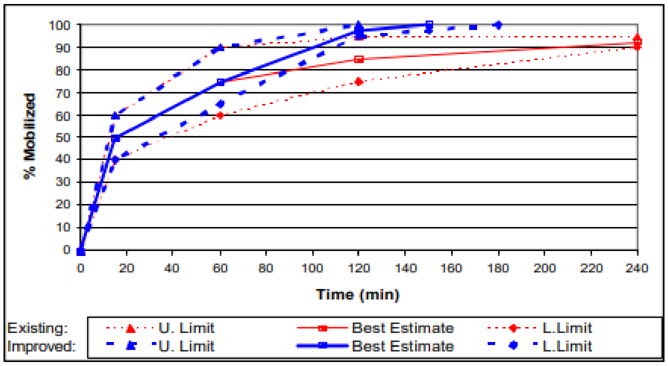

Figure 3 responses: Existing and improved mobilization distributions Aboelata et al. (2003)

Aboelata, M., Bowles, D. S., & McClelland, D. M. (2003, October). A model for estimating dam failure life loss. In Proceedings of the Australian committee on large dams risk workshop, Launceston, Tasmania, Australia

Comment 15 R1:

P14 L1-25. This paragraph mostly repeats the erroneous claims that I have noted earlier. However, lines 10 -13 go beyond the authors' previous unsubstantiated claims by reporting a difference due to social vulnerability that they admit is not statistically significant. In addition, lines 23-24 claim, without substantiation, that the components they used "are similar if not the same to what the literature review indicated."

Response to Comment 15 R1: We have rewritten the discussion section and now it reads as follows:

"4 Discussion

This paper proposes a methodology to integrate social vulnerability into the calculation of the people evacuation rate after an EWS is activated. We 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.

We found that the aggregated evacuation rate curve for the 2015 tsunami in Coquimbo has similarities with the evacuation curve for the 2009 tsunami in American Samoa after a 8.1

earthquake described in Lindell et al. (2015). This similarity is notable considering the distance, and socioeconomic and cultural differences. The evacuation results in both studies show that in the first 15 minutes the aggregated evacuation rate falls between 50-70%, in 30 minutes from 80-90% and after an hour is close to 100%. These aggregated evacuation curves for tsunamis are faster than the results from Equation 1 (Figure 4), and the results from Abolaeta et al. (2003) that deal with rivers and dam break floods, suggesting that the process is understood earlier by the population. This could be due to awareness/training or to the shaking that is felt by most of the people immediately.

When we separate the results by social vulnerability, the results suggest that people with higher level of vulnerability needs more time to evacuate than people with lower level of vulnerability. However, in our results, the differences between the evacuation curves are not statistically significant. In Figure 9, where we compare the aggregate survey responses with the evacuation responses categorized by social vulnerability level, we find that people at a medium level of vulnerability respond similarly to the aggregated values. Then, people with low and high vulnerability behave almost symmetrically around the average. Which in a more general application could be used to generate boundaries for the evacuation curves.

Insert Figure 9

To overcome the limitation of the no-significance in the difference between the evacuation curves more data need to be collected.

A limitation that arises when we apply a methodology such us ReTSVI, which relies on the construction of a social vulnerability index, is that we could not find studies that relate evacuation rates with social vulnerability for inundations that take less than an hour from the triggering to the flooding. In this study we used an SVI based on PCA to select the variables as proxy; however, this index was created and validated for post event assessments. Therefore, this is a limitation that needs to be addressed before applying this framework.

Traditionally, the evacuation rate is calculated using one evacuation rate curve; therefore, ReTSVI seeks to overcomes this limitation by allowing the user to include social vulnerability. The user decides which social vulnerability index use and the evacuation curves for the levels of vulnerability. Here we provide an example using as a proxy a social vulnerability index for post disaster and evacuation curves that have not statistical significance. However, it still provides valuable information (Figure 8) of the implications of including social vulnerability that needs to be validated. For example, more vulnerable people, according to the SVI based on PCA and census data, live closer to the river where the inundation strikes earlier and harder, having less time to evacuate while at the same time they evacuate later. Additionally, social vulnerability seems to be less important as the EWS gets delayed.”

Comment 16 R1:

L38 through line 3 on the next page reports differences in evacuation rates between vulnerability groups even though there are no significant differences among the evacuation curves for the three social vulnerability groups.

Response to Comment 16 R1:

We change the paragraph.

Before it read:

"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."

Now it reads:

"The survey shows, without statistical significance (Table1), 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."

Reviewer 2

The authors responded accurately to almost all of the issues raised. However, several points need to be solved already.

Comment 1 R2: The authors used 0.3 and -0.3 in the factor loading. Can the authors justify their choice? Without seeing the other values, this choice is difficult to explain.

Response comment 1: Fekete (2009) used this criteria to select the variables to create his social vulnerability index: "For the interpretation, only eigenvalues greater than one are regarded and absolute loading values below 0.30 suppressed (Nardo et al., 2005: 40, 43; Buhner, 2006: 200, 211; Bernard, 2006: 677)".

Fekete A (2009) Validation of a social vulnerability index in context to river-floods in Germany. Nat. Hazards Earth Syst. Sci. 9(2), 393–403 (doi:10.5194/nhess-9-393-2009)

Comment 2 R2: I understand that advancing the research in social vulnerability is not on the scope of the current paper. However, the authors are using variables to explain people vulnerability to evacuation purposes. Thus, an approximate justification of those is necessary to address the aim of the paper. I still have some doubts about the association between types of jobs (with a difference in commerce, construction and manufacturing) with the evacuation vulnerability. The same is for renters and houses without electricity. I find instead proper the relation with strictly socio-demographic variables that are supported by the mentioned literature (Kusenbach et al., 2010, that however does not include marital status as addressed by the authors in the rebuttal). Pelling (1997) addresses the complex issue of disaster vulnerability without any mention of evacuation. He is referring to mitigation/preparedness actions instead (e.g. pg 216). Thus I think the authors should find references supporting the variables selection or strongly justify their choice. If authors are not able to do so, I might suggest to replace those variables or delete them. This issue has nothing to deal with the issue raised in the first round of revision when asking to set up a background for variables selection in Peru.

Response comment 2: One of the primary variables that are linked to social vulnerability is the household income (Cutter et al. 2003), but in the case of Peru, this variable is not surveyed in the census. Consequently, we used proxy variables of income such us job types, marital status, renters and house without electricity. The relationship between income distribution and the job type has been established worldwide (Galbraith, 2001) as well as in literature linked to social vulnerability (post disaster) "Some occupations, especially those involving resource extraction, may be severely impacted by a hazard event" (Cutter, 2003 page 248). In relation to renters, they are considered to be more vulnerable to disaster "People that rent do so because they are either transient or do not have the financial resources for home ownership. They often lack access to information about financial aid during recovery. In the most extreme cases, renters lack sufficient shelter options when lodging becomes uninhabitable or too costly to afford". (Cutter 2003, page 247). Regarding to "houses without electricity," we assumed that it indicates more precarious conditions and the same is true for many other variables in the Census such as houses without restroom and tab water which were disregard in the collinearity test. Finally, "adult population divorced" as proxies to household income, for example Schoeni (1995) found that "In most cases, both separated and divorced men earn more than men who are never married but less than those who are currently married".

We recalculate the SVI excluding marital status (adult population divorced) and gender, and we found differences between the former and the recalculated SVI. However, after a lengthy discussion, we do not have strong arguments to support such changes specially because the variables initially selected are easily found in the literature to influence the level of Social Vulnerability.

Cutter SL, Boruff BJ and Shirley WL (2003) Social Vulnerability to Environmental Hazards. *Soc. Sci. Queartely* **84**(2), 242–161

Galbraith, J. K., & Berner, M. (Eds.). (2001). Inequality and industrial change: a global view. Cambridge University Press.

Schoeni, R. F. (1995). Marital status and earnings in developed countries. Journal of population economics, 8(4), 351-359.

Comment 3 R2: Revise carefully the new statement at pg. 6 lines 20-26 since not all the mentioned literature is related to evacuation, at all.

Response comment 3:

We revised the literature cite and the author is correct so we modify the paragraph

It originally read:

“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)”

Now it reads:

“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), gender, household size, elderly, children (Dash & Gladwin, 2007)”

Comment 4 R2: What’s the p-value obtained by Bartlett's test of sphericity?

Response comment 4:

The p-value is close to 0 as it is shown in figure below.

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Bartlett test of sphericity

Chi-square         =          4014.630
Degrees of freedom =               190
p-value            =             0.000
H0: variables are not intercorrelated
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Comment 5 R2: Did the authors perform a multicollinearity analysis before running the PCA to be sure that none of the variables has been taken twice?

Response comment 5:

Yes, we did. In the step 1 when we calculate SOVI. We unfortunately did not mention that in the original document, so we appreciate your questions. We also move the sphericity test from step 2 to step 1 as it was pointed out by another reviewer.

Step one originally read:

"(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."

Now it reads:

"(1) First we perform a multicollinearity test call Variance Inflation Factor (VIF). Variables with VIF>10 were excluded. Then, we normalize all variables as percentage, per capita or density functions. For the purposes of this paper, we normalized all variables as percentages; for example, the percentage of independent houses per block or the percentage of elderly people per block. Then standardize all input (census) variables to z-scores $z = \frac{x-\mu}{\sigma}$. This creates variables with mean 0 and standard deviation 1. Finally, we use the Bartlett's test of sphericity to determine if the variables are suitable for structure detection."

Comment 6 R2: Can you discuss more in-depth table 1?

Response comment 6:

We modified the document where we talk about Table 1,

Before it said:

"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."

Now it says:

“We test if the mean response time to the evacuation alarm between the three types of neighborhoods was statistically significant using two methods: Anova (parametric method) and Kruskal-Wallis (non-parametric method). The table 1 shows that the p-values between the time of response and level of social vulnerability (low, medium and high) are not statistically significant. All the p-values are higher that 0.05 (alpha level), and therefore we accept the null hypothesis that the time of responses between the three groups of social vulnerability are not statistically significant (p-value >.05). 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 we also modified table 1:

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

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

Comment 7 R2: Can you explain why three classes quartile has been chosen in classifying the Social Vulnerability index?

Response comment 7: Traditionally risk studies use three level of vulnerability which are normally present as a matrix of 3 by 3 where the physical and social vulnerability are intersected. Therefore, we decided to replicate this nomenclature to make our results easier to understand since the parallel is straightforward.

Comment 8 R2: I suggest providing some discussion related to the role of proximity to the river and the differences in SVI results.

Response comment 8: We provide some discussion this in the new reworked discussion section

Comment 9 R2: The discussion chapter is still not adequately addressed. There is a lengthy introduction that sums up the justification of the research and the methodology undertaken. The new chapter on page 17 lines 1-20 is a repetition of the introduction. Thus the discussion is still lacking of a new light to results. Discussions should include similarities and criticisms to findings. For all these reasons, I suggest rearranging this chapter again.

Response comment 9: We have rewritten this section and now it reads as follows:

“4 Discussion

This paper proposes a methodology to integrate social vulnerability into the calculation of the people evacuation rate after an EWS is activated. We 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.

We found that the aggregated evacuation rate curve for the 2015 tsunami in Coquimbo has similarities with the evacuation curve for the 2009 tsunami in American Samoa after a 8.1 earthquake described in Lindell et al. (2015). This similarity is notable considering the distance, and socioeconomic and cultural differences. The evacuation results in both studies show that in the first 15 minutes the aggregated evacuation rate falls between 50-70%, in 30 minutes from 80-90% and after an hour is close to 100%. These aggregated evacuation curves for tsunamis are faster than the results from Equation 1 (Figure 4), and the results from Abolaeta et al. (2003) that deal with rivers and dam break floods, suggesting that the process is understood earlier by the population. This could be due to awareness/training or to the shaking that is felt by most of the people immediately.

When we separate the results by social vulnerability, the results suggest that people with higher level of vulnerability needs more time to evacuate than people with lower level of vulnerability. However, in our results, the differences between the evacuation curves are not statistically significant. In Figure 9, where we compare the aggregate survey responses with the evacuation responses categorized by social vulnerability level, we find that people at a medium level of vulnerability respond similarly to the aggregated values. Then, people with low and high vulnerability behave almost symmetrically around the average. Which in a more general application could be used to generate boundaries for the evacuation curves.

Insert Figure 9

To overcome the limitation of the no-significance in the difference between the evacuation curves more data need to be collected.

A limitation that arises when we apply a methodology such us ReTSVI, which relies on the construction of a social vulnerability index, is that we could not find studies that relate evacuation rates with social vulnerability for inundations that take less than an hour from the triggering to the flooding. In this study we used an SVI based on PCA to select the variables as proxy; however, this index was created and validated for post event assessments. Therefore, this is a limitation that needs to be addressed before applying this framework.

Traditionally, the evacuation rate is calculated using one evacuation rate curve; therefore, ReTSVI seeks to overcomes this limitation by allowing the user to include social vulnerability. The user decides which social vulnerability index use and the evacuation curves for the levels of vulnerability. Here we provide an example using as a proxy a social vulnerability index for post disaster and evacuation curves that have not statistical significance. However, it still provides valuable information (Figure 8) of the implications of including social vulnerability that needs to be validated. For example, more vulnerable people, according to the SVI based on PCA and census data, live closer to the river where the inundation strikes earlier and harder, having less time to evacuate while at the same time they evacuate later. Additionally, social vulnerability seems to be less important as the EWS gets delayed."

Comment 10 R2: Citations in the conclusions are not necessary.

Response comment 10: We have deleted the references from the conclusions

Comment 11 R2: What's quality of dwelling materials expressed in line 6 of page 18?

Response comment 11: This refers to the quality of the house which were used in the older versions of the SVI. However, as this work progressed we decided to exclude variables related to physical vulnerability from this index, because that should be account into a physical vulnerability study that evaluates the risk of failure and then it should be combine to this or another version of SVI. However, we did not delete this sentence from the previous versions of this document and now we did it.

Comment 12 R2: Conclusions must give some critical final remarks about the "so what" of the paper for planners and risk managers. Limitations should be addressed in the discussion.

Response comment 12: We have rewritten this section and now it reads as follows:

"5 Conclusion

This article proposes a methodology to incorporate social vulnerability into current methodologies to estimate the percentage of people that evacuate an inundation hazard zone. Previous research recognizes the relevance of social vulnerability in risk assessments; however, in general the methodologies available fail to connect the physical vulnerability or the characteristics of an inundation event with social vulnerability in a quantitative framework. The results of the example of ReTSVI in Huaraz show how a social vulnerability index could be used in the evacuation planning process. For example, such an analysis might show that there are distinct differences in the percentage of people evacuated in Huaraz for blocks that are close to each other, which could be explained by 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, although it seems intuitively probable that people with different levels of social vulnerability would differ in their evacuation rates and departure times, there is no empirical data that 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. We faced a similar situation when constructing a pre-inundation social vulnerability index. It is unclear which variables explain the differences in departure time, which is critical to apply the ReTSVI framework, therefore, it also needs further study."

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

Alvaro Quezada ~~-~~Hofflinger[1,2], Marcelo A. Somos-Valenzuela[2,3], Arturo Vallejos-Romero[1]
[1]Nucleo de Ciencias Sociales, Universidad de la Frontera, Temuco, 4780000, Chile
[2]Research Center Butamallín, Agricultural and Forestry Sciences Department, Universidad de La Frontera, Temuco 4780000, Chile
[3] Northeast Climate Science Center, University of Massachusetts, Amherst, 01003, USA

Correspondence to: Marcelo A. Somos-Valenzuela (marcelo.somos@ufrontera.cl)

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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~~do not consider ~~respond differently based on their~~ socioeconomic and demographic characteristics of the population. This article develops the Response Time by Social Vulnerability Index (ReTSVI). ReTSVI combines a series of modules which are pieces of information that interact during an evacuation, such us 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~~The result of example of application have no statistica~~, with not statistica~~l significance, which should be considere in a real case of application. Using a methodology such as ReTSVI could allow~~s~~ to combine social and physical vulnerability in a qualitative framework for evacuation, although, first more research needs to be done to understand the socioeconomic variables that explain the differences in evacuation rate. ~~first responders to identify areas where the same level of physical vulnerability affects distinct groups differently.~~

Keywords: ReTSVI, Social Vulnerability, Flood Hazard Evacuation

1 INTRODUCTION

The costs associated with health, food security and the physical environment produced by climate change are expected to reach between 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, 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 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 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). 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

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.~~ In the case of floods; however, we have not found studies that link demographic and socio economic variables to the evacuation process.

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~~, 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 t~~o have~~hat has 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)~~

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. In order to have a methodology that enable researcher and practitioner to include social vulnerability and test if it has any impact on the evacuation process during a flood event,~~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

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2.1 Conceptual model of ReTSVI

The objective of this work is to propose a conceptual model 'The Response Time by Social Vulnerability Index (ReTSVI)' 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.”

Insert Figure 1

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

In 1941, the city of Huaraz was affected by a Glacier 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~~ survey 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 actived, 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).

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. 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}). 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.

[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).

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 critique~~es~~ 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 7 steps to calculate the Social Vulnerability Index (SVI): (1) First we perform a multicollinearity test call Variance Inflation Factor (VIF). Variables with VIF>10 were excluded. Then, we normalize all variables as percentage, per capita or density functions. For the purposes of this paper, we normalized all variables as percentages; for example, the percentage of independent houses per block or the percentage of elderly people per block. Then standardize all input (census) variables to z-scores $z = \frac{x-\mu}{\sigma}$. This creates variables with mean 0 and standard deviation 1. Finally, we use the Bartlett's test of sphericity to determine if the variables are suitable for structure detection. ~~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~~ $\cancel{z = \frac{x-\mu}{\sigma}}$~~. 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 and corroborate the selection with a scree test. (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) 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

Formatted: Font: Times New Roman, 12 pt, Font color: Auto 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.~~

We test if the mean response time to the evacuation alarm between the three types of neighborhoods was statistically significant using two methods: Anova (parametric method) and Kruskal-Wallis (non-parametric method). The table 1 shows that the p-values between the time of response and level of social vulnerability (low, medium and high) are not statistically significant. All the p-values are higher that 0.05 (alpha level), and therefore we accept the null hypothesis that the time of responses between the three groups of social vulnerability are not statistically significant (p-value >.05). 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.

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Insert Table1

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

3.2.1 Social Vulnerability Index

Peru has a long history of mudflows generated from glacial lakes in the Cordillera Blanca. As global warming progresses and glaciers start shrinking at a higher rate,this problem is growing. In some cases, glaciers leave behind a weak moraine that holds a large amount of water that can suddenly release and generate 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~~E~~ e~~lderly, 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.

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). In those situations, k ~~=~~ tend to 1 in Equation 3, which makes the time-consuming contagion process ~~unnecessary~~less important.

Insert Figure 7

Insert Figure 8

4 Discussion

This paper proposes a methodology to integrate social vulnerability into the calculation of the people evacuation rate after an EWS is activated. We 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.

We found that the aggregated evacuation rate curve for the 2015 tsunami in Coquimbo has similarities with the evacuation curve for the 2009 tsunami in American Samoa after a 8.1 earthquake described in Lindell et al. (2015). This similarity is notable considering the distance, and socioeconomic and cultural differences. The evacuation results in both studies show that in the first 15 minutes the aggregated evacuation rate falls between 50-70%, in 30 minutes from 80-90% and after an hour is close to 100%. These aggregated evacuation curves for tsunamis are faster than the results from Equation 1 (Figure 4), and the results from Abolaeta et al. (2003) that deal with rivers and dam break floods, suggesting that the process is understood earlier by the population. This could be due to awareness/training or to the shaking that is felt by most of the people immediately.

When we separate the results by social vulnerability, the results suggest that people with higher level of vulnerability needs more time to evacuate than people with lower level of vulnerability. However, in our results, the differences between the evacuation curves are not statistically significant. In Figure 9, where we compare the aggregate survey responses with the evacuation responses categorized by social vulnerability level, we find that people at a medium level of vulnerability respond similarly to the aggregated values. Then, people with low and high vulnerability behave almost symmetrically around the average. Which in a more general application could be used to generate boundaries for the evacuation curves.

Insert Figure 9

To overcome the limitation of the no-significance in the difference between the evacuation curves more data need to be collected.

A limitation that arises when we apply a methodology such us ReTSVI, which relies on the construction of a social vulnerability index, is that we could not find studies that relate evacuation rates with social vulnerability for inundations that take less than an hour from the triggering to the flooding. In this study we used an SVI based on PCA to select the variables as proxy; however, this index was created and validated for post event assessments. Therefore, this is a limitation that needs to be addressed before applying this framework.

Traditionally, the evacuation rate is calculated using one evacuation rate curve; therefore, ReTSVI seeks to overcomes this limitation by allowing the user to include social vulnerability. The user decides which social vulnerability index use and the evacuation curves for the levels of vulnerability. Here we provide an example using as a proxy a social vulnerability index for post disaster and evacuation curves that have not statistical significance. However, it still provides valuable information (Figure 8) of the implications of including social vulnerability that needs to be validated. For example, more vulnerable people, according to the SVI based on PCA and census data, live closer to the river where the inundation strikes earlier and harder, having less time to evacuate while at the same time they evacuate later. Aditionally, social vulnerability seems to be less important as the EWS gets delayed.

5 Conclusion

This article proposes a methodology to incorporate social vulnerability into current methodologies to estimate the percentage of people that evacuate an inundation hazard zone. Previous research recognizes the relevance of social vulnerability in risk assessments; however, in general the methodologies available fail to connect the physical vulnerability or the characteristics of an inundation event with social vulnerability in a quantitative framework. The results of the example of ReTSVI in Huaraz show how a social vulnerability index could be used in the evacuation planning process. For example, such an analysis might show that there are distinct differences in the percentage of people evacuated in Huaraz for blocks that are close to each other, which could be explained by 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, although it seems intuitively probable that people with different levels of social vulnerability would differ in their evacuation rates and departure times, there is no empirical data that 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. We faced a similar situation when constructing a pre-inundation social vulnerability index. It is unclear which variables explain the differences in departure time, which is critical to apply the ReTSVI framework, therefore, it also needs further study.

~~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.~~

~~Insert Figure 9~~

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~~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 & 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.~~

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List of Tables

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

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

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Table 2: Summary of PCA Results

Selected Census variables after PCA analysis to estimate Social Vulnerability Index (SVI)	Sign Adjustment	Components					
		1	2	3	4	5	6
Household with 5 or more rooms	-	.31					
Population with health insurance		.40					
Population with primary education		-.37					
Population with college education		.43					
Population with “white collar jobs”		.40					
Indigenous population		-.35					
Population with disabilities	+		.53				
Population older than 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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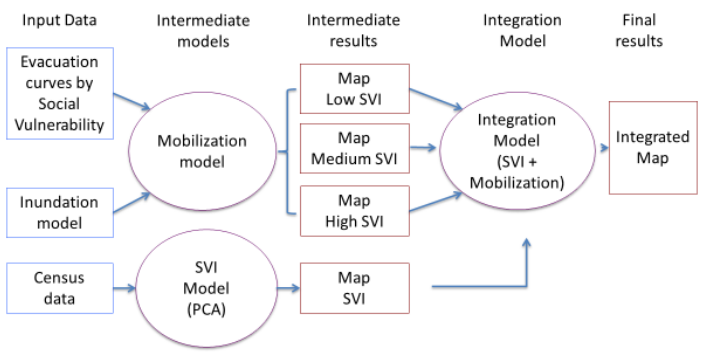

Figure 1: ReTSVI chart

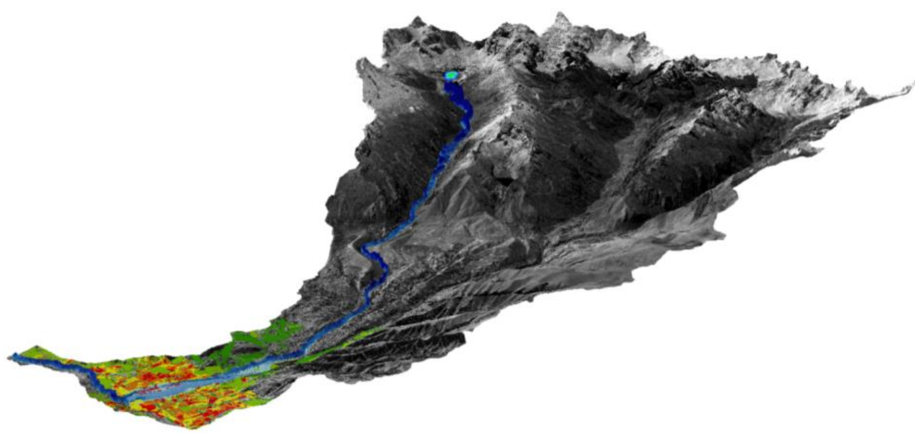

Figure 2: Huaraz City in Peru at the bottom of the Cojup River. Palcacocha Lake, a potential source of a GLOF, is located at the head of the river.

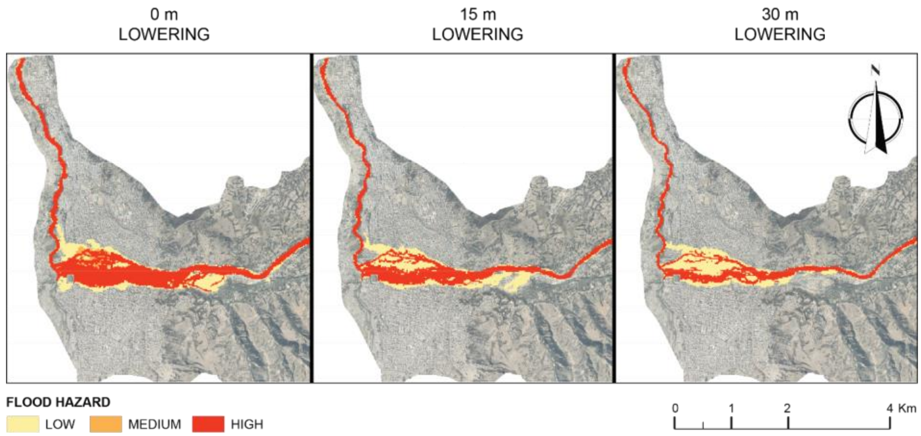

Figure 3: This image corresponds to Figure 9 from (Somos-Valenzuela et al., 2016). Preliminary hazard map of Huaraz due to a potential GLOF originating from Lake Palcacocha with the lake at its current level (0 m lowering) and for the two mitigation scenarios (15 m lowering, and 30 m lowering).

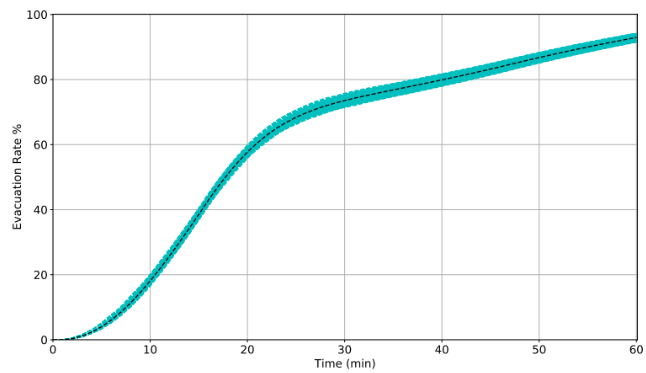

Figure 4: Evacuation rate during the first hour calculated using 1000 samples in a Monte Carlo Simulation

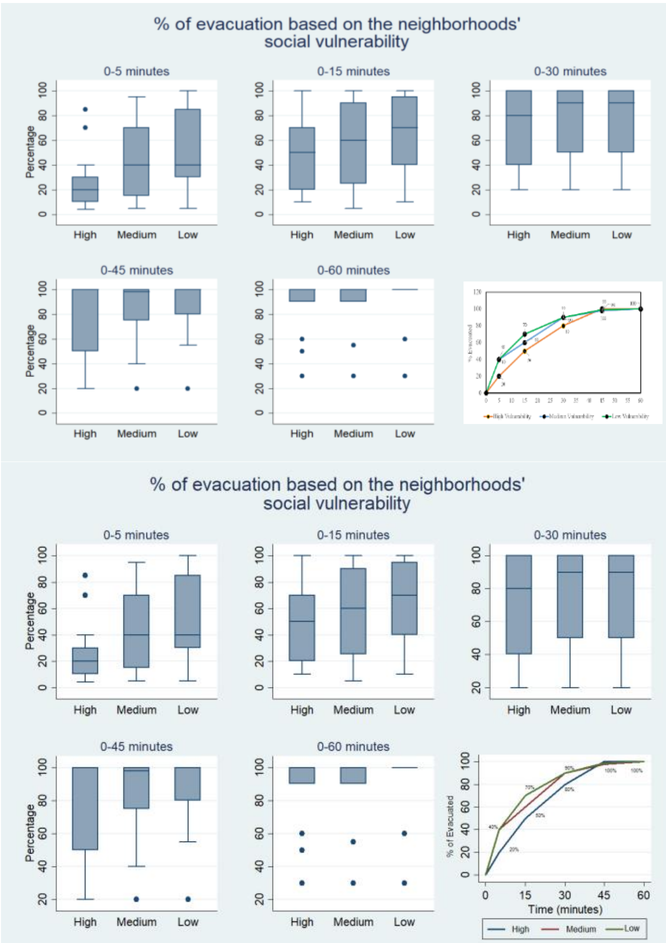

Figure 5: First responder's results by social vulnerability group.

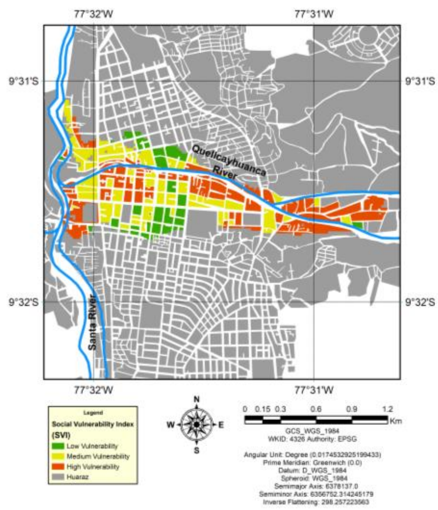

Figure 6: Comparative Vulnerability of Blocks in Huaraz using Social Vulnerability Index (SVI)

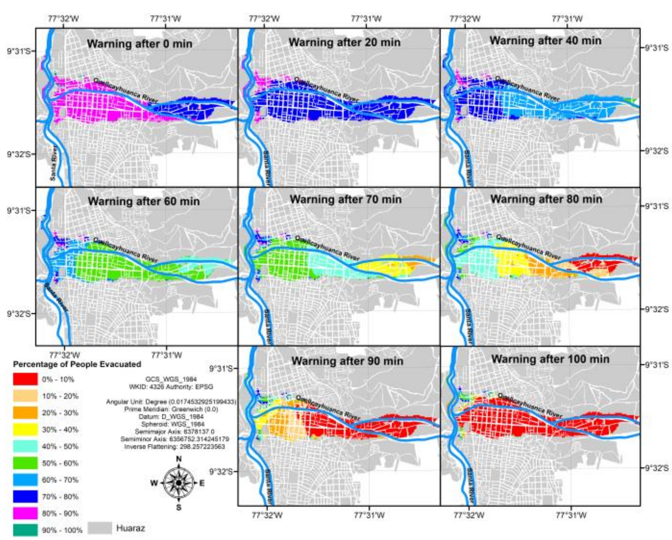

Figure 7: Evacuation using empirical equations.

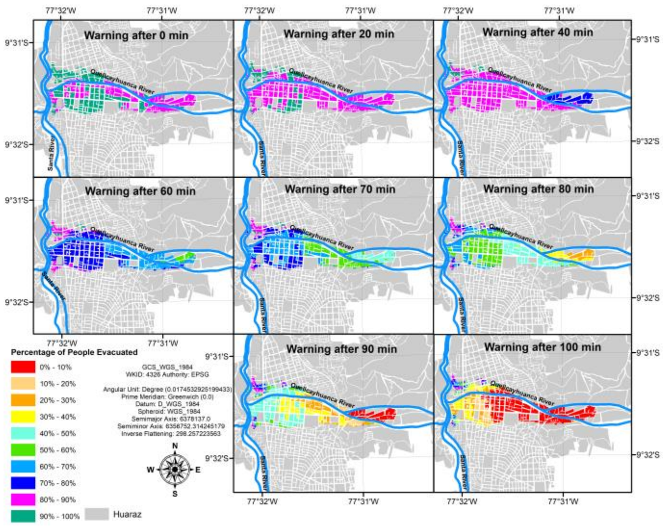

Figure 8: Evacuation using Social Vulnerability Index.

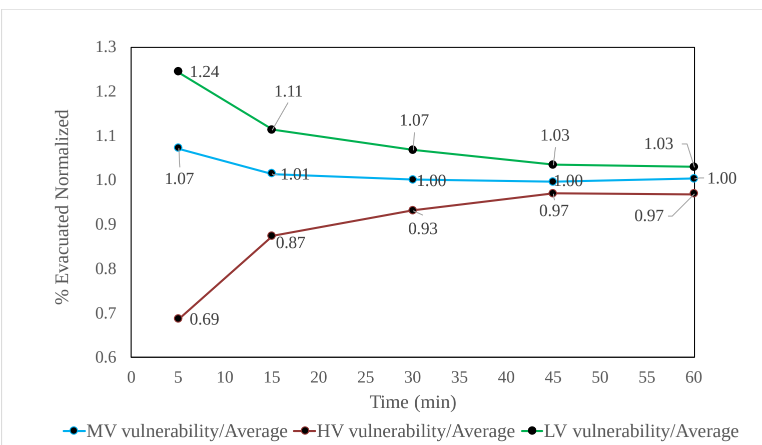

Figure 9: People evacuated per social vulnerability level normalized by the average number of people evacuated.