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DEVELOPING A MULTI-HAZARD WEIGHTING SCHEME FOR COMMUNITY RESILIENCE INDICATORS

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Abstract

Community resilience is the ability of a community to resist and recover from adversity, such as natural disasters, terror attack, and influenza pandemic. Quantifying community resilience can help communities better understand their strengths and vulnerabilities, prepare for different types of hazards, estimate losses in case of adverse situations, and take effective measures to reduce losses. However, such a task is extremely challenging, because community resilience is essentially a comprehensive and complex concept with entrenched difficulties in defining appropriate criteria for its quantification. The commonly-used approach usually considers multiple domains of a community and selects some indicators to capture features of each domain. Then, indicators are equally weighted across the domain and aggregated together to come up with an index to quantify community resilience. This study chooses a set of commonly used indicators in the engineered system domain and aims to develop a multi-hazard weighting scheme for these indicators. A multi-hazard weighting scheme is meaningful because the importance of each indicator, as a contributing factor to worsen or lessen damages, could vary significantly across different hazards. In this study, we mainly focus on earthquakes and hurricanes, which are the two typical representatives of natural hazards. We choose different response variables from recent earthquakes and hurricanes. The historical data of engineered system indicators and hazard response variables can be collected from publicly available databases. Based on these data, we apply linear regression method to form statistical models and use these models to determine the variable importance for each indicator for different hazards. By comparing the weighting schemes for earthquakes and hurricanes, we discuss the possible reasons accounting for the differences and summarize the pros and cons of our multi-hazard weighting scheme. Moreover, the direction of indicators obtained by the regression models coincides with the direction obtained from expert judgment, which validates our methodology and choice for response variables. This multi-hazard weighting scheme contributes to quantifying community resilience and assessing urban risks under attacks of earthquakes and hurricanes.

Keywords: multi-hazard; community resilience; damage estimation

1. Introduction

Community resilience refers to the ability of a community to resist and recover from adversity, such as natural disasters, terror attack, and influenza pandemic. Quantifying community resilience can help communities better access their strengths and weaknesses, prepare for different types of hazards, estimate losses in case of adverse situations, and take effective measures to reduce losses. However, such a task is extremely challenging, because community resilience is essentially a comprehensive and complex concept with entrenched difficulties in defining appropriate criteria for its quantification. The commonly-used approach usually considers multiple domains of a community, such as ecological, social, economic, institutional, infrastructure, community competence [1], and selects some indicators to capture features of each domain. Then, indicators are equally weighted across the domain and aggregated together to come up with an index to quantify community resilience. However, when it comes to natural hazards, we may notice that some indicators are probably more important than others, so if we put equal weights to all the indicators, the corresponding index cannot correctly and accurately represent the resilience of the community. In addition, we may also find that the weighting scheme should vary by disaster type. To address this weighting issue, this paper chooses a set of commonly used indicators in the engineered system domain and develops a multi-hazard weighting scheme for these indicators.

Existing disaster resilience approaches are an important foundation to our work. To be specific, Norris et al. [2] proposed a conceptual model of community resilience for disaster readiness, which emerges from four primary sets of adaptive capacities, namely, economic development, social capital, information and communication, and community competence. Then, Cutter et al. [1] put forward the disaster resilience of place (DROP) model to quantify community resilience exposed to natural hazards; the methodology of DROP model included 3 major steps, namely, variable selection, weighting, and aggregation. However, when it comes to weighting, they found no theoretical or practical justification for allocating different weights across indicators, so they used an equally weighted index [3]. In 2011, RAND [4] identified eight "levers" to define community resilience, including wellness, access, education, engagement, self-sufficiency, partnership, quality, and efficiency. Around the same time, Foster [5] developed a resilience capacity index (RCI) based on U.S. metropolitan regions, which is a composite statistic summarizing a region's score on 12 equally weighted indicators, where four indicators are in each of three domains, i.e., regional economic capacity, socio-demographic capacity, and community connectivity capacity. In 2016, an index, called Composite of Post-Event Well-being (CoPE-WELL), has been developed [6] to help practitioners and policymakers to frame high-level policy discussions about community resilience towards hazards. CoPE-WELL is a county-based national model which considers many indicators from various domains to represent the pre-event functioning, short-term post event functioning, and long-term post event functioning of the community after a disaster.

However, all these indices use an equal weighting scheme when aggregating indicators of community resilience. Admittedly, there are some good reasons behind that. To be specific, unit weights can avoid sampling error and are robust to outliers [7], which makes it a valid approach to aggregating data. However, we need to point out that unit weights may bring bias to the prediction model, especially when some indicators are much more important than the others. Therefore, in this study, we put forward a concept of multi-hazard weighting scheme for community resilience indicators. Furthermore, our study is based on publicly available data and statistical learning methods, validating expert judgment and drawing inference from the model.

Considering the critical role that infrastructure plays both before and after the event, we should attach more importance to the engineered system, considered in CoPE-WELL [6], when compositing a community resilience index. The goal of the paper is to present a novel approach to quantifying the importance of indicators in the engineered system domain of community resilience. To be specific, in section 2, we describe the methodology, and also propose an algorithm including 8 steps to guide us to determine the relative weights and direction of the indicators. In section 3 and 4, we choose hurricane and earthquake as case studies to show the strength of this methodology. In section 5, we compare the results obtained by the hurricane model and earthquake model, and draw inference from the different weighting schemes suggested by these two models. We conclude the paper and suggest the future work in section 6.

2. Methodology

In this section, we present the methodology of our multi-hazard weighting scheme, including identifying indicators and acquiring data, identifying response variable and acquiring data, deleting observations with missing data, deleting some variables when lacking observations (optional step), normalizing indicators, removing collinearity, determining final model, obtaining final results (importance and weights). The illustration of the methodology of determining the multi-hazard weighting scheme is shown in Fig.1.

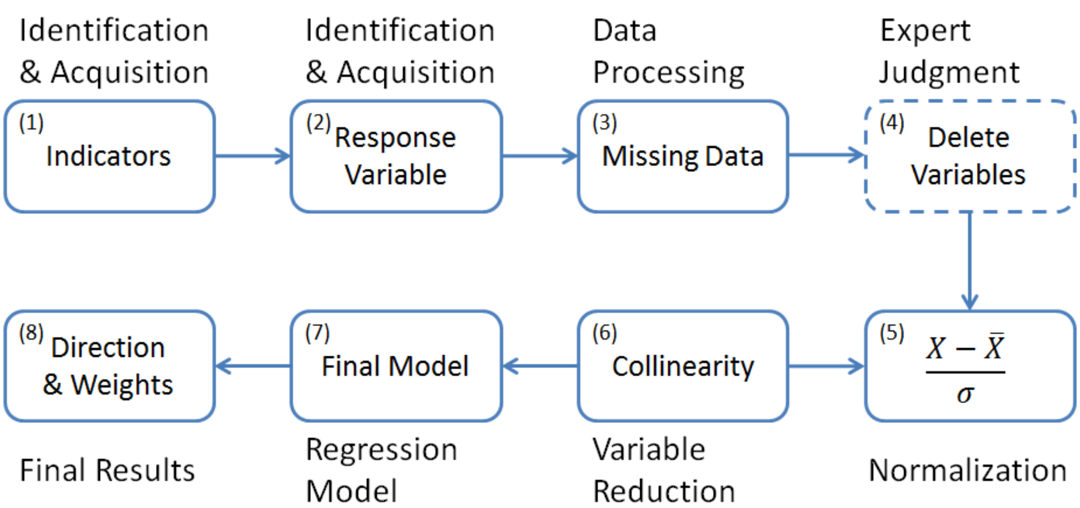

Fig. 1 – Illustration of the methodology of determining the multi-hazard weighting scheme

In this paper, we will follow the regime shown in Fig.1 to determine the relative weights of indicators in the engineered system. So, first, we need to identify the indicators in the engineered system and acquire the data of these indicators. Specifically, the engineered system, also referred to the infrastructure system, contains multiple subsystems including building, communication/cyber, transportation, water, wastewater, power, and natural gas. In this paper, we only choose indicators with publicly available data, so every stakeholder, emergency manager, urban planner, and researcher can easily gain access to the data and reproduce the work. Since we could not find publicly available data for appropriate indicators to represent wastewater, power, and natural gas, we finalize seven indicators in the aspects of building, communication/cyber, transportation and water to indicate the resilience of the engineered system. Notably, we need to choose a regional scale for the data, such as county-level, metropolitan-level, and state-level. The data collected in this study are all county-based. The indicators' category, description, direction, and source in the engineered system domain are listed in Table 1. Note that the direction of indicators means their effect on the resilience of engineered system and is determined by expert judgment.

Then, we need to identify a reasonable response variable that can quantify resilience after the event for different types of hazards and collect data for it. Hazards can be divided into two major types, natural hazards and man-made hazards. Natural hazards include earthquake, hurricane, tsunami, flood, etc., and man-made hazards mainly refer to cyber attack, terror attack, nuclear blast, civil unrest, etc. Since our method is a multi-hazard weighting scheme, the response variable is hazard-specific.

After obtaining all the data of indicators and response variable, we remove observations with missing data. The reason why we do not use missing data imputation here is because it is hard to determine whether the data are (completely) missing at random. Therefore, removing observations with missing data is the simplest and most straightforward way to deal with missing data problem. Afterwards, it's an optional step – remove "not-so-important" variables mainly based on the expert judgment, if we have too few observations compared to the number of indicators. This step is not ideal, but we have to admit the fact that hazard data are so limited for certain hazards in U.S. To be specific, if the number of observations is less than $n+2$, where n represents the number of variables in the engineered system domain, we might need to remove some "irrelevant", or least important, variables before conducting linear regression. Next, we need to normalize all the variables. Normalization can adjust variables measured on different scales to a notionally common scale, so after normalization, the importance of variables obtained by the regression model can be compared directly. After this step, we need to remove highly correlated variables, in that collinearity among indicators will increase the sampling variation of regression weights [7], making the model less powerful and convincing. Therefore, the first six steps provide us a dataset with parsimonious indicators and an appropriate response variable. A similar multivariate analysis of determining a parsimonious indicator set was also conducted by [8].

Lastly, we fit a linear regression model to the remaining variables and obtain the direction and weights of each indicator accordingly. Apparently, we need to compare the direction obtained by the regression model with the direction according to the expert judgment shown in Table 1, which is a well-defined validation approach of our methodology. More generally, the direction of indicators is not always clear, so this framework can actually help us to determine the direction of some "not-so-sure" indicators.

Table 1 – Indicator description and data source of engineered system

#	Category	Description	Direction	Data Source
1	Building	Average age of housing stock	NEG	American Housing Survey by the U.S. Census Bureau
2	Building	Percentage of housing units that are not mobile homes	POS	American Housing Survey by the U.S. Census Bureau
3	Communication/ cyber	Median residential down-load speed	POS	National Broadband Map created and maintained by the National Telecommunications and Information Administration and in collaboration with the Federal Communications Commission
4	Communication/ cyber	Median mobile download speed	POS	National Broadband Map created and maintained by the National Telecommunications and Information Administration and in collaboration with the Federal Communications Commission
5	Transportation	Road miles per square mile	NEG	Topologically Integrated Geographic Encoding and Referencing by the U.S. Census Bureau
6	Transportation	Number of bridges per 100 square miles that are structurally deficient or functionally obsolete	NEG	National Bridge Inventory by the U.S. Department of Transportation Federal Highway Administration
7	Water	Percentage of population affected by water vio-lation of those served by public water systems	NEG	Safe Drinking Water Information System by the U.S. Environmental Protection Agency

As a result, the steps of the algorithm are summarized below:

Step 1: Identify the indicators in the engineered system domain and acquire the data for each of the indicators;

Step 2: Identify response variable of the specific natural disaster which can quantify resilience after the event and acquire the corresponding data for the response variable;

Step 3: Remove observations with missing data;

Step 4 (Optional): Remove certain "not-so-important" variables using expert judgment, if the number of observations is less than $n+2$, where n represent the number of variables in the engineered system domain;

Step 5: Normalize all the variables and fit a linear regression model with all the variables;

Step 6: Compute the variance inflation factor (VIF) to remove collinear variables and repeat this step until all the variables' VIF are less than 10;

Step 7: Fit a linear regression model with the remaining variables;

Step 8: Obtain the relative weights and direction of each indicator.

Note that for step 4, we need to guarantee the number of observations is no less than $n+2$, because we want to make sure the *t*-test for an estimator has at least one degree-of-freedom. Besides, VIF is a commonly-used method to determine the multi-collinearity in a linear regression model. VIF provides a statistic that measures how much the variance of the parameter estimates is increased due to collinearity. A common choice of VIF threshold is 10; a VIF of 10 represents that with other things being equal, the variance of the *i*th regression coefficient is 10 times greater than it would have been if the *i*th variable had been linearly independent of other variables [9]. In this study, we maintain every indicator in the regression model with VIF less than 10.

Overall, we develop a novel concept of multi-hazard weighting scheme, even though people admitted that different hazards would make certain indicators more important than others. Besides, one of the strengths of our methodology is transparency. By following the 8 steps described above, people can determine a multi-hazard weighting scheme for different community resilience indicators from different domains. Although we only focus on indicators in the engineered system domain in this paper, the algorithm can be easily extended to other domains of the community. Moreover, although we only include two hazards in this paper, namely, hurricane and earthquake, researchers can easily apply this methodology to other hazards, such as drought, flood, terrorist attack, etc., based on the methodology proposed in the paper.

3. Weighting Scheme for Hurricanes

In this section, we introduce the weighting scheme for hurricanes. First, the step 1 is completed as mentioned in section 2. Seven indicators are considered to quantify the resilience of the engineered system. Second, we choose the Hurricane Sandy, which happened on October 29, 2012, as the natural disaster, because Sandy is a recent hurricane disaster with significant damage to the local community, including lots of counties in the east coast. Then, according to the damage map of Hurricane Sandy, shown in Fig. 1, we choose the counties with purple color as the target counties, because in the damage map, the counties in the same color experience same level of damage. Note that purple-colored counties have the most severe damage during the Hurricane Sandy, so they are the most representative counties to show the community resilience.

In addition, considering economic impact can well represent the performance of a county's resilience, July 2013 unemployment rate is chosen here as the response variable which can measure the long-term impact of disruption of economic activity caused by the storm especially in the Travel and Tourism industry [10]. July 2013 unemployment rate in counties impacted by Sandy is shown in Fig. 3. The data were collected by the Bureau of Labor Statistics (BLS). Note that the unemployment data is preliminary and not seasonally adjusted.

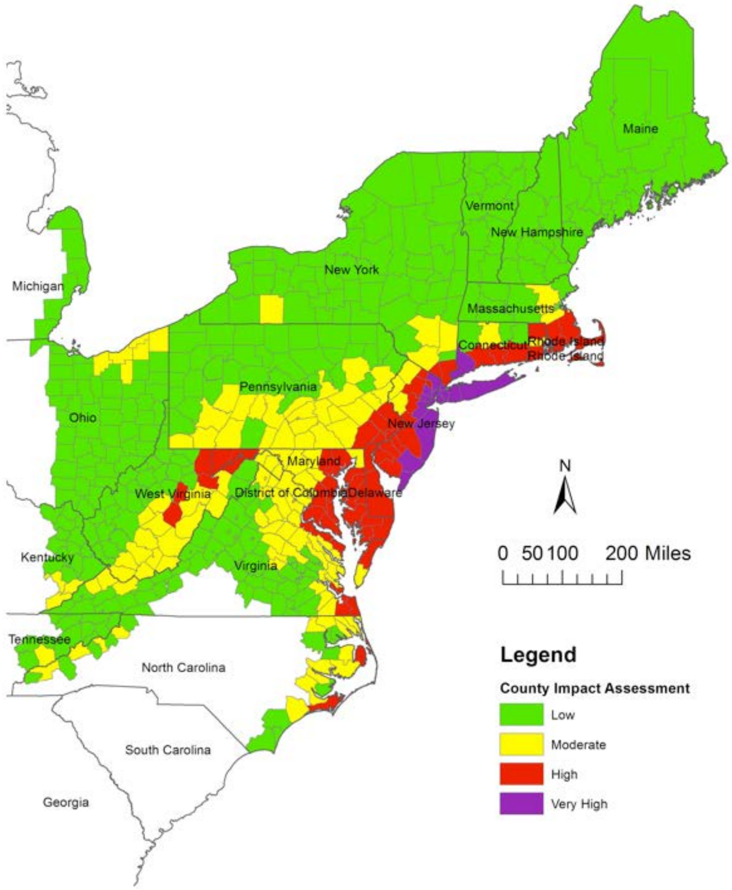

Fig. 2 – October 2012 damage map of Hurricane Sandy: areas with very high damage in purple, high damage in red, moderate damage in yellow, and low damage in green, adapted from [11]

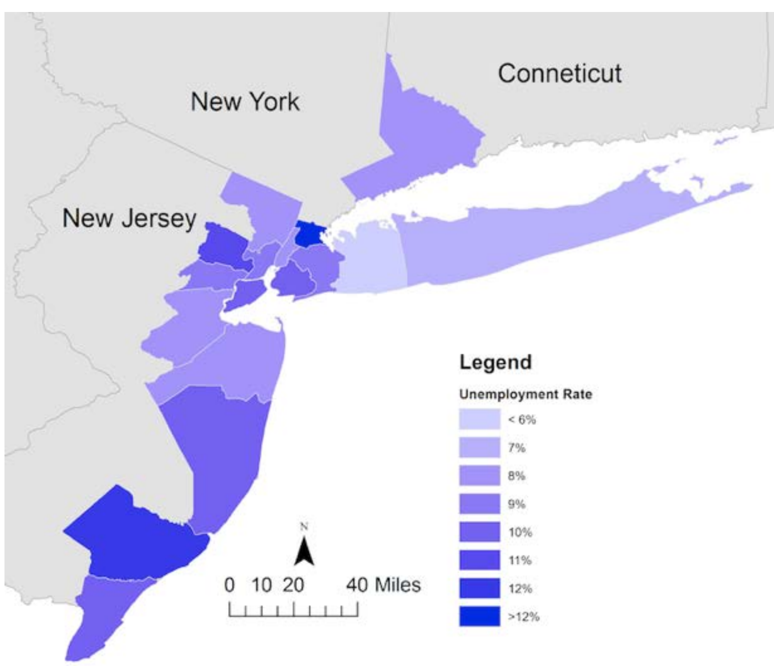

Fig. 3 – July 2013 unemployment rate in New Jersey, New York, and Connecticut counties that experienced high damage impacted by Hurricane Sandy

Third, we delete observations with missing data. We skip the fourth step, because we have adequate observations to compute the linear regression model. Fifth, all the indicators and response variable are normalized. Sixth, we fit a linear regression model with all variables included and compute the VIF, and we find that the first indicator has the highest VIF, around 10. So we remove the first indicator, and then fit another linear regression model with remaining variables and compute VIF. Now all the indicators have VIF less than or equal to 5, so we may draw the conclusion that collinearity problem has been solved in a large measure.

Table 2 – Relative weights and direction of indicators computed by regression model

#	**Description**	**Relative weights**	**Regression Model**		**Expert Judgment**
			Effect on unemployment rate	**Effect on resilience**	**Effect on resilience**
2	% of not moible homes	7.39	NEG	POS	POS
3	Median residential download spped	1.05	NEG	POS	POS
4	Median mobile download speed	1.72	NEG	POS	POS
5	Road miles per square mile	3.21	POS	NEG	NEG
6	# of deficient or obsolete bridges	2.03	POS	NEG	NEG
7	% of population affected by water violation	1.00	POS	NEG	NEG

Seventh, the model is thus finalized with 6 indicators. Eighth, the relative weights and direction of indicators are obtained, shown in Table 2. It is apparent that the indicators' effect on unemployment rate is opposite to their effect on resilience, so we find that the direction of indicators obtained by our model is same as the direction identified by the expert in terms of effect on resilience. Therefore, we may draw the conclusion that the results obtained by the regression model are consistent with the expert judgment, which essentially validates our model.

4. Weighting Scheme for Earthquakes

In this section, we introduce the weighting scheme for earthquakes. Similarly, we compute the relative weights and direction of the indicators in line with the algorithm proposed in section 2.

First, we consider seven indicators as mentioned in the section 2 to represent the resilience of the engineered system. Second, we choose the Virginia Earthquake, which happened in the Piedmont region of the state of Virginia on August 23, 2011, and South Napa Earthquake, which occurred in the North San Francisco Bay Area on August 24, 2014, as the natural disasters, because these two earthquakes are quite recent and have medium level damage to the community. Then, according to the damage zone intensity map for the Virginia Earthquake, shown in Fig. 4(a), we choose the Spotsylvania county, Fluvanna county, and Goochland county, because these counties seem to experience same level of damage. Similarly, we choose the Sonoma county, Solano county, Marin county, and Contra Costa county as target counties for South Napa Earthquake, based on the USGS shake map shown in Fig. 4(b). Note that we choose USGS shake map for South Napa Earthquake to help us determine the damage level of these California counties, because the authors fail to find damage map for South Napa Earthquake. Because these two earthquakes' magnitudes are less than $6M_w$, local businesses mainly underwent short-term economic disruption and the long-term economic impact was not obvious. Thus, instead of choosing unemployment rate in the next touriest season as we did for Hurricane Sandy, we choose the unemployment rate decline from August 2011 to September 2011 for Virginia Earthquake, and the unemployment rate decline from August 2014 to September 2014 for South Napa Earthquake. Because we should expect the unemployment rate to increase right after the earthquake occurs and it will drop back to pre-earthquake levels in a few weeks for moderate events like these two mentioned above, here we quantify resilience as the unemployment rate decline in one month after the event, shown in Eq. (1):

$$\text{resilience: } \Delta\% \text{ unemployment rate} = \% \text{ unemployment rate}_{t_0} - \% \text{ unemployment rate}_{t_1} \tag{1}$$

where t_0 represent the month that earthquake occurs and t_1 represent the follwing month after t_0. More resilient counties should have less increase in the unemployment rate. The data were collected by BLS. Note that the unemployment data is preliminary and not seasonally adjusted.

A **B**

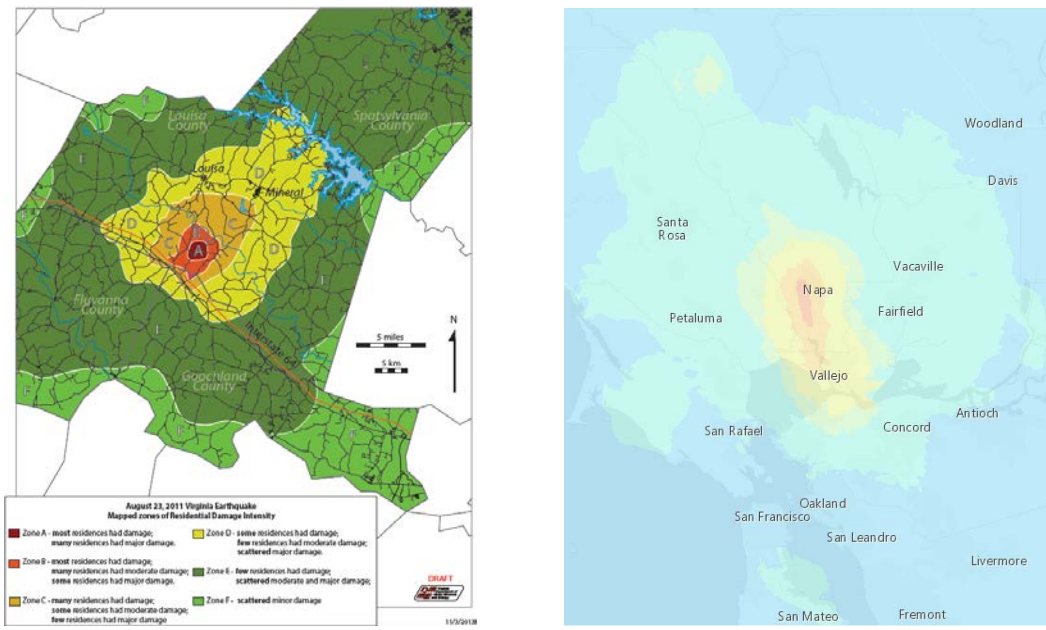

Fig. 4 – Damage Maps of Earthquakes: (a) damage zone intensity map for the Virginia Earthquake [12]; (b) USGS shake map for the South Napa Earthquake [13]

A **B**

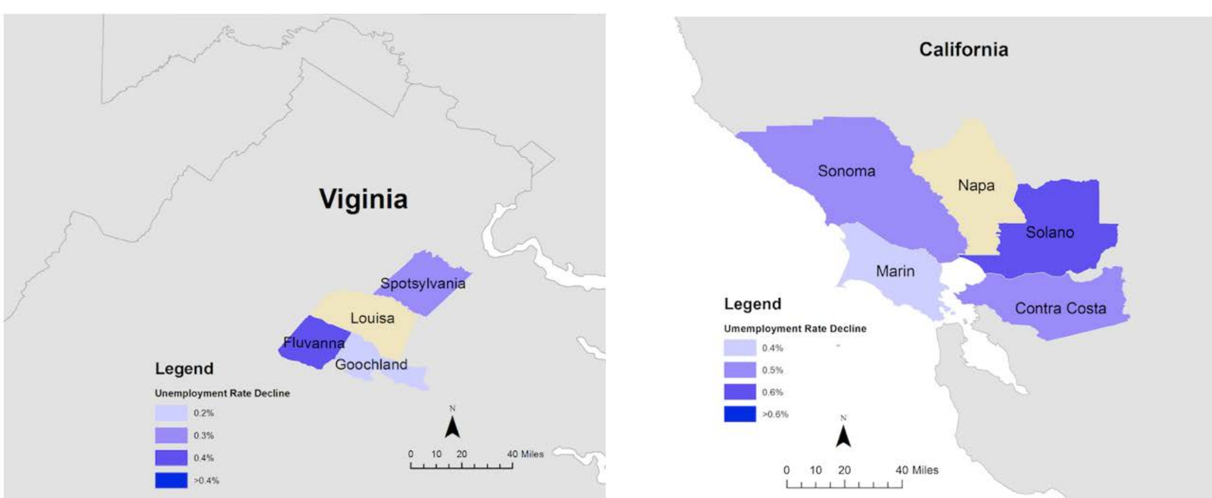

Fig. 5 – Unemployment rate decline: (a) unemployment rate decline from Aug. 2011 to Sept. 2011 in Virginia counties; (b) unemployment rate decline from Aug. 2014 to Sept. 2014 in California counties

Third, there is no missing data, so we pass this step. Fourth, since the dataset is very small – we only have 7 observations versus 7 variables, we could not conduct the linear regression with all the variables directly. Hence, we need to choose a subset of all the variables, which include the five most relevant variables towards earthquakes. Considering expert judgment, we choose not to include No.1 and No.7. Because in the hurricane model, we find that No.1 is correlated with other indicators. The correlation between indicators will not change, as the natural disaster changes, since the correlation are computed between indicators, having nothing to do with the response variable . Besides, in many cases, the housing age has no direct relation to the state of the building after earthquakes, since a lot of historic buildings were renovated and reinforced, making them probably perform better in the earthquakes than "younger" buildings do. Hence, No.1 is advised to be deleted. In addition, for No.7, according to the hurricane model derived in section 3, we find the water system plays the least important role in the model. Considering this indicator may have similar impact to the earthquake model as it did to the hurricane model, we decide to delete No.7 for now. Therefore, this model includes following five indicators: No.2, No.3, No.4, No.5, and No.6.

Fifth, we normalize all the indicators and response variable. Sixth, we compute the VIF and find these five indicators all with VIF less than 5. Therefore, colliearity is not a problem for this earthquake model. Seventh, we finalize all the indicators and then obtain the final linear regression model. Eighth, the relative weights and direction are illustrated in Table 3. It is obvious that the direction of indicators obtained by our model is same as the direction identified by the expert in terms of effect on resilience. As a consequence, the results obtained by the regression model are consistent with the expert judgment, so our earthquake model is validated.

Table 3 – Relative weights and direction of indicators computed by regression model

#	**Description**	**Relative weights**	**Regression Model**		**Expert Judgment**
			Effect on unemployment rate	**Effect on resilience**	**Effect on resilience**
2	% of not moible homes	3.21	NEG	POS	POS
3	Median residential download spped	3.13	NEG	POS	POS
4	Median mobile download speed	1.00	NEG	POS	POS
5	Road miles per square mile	1.41	POS	NEG	NEG
6	# of deficient or obsolete bridges	5.64	POS	NEG	NEG

5. Discussion

In this section, we discuss the similarities and differences between the hurricane model and earthquake model. Also, we discuss the reasons behind the results and draw inferences from them. The summary of weights determined by hurricane and earthquake models is shown in Table 4.

There is an interesting discovery is that the first indicator, average age of housing stock, seems to be an important indicator to quantify the community resilience, because it's considered in several famous community resilience index models, such as DROP [1]. But this indicator is removed for both models of earthquakes and hurricanes due to collinearity. In other words, we may reconsider whether we want to include this indicator into future community resilience index models.

In the hurricane model, we find that No.2, the percentage of housing units that are not mobile homes, is the most important indicator. This suggests that for communities in the hurricane zone, mobile homes are more vulnerable to hurricanes. Obviously, this result is very coherent with expert judgment, because the prevalence of structures that are not mobile homes directly link to the number and type of structures in damage [14]. Then, No.5, the road miles per square mile, and No.6, the number of bridges per 100 square miles that are structurally deficient or functionally obsolete, are the second and third important indictors in the hurricane model. This result is actually very reasonable, because transportation is essential for the community to withstand and recover from the natural hazards, like hurricanes.

In the earthquake model, No.6, number of bridges per 100 square miles that are structurally deficient or functionally obsolete, becomes the most important indicator. One interpretation is that bridge, often as critical transportation junction, plays an important role in after-earthquake rescue and recovery. Then, No.2, the percentage of housing units that are not mobile homes, is the second important indicator in the earthquake model. It suggests that mobile homes are also very vunerable when it comes to earthquakes.

We find that the most important indicator varies for hurricane model and earthquake model, in that these two natural hazards have different impact parttens to the community. However, we can find that building's type and transportation condition are two key aspects of the community, when it comes to hurricanes and earthquakes. In addition, it's not surprising that the median mobile download speed is "not-so-important" in both earthquakes and hurricanes. But it is expected be more important in the case of cyber attack.

Compared to unit weighting scheme, our method prevails in the way that more important variables are correctly recognized and more accurate quantification of the engineered system's resilience is obtained. Notably, the response varible choice needs to be careful and justifiable; in this study, the response varible's choices are proved to be appropriate in both hurricane and earthquake case, because the indicators' direction obtained by the regression models coincides with the direction obtained by the expert judgment.

Moreover, we have to admit that the hurricane model is more convincing, in the sense that we have more data/observations support this model. But we need to clarify that the earthquake data issue is intrinsic. As we all know, only two large earthquakes (i.e., 2011 Virginia Earthquake and 2014 South Napa Earthquake) occurred on the continental U.S. during the past decade. The magnitude of these two earthquakes is around $6M_w$, so only several counties are impacted with medium-level damage.

Table 4 –Summary of weights determined by hurricane and earthquake models

#	Description	Relative Weights		Direction
		Hurriance	**Earthquake**	
1	Average of housing stock	/	/	/
2	% of not moible homes	7.39	3.21	POS
3	Median residential download spped	1.05	3.13	POS
4	Median mobile download speed	1.72	1.00	POS
5	Road miles per square mile	3.21	1.41	NEG
6	# of deficient or obsolete bridges	2.03	5.64	NEG
7	% of population affected by water violation	1.00	/	NEG

6. Conclusion

Above all, this paper proposes a generic multi-hazard weighting scheme to determine the relative weights and direction of the indicators for different types of disasters. Specifically, we choose a set of commonly-used indicators in the engineered domain of community resilience, and use hurricane and earthquake as case studies to show the advantage of this method. The results obtained by the regression models also validate our guess that indicators have different importance when it comes to different hazards. Furthermore, the percentage of housing units that are not mobile homes is the most important indicator when we want to estimate the resilience towards hurricanes; the number of bridges per 100 square miles that are structurally deficient or functionally obsolete is most fundamental to the engineered system, when earthquakes occur. This multi-hazard weighting scheme is devoted to quantifying community resilience and assessing urban risks under attacks of earthquakes and hurricanes.

However, this method is not perfect. We need to admit the sample size is relatively small, especially for earthquakes, but, as we mentioned above, this issue is intrinsic. Besides, indicators for the engineered system may not be very comprehensive, since we only include several typical indicators with publicly available data. If the federal and local government can collect more data for the engineered system, we will be able to build up a more accurate model to quantify the resilience of the infrastructure system.

In the final analysis, we will try more indicators and possible reponse variables in the future, in order to come up with a more comprehensive weighting scheme for the engineered system domain. Moreover, this multi-hazard weighting scheme contributes to quantifying community resilience and assessing urban risks under attacks of earthquakes and hurricanes, and can be combined with expert judgment from a panel to form a more comprehensive Bayesian model. Furthermore, this methodology can be applied to other domains or sub-domains, such as the economy, education, government, and so on.

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