

Interactive comment on “Measuring county resilience after the 2008 Wenchuan earthquake” by X. Li et al.

X. Li et al.

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The authors gratefully acknowledge the Reviewer for the valuable comments. We agree with the comments, which are highly addressable and will help improve the manuscript. We would like to modify our manuscript on the basis of the comments, and all the comments will be carefully included in the revised version of the manuscript. We provide the response to the Reviewer's comments one by one as follows:

Anonymous Referee #2: This paper examines earthquake resilience of counties significantly impacted by the 2008 Wenchuan Earthquake. Through application of the RIM model, this paper aims to measure and validate disaster resilience within this study region. The paper addresses an important topic in the hazards and disasters field and

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may be of interest to scholars studying in this area. However, the claims that the authors have developed a valid and theoretically sound metric of disaster resilience and have subsequently validated this model may be somewhat overstated. Below are my specific comments that I hope will aid in improving this manuscript.

Introduction: Page 82 Lines 25 through Page 83 Line 2: Citation Needed.

Our response: Thanks for the comment. The citation will be added in the revised version of the paper at the end of the discussion period.

Page 83 Line 10-11. You note that “. . . few convincing approaches measured resilience quantitatively and with validation.” Please provide some description either here or in the literature review of some of these studies that have been successful in doing this.

Our response: We will add some description in the revised version of the paper at the end of the open discussion period.

Pages 84 and 85. It is unclear why you are emphasizing indicators of vulnerability as opposed to those utilized in the examination of disaster resilience. Why discuss SOVI when Cutter et al. propose the DROP Model for measuring disaster resilience?

Our response: We will modify the manuscript by adding the discussion of the DROP model here. We would like to point out that the RIM model does consider both vulnerability and adaptability, and some of the socioeconomic indicators could be used for both.

Page 88 Lines 22-24 – need to cite your sources. Page 89 Lines 11-14: Citation needed. Page 91 – Footnote: Should read: 1”Without special note, Lixian County is the one which is located in Sichuan Province.” Section 2 Lines 17-20. You need a citation at the end of this sentence.

Our response: Thanks for the detailed suggestion. We will add the sources, citations, and modify the footnote in the revised version of the paper at the end of the open discussion period.

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Related Work: There needs to be a more thorough discussion of the research that has been done examining disaster resilience. While the limitations of the previous studies are emphasized in this section, more attention should be placed on the work that has been done and how it guides your study. In particular, since your study focuses on using socio-demographic variables to measure disaster resilience, work done in this area should be adequately discussed.

Our response: Thanks for the valuable suggestion on this section. We were concerned with the length of the manuscript and hence limited our discussion on related work to three pages. We will incorporate more discussion on measurement of disaster resilience by socio-demographic variables in the revised manuscript.

Somewhere in the paper (either in the Related Work or Methods section) there needs to be a general discussion of model validation. For example: What does validation mean in the context of your paper and in the context of examining disaster resilience? Are you doing internal or external validation? What are the pros and cons to these approaches?

Our response: In the RIM model, the a priori groups are derived by K-means using actual exposure and damage data. Then discriminant analysis (DA) is employed to valid the a priori grouping result by the 15 socioeconomic variables. The validation here means that the accuracy of the resilience groups derived by the DA using the variables is compared with the groups derived from the cluster analysis. High classification accuracy means that the groups derived by the K-means are valid and the socioeconomic indicators can be used to characterize these resilient groups. So in this sense it is an "internal" validation to see whether the socioeconomic indicators are related to the actual damages and exposure. It is not an external validation with stakeholders or planners. The pros of this approach are that we use the actual damage data to derive the socioeconomic metrics. In addition, since DA is an inferential technique, unlike the factor model, the resultant classification functions can be used to predict resiliency in other regions, provided that the assumptions are met. This approach is similar to

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some studies in the literature that use actual damage as the dependent variable and a number of other variables in a regression form (Lam et al., 2014; Peduzzi et al., 2009). That is what we meant validation; the metrics were validated with actual damages in a statistical form. The cons of this approach, as in any statistical/ quantitative analysis (including factor analysis, regression), are that all the variables used in the RIM framework are subject to different interpretations and definitions, time periods, and the type of damages or recovery variables used. (A side note is that the DA procedure does have a case validation procedure, i.e., running the DA by removing one case.) However, by applying the model in different contexts (type of hazards), scales (spatial and temporal), and regions (different countries), we should be able to derive some generalizable indicators that may help in increasing resilience ultimately. The findings from this paper should provide useful benchmark information on earthquake resilience in China. References: Lam, N.S.N., Arenas, H., Brito, P.L., Liu, K.B., 2014. Assessment of vulnerability and adaptive capacity to coastal hazards in the Caribbean region. *Journal of Coastal Research*, Special Issue No. 70, pp. 473-478. Peduzzi, P., Dao, H., Herold, C., and Mouton, F., 2009. Assessing global exposure and vulnerability towards natural hazards: the Disaster Risk Index. *Natural Hazards and Earth Systems Science*, 9, 1149-1159.

You need to provide some background acknowledging other studies that have been conducted on issues pertaining to the validation of vulnerability and resilience models. I recommend looking at these papers as a starting point: Tate, E. (2012). Social vulnerability indices: a comparative assessment using uncertainty and sensitivity analysis. *Natural Hazards*, 63(2), 325-347. Fekete, A. (2009). Validation of a social vulnerability index in context to river-floods in Germany. *Natural Hazards and Earth System Sciences*, 9, 393-403.

Our response: Thanks for the great suggestion. We will be glad to provide discussion of further related work, including these papers as the starting point.

Methods: It is unclear why the variables noted in Table 2 were selected for inclusion

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in your resilience model. What guided the selection of these variables? You need to provide justification as to why these variables are appropriate for examining and measuring disaster resilience in China. This information should be included in the literature review section. You do note that some of these variables are mentioned in Cutter et al.'s 2010 paper, however are indicators used in the US appropriate for studies of a different country? Or are specific modifications need to be made in order to best reflect the Chinese culture?

Our response: We realize that applying the U.S. case to China would be challenging. The variables were chosen based on their similar meanings with the U.S. variables and the data availability. We also had to choose the statistical data at the county scale from the most credible source. In addition, the variables that may deem to be useful to the developing countries, such as sex ratio, were included if they were available.

How do the identified sociodemographic variables influence (e.g. increase or decrease) resilience? For example, do you hypothesize that a higher percentage of population in urban areas increases or decreases disaster resilience? Please note how you expect these variables to influence resilience in your model.

Our response: The potency index of each variable can be used to evaluate the influence extent on resilience. And from the two plots of discriminant scores and variable loadings (figures 11 and 12), as well as Table 5 (mean value of each variable in each group), we can identify the variables' influence on resilience. For example, Table 5 shows that Population Density is lowest in the Susceptible group (meaning rural areas). We will add the details in the revised paper.

The disaster resilience model for this study only examines one dimension of disaster resilience: the socioeconomic dimension. It may be helpful to examine other dimensions identified in the literature (see DROP model) in order to get a more holistic representation of disaster resilience in your study area.

Our response: We totally agree this comment. Limited by the data resource and avail-

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ability, we had to use the census and other statistical data to describe the social, economic, health and social welfare characteristics. It took a long time to find out the data for this study. When we can find the other type of data from credible sources, we will examine the more holistic representation of disaster resilience in future study. For this study, we trust that it has provided useful insights and should contribute to the literature on socioeconomic resilience.

The RIM Model: As noted in the manuscript, the RIM model accounts for exposure, damage, and recovery. The technical aspects of how the analysis was conducted were adequately described, however, further discussion needs to be provided as to how and why the indicators representing exposure, damage, and recovery were selected. It seems problematic that the damage dimension is only reflected by economic losses, when there are many different kinds of losses (social, long-term economic, short-term economic, structural, environmental, etc.) that result from disaster. Similarly, the use of population growth as the sole indicator of recovery is also problematic, and many different indicators of recovery have been identified in the disaster literature. I am curious as to how sensitive the model validation process is to the selection of these variables. If you switched out an indicator or added more, how much would your model change? For example, if you substituted GDP growth for population, would you get similar results?

Our response: From the government reports and statistic data, the damage data is limited at the county scale. The direct economic loss is the only loss data we could collect and are available for most of the counties in the study area. Moreover, economic loss is used as a variable of damage in many databases including the United Nation's EMDAT (Emergency Disasters Data Base) and NOAA, and is often the key variable used in some disaster studies. We used population return/growth as a recovery variable because it reflects the longer-term cumulative effects of recovery, and it is more stable and is probably the more accurate and most-available data in this region as well as in other developing countries. These common variables should help in future gen-

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eralization of our findings. As mentioned above, the results may change with different definitions of variables as in most studies. For this study, we did experiment the use of the GDP growth ratio to represent the recovery, and the results are quite similar to those obtained from using the population growth ratio.

Are there any limitations of using population data from 2002 and 2011? Why not use 2007 or 2008 data for pre-event population? Why did you select 2011 to reflect post event population? Was there a significant change in population between 2002 and the earthquake? To what extent did fatalities influence population, especially in the areas highlighted as having a largest population decreases? Also, if 2002 population data was selected because data was not available for years closer to 2008, how do you think this impacts your model?

Our response: We chose the 2002 population to represent the pre-event status, and the 2011 to reflect the post event status, because the years are close to the years of national population census, which is conducted every 10 years. By aligning with the national census, we can use the other socioeconomic variables from the census in the same time period, which is critical to this study. There were not any major changes in government policies during that time that could cause changes in the population growth rate. It is assumed that the population growth rate would otherwise remain stable if there was no earthquake damage in 2008.

Do you happen to know what percentage of the population left the counties near the epicenter and migrated to neighboring counties following the event? Since recovery was measured by population change, I wonder if this partially explains why your model indicated that resilience in the epicenter counties was low, resilience increased in the neighboring counties, and then decrease as distance from the epicenter increased.

Our response: People moving to nearby counties might partly affect the result. However, the data for tracking population migration is not available especially for a large study region like this study. This data problem is similar to the event of Hurricane Ka-

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trina where migration data is difficult to obtain and verify at a larger spatial scale. We will add this possibility in the revised manuscript.

Figure 3: It is difficult to find the epicenter on this map. Please make the symbol larger and / or a different color. Overall, the maps are well done and informative.

Our response: We will be glad to improve the map in the revision.

Discussion Discussion / Conclusion – There is no discussion of limitations in this model and only one recommendation for future research is provided. Please expand on these. Page 98 Lines 20 and 21. You note that “Counties that were farther away from the epicenter returned to the normal level of resilience.” What is implied by “normal resilience”? Did you intend to say that counties further away from the epicenter recovered more quickly? Resilience and recovery are not synonymous.

Our response: The “normal resilience” here refers to the Recovering Group, which has average vulnerability and adaptability. We will change the wording to the Recovering Group to avoid any confusion. Thanks for pointing this out!

One of your findings is that the counties near and adjacent to the epicenter had the lowest resilience values (sections 4.2 and 5.1). Was this a result of pre-event conditions (such as sociodemographic characteristics) that made the counties less resilient? Or is the model showing that these counties were less resilient as a result of their proximity to the epicenter?

Our response: We think the Reviewer meant “highest” in the sentence “One of your findings is that the counties near and adjacent to the epicenter had the lowest resilience values”. The Reviewer is correct: the counties surrounding the epicenter-counties (not at the epicenter) had the highest resilience values was largely a result of pre-event conditions, and the degree of usefulness of the pre-event conditions to inform resiliency is dependent on the discriminant analysis’s classification accuracy.

Interactive comment on Nat. Hazards Earth Syst. Sci. Discuss., 3, 81, 2015.

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