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The Resilience Inference Measurement (RIM) Approach to Measuring and Predicting Community Resilience to Coastal Hazards

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ABSTRACT

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Improving community resilience to coastal hazards has been a key societal issue and studied widely by multiple disciplines. However, despite the huge literature on community resilience to coastal hazards, there is no consensus on the best approach to measuring it. We first provide an overview of the challenges in measuring community resilience to natural hazards. We then describe our effort in developing the Resilience Inference Measurement (RIM) model, which is designed to overcome two major challenges in resilience measurement: (i) the lack of empirical validation to support the derived indices and their associated indicators influencing the resilience level, and (ii) the lack of statistical inferential power. We highlight how RIM can be applied to different types of hazards and its extension to dynamic resilience analysis via methods such as Bayesian Networks. We conclude that through more experiments with the RIM approach, it is possible to develop a set of common resilience predictors that would address multiple hazards simultaneously.

ADDITIONAL INDEX WORDS: *Resilience Inference Measurement (RIM), community resilience, dynamic resilience, coastal hazards, drought hazards.*

INTRODUCTION

Devastating coastal hazards, including hurricanes, storm surges, subsidence, erosion, and flooding, have affected the coastal communities enormously throughout the world. The effects of these natural coastal hazards are often worsened by human activities, such as dense population living in low-lying flood-prone areas, inadequate infrastructure planning, and unwise resource utilization and land-use decisions, making communities near the coasts even more vulnerable (Lam *et al*., 2015). At the same time, climate change impacts are showing obvious signs all over the world. For instance, Earth's average surface temperature in 2023 was the warmest on record since recordkeeping began in 1880. Earth was about 2.45 degrees Fahrenheit (or about 1.36 degrees Celsius) warmer in 2023 than in the late 19th-century (1850-1900) preindustrial average (NASA, 2024). Another NASA study estimated that sea-level rise for the contiguous U.S. coastlines will reach the 1-foot (30 cm) mark by 2050. The Gulf Coast and southeastern USA will see the most change, which is about 14 to 18 inches (35.6 to 45.7 cm) in sea-level rise (NASA, 2022). Most recently (May 2024), the U.S. National Oceanic and Atmospheric Administration forecast that the 2024 hurricane season will be the most active, with four to seven storms likely strengthening into major hurricanes (NOAA, 2024). Climate change threats are imminent. It is imperative for society to find ways to confront these hazards by reducing their impact and increasing the resilient capacity of communities so that sustainable livelihoods can be reached.

Depending on the vulnerability and resilience capacity of the communities, the impact from the same strength of hazard could differ greatly on different communities (Lam *et al*., 2015, 2016; NRC, 2012). This type of uneven impact from natural hazards is the main reason why we need to look at the factors that could make a region less vulnerable and more resilient to natural hazards. However, before we can establish which resilience factors (e.g., social and environmental variables) should be included and how they can be improved, we are faced with the most crucial task, which is how to measure community resilience to natural hazards. Community resilience measurement has become a topic that has received extensive research from diverse disciplines worldwide, aiming to find an approach that can be used as an effective decision tool to promote resilience (Koliou *et al*., 2018; Mehryar *et al*., 2022; NASEM, 2019). Despite that the literature on community resilience to natural hazards has been expanded with many contributions, these studies often vary in their approach to resilience measuring. Without a consensus, it would be difficult to move the resilience measurement field forward.

In this paper, we first provide an overview of the challenges in measuring community resilience to hazards. We then describe

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our effort in developing the Resilience Inference Measurement (RIM) model, which is designed to address two major issues in resilience measurement, which are: (i) the lack of empirical validation to support the developed indices and the selection of predictors influencing the resilience level, and (ii) the lack of statistical inferential power. We demonstrate how RIM can be applied to different types of hazards, and its extension to predictions and scenario simulations through dynamic resilience analysis. We conclude by emphasizing the need to develop a set of high-level resilience predictors to inform resilience policy making.

CHALLENGES IN RESILIENCE MEASUREMENT

Community resilience measurement is considered the first and critical step in building resilience (NRC 2012). Increasingly, it has been recognized as a powerful tool for providing substantive support for decision-making in fields such as hazard mitigation, risk assessment, and other environmental, social, economic, or technological improvements. There have been numerous efforts from organizations and researchers in developing their own tools and metrics for measuring resilience. However, there is little agreement nor standard guidelines on the methods and the metrics used. Lam *et al*. (2016) described two levels of challenge in resilience measurement. First, on the conceptual level, researchers cannot come to a consensus on what the term resilience really encompasses. Some defined resilience as engineering resilience, which refers to how fast a system can return to the original state after a disturbance, while others referred resilience as ecological resilience, which is how far the system could be perturbed without shifting to a different state (Holling, 1996). Adger *et al*. (2005) considered resilience as the capacity of a linked social-ecological system to absorb recurrent disturbances, whereas Norris *et al*. (2008) advocated that resilience is a process linking communities. These various definitions suggest that resilience can be regarded as a capacity, a process, an outcome, or a combination of the three (Lam et al., 2016). The concept of resilience is further complicated by related concepts of vulnerability, adaptability, and sustainability. In this paper, we simplify the definition used in the 2012 NRC report and define resilience as the ability to bounce back after a disastrous event, thus resilience includes both aspects of vulnerability and adaptability. Moreover, we conceptualize that long-term resilience is sustainability (Lam *et al*., 2016).

The second level of challenge refers to the resilience measurement method itself, though the method used is closely related to how resilience is defined. A popular approach to measuring community resilience is to develop a composite index by aggregating a set of variables selected from multiple dimensions (e.g., natural, human, social, economic, infrastructure). Four issues are associated with this popular approach. First, there is ambiguity and subjectivity involved in choosing an appropriate set of predictor variables and their weights for aggregation. Second, most studies utilizing this approach do not validate their indices with empirical evidence to verify if the derived index can adequately reflect the severity of the disaster impact and the recovery status of the affected communities. Without validation, it is difficult to justify the use of the derived index as an objective decision-making tool to monitor progress in resilience across space, time, and hazard type (Lam *et al*., 2016; Rufat *et al*., 2019, 2021). Third, the resilience measurement method should have an inferential property such that it can be applied to estimate the resilience levels of communities through time and across space. Fourth, the measurement method should be amenable and adaptable to dynamic resilience analysis to allow simulation of scenarios to inform policy making (Cai *et al*. 2018; Mihunov and Lam, 2020). These last two issues have seldom been considered in the resilience measurement literature, but they are vital steps to lift the practice of resilience measurement into acceptable objective decision-making tools to combat climate change.

We conducted a synthesis study on the state of resilience measurement based on 174 scholarly articles published from 2005 to 2017 (Cai *et al*., 2018). The findings echo the challenges mentioned above. Some of the findings in this synthesis study are: (i) there are wide discrepancies in the definition of resilience (and associated concepts of risk and vulnerability) across disciplines, which have resulted in very different measurement frameworks. (ii) Less than half of the articles reviewed have attempted to create quantitative resilience indices, and only a few of them have validated their indices either qualitatively or quantitatively. (iii) Few existing resilience measurement methods have the statistical inferential power to enable comparison and monitoring across space and through time. (iv) Studies on dynamic resilience analysis are rare but are needed to yield a better understanding of the underlying resilience process. (v) There is a big gap between resilience science and practice. Given that resilience measurement is intended to help decision making in risk reduction and mitigation, there is a pressing need to develop science-based, empirically validated measurement models, as well as translating and disseminating the findings to inform decision making.

RESILIENCE INFERENCE MEASUREMENT (RIM)

We developed the Resilience Inference Measurement (RIM) model to measure community resilience, aiming to overcome the issues of lacking empirical validation and inferential ability in most existing measurement methods (Lam et al., 2016). The RIM model uses three elements (hazard threat, damage, and recovery) to denote two relationships (vulnerability and adaptability) (Fig. 1). If a community (e.g., county) has high hazard threat but sustains low damage, then the community is considered to have low vulnerability. Similarly, if the community has high damage but recovers quickly, then the community has high adaptability. Resilience is measured according to the two relationships.

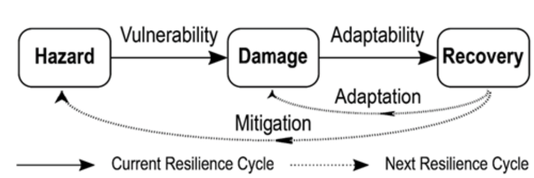

Figure 1. The Resilience Inference Measurement (RIM) model (Lam *et al*., 2016).

Previous ecological literature suggests that the recovery pattern of an ecological system generally falls into four categories (Bellingham *et al*., 1995; Batista and Platt, 2003). We modified the four categories into four resilience rankings in the RIM framework, and from low to high resilience, they are susceptible, recovering, resistant, and usurper states (Fig. 2 & Fig. 3). Figure 3 (top left diagram) shows that if a community suffers below-average hazard threat but sustains above-average damage and below-average recovery, then the community is susceptible, i.e., having the lowest resilience level. On the contrary, if a community has above-average hazard threat, but sustains average or below-average damage and above-average recovery, then the community is a usurper community, having the highest resilience level.

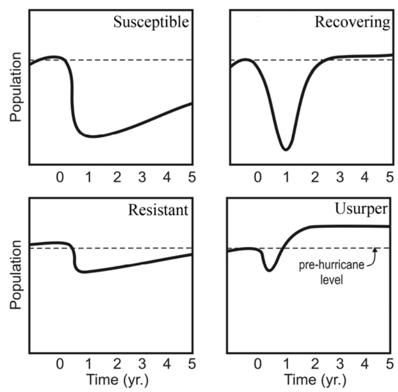

Figure 2. Four states of ecological resilience (Lam *et al*., 2016).

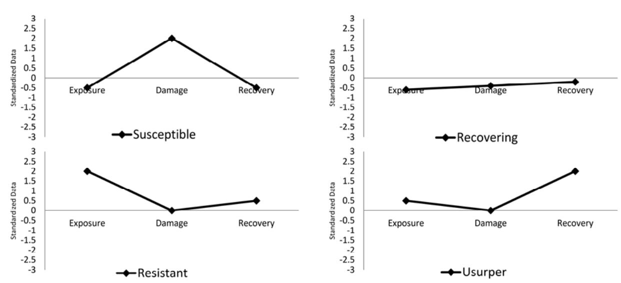

Figure 3. The four states of resilience depicted in the RIM framework. The y-axis shows the standardized scores of the three elements from their means (the zero-value line). See explanations in text (Lam *et al*., 2016).

To run the RIM model, we first collect empirical data representing the three elements (Fig. 4). For instance, hazard threat can be represented as the number and intensity of hurricane strikes in a community over a period, damage is the corresponding property damage per capita in the community, and recovery is population change before and after the events. In addition, a series of resilience predictors (typically over 25 attributes) representing the social and environmental capacity of the community are collected.

The RIM model utilizes two commonly used statistical procedures (Fig. 4). First, K-means clustering is applied to classify communities into four groups (*a priori* groups) based on the empirical data collected for the three elements. Then, discriminant analysis is used to verify the group membership of each community based on the set of natural-human predictors. The stepwise option can be used to eliminate variables that are highly correlated to help simplify the interpretation. The output of discriminant analysis includes three items: (i) a set of discriminant functions which indicate the importance (discriminant coefficients or weights) of the variables in separating the four groups; (ii) classification accuracy which shows how good the set of variables is in predicting the four *a priori* group memberships; and (iii) re-classification of each community with the probabilities of each community belonging to each of the four posterior groups.

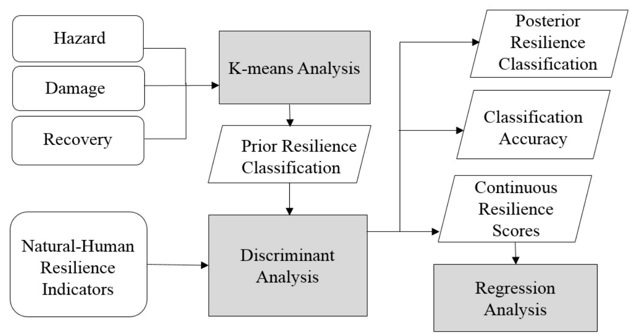

Figure 4. Flowchart of the RIM procedure (Cai *et al*., 2016; Lam *et al*., 2018).

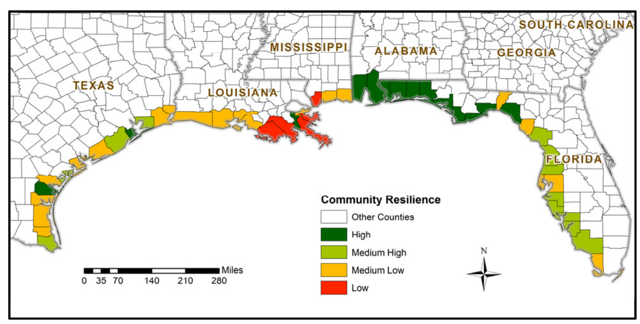

Figure 5. Community resilience rankings derived by RIM of the 52 counties along the northern Gulf of Mexico, USA (Lam *et al*., 2016).

RIM scores from the original discriminant analysis have a discrete range from 1-4, with one being the lowest (susceptible) and four the highest resilience (usurper). We can convert the discrete resilience categories into continuous resilience scores using the following equation:

$$RIMscore = \sum_{i=1}^{m} i \times Prob(i)$$

where m is the number of resilience groups (m=4), i is the resilience group number, and $Prob(i)$ is the posterior probability of a community belonging to resilience group i. For example, if a community's probabilities of belonging to group 1-4 are 0.6, 0.3, 0.1, and 0.0, respectively, then its $RIMscore$ is: (1×0.6)+(2×0.3)+(3×0.1)+(4×0.0)=1.5 (Cai *et al*., 2016; Mihunov *et al*., 2018).

Figure 5 shows the first application of RIM to assess the resilience level of 52 counties bordering the northern Gulf of Mexico, USA. The period of assessment was 2000-2010. A total of 28 predictor variables selected from multiple sectors (demographic, social, economic, government, environmental, and health) were used. Discriminant analysis based on the 28 variables correctly classified 94.2% of the counties, which is considered a high degree of accuracy. Coastal counties in Florida and Alabama were found to have higher resilience than most of the coastal counties in Mississippi, Louisiana, and Texas. The lowest resilience counties (called parishes in Louisiana) were those on the Mississippi River Delta near New Orleans. Hurricane Katrina devastated New Orleans and nearby Mississippi counties in 2005. This disastrous event occurred in the middle of the assessment period. Since it takes time for a region to recover (i.e., population return) after a catastrophic event, resilience assessment of the region may be affected. In general, this first application shows that high percentage of employment and high elevation were associated with high resilience, whereas high percent of population living in poverty, high percentage of the population without high-school diploma, and high percentage of female-headed households were associated with low resilience.

APPLICATIONS AND EXTENSIONS

The RIM model provides a general methodological framework where the three elements can be modified to analyze different types of hazards and at different spatial and temporal scales. The model has been applied to assess coastal community resilience of the Caribbean countries (Lam *et al*., 2015), the 534 counties in the northern Gulf of Mexico, the 2,086 census block groups in the Mississippi River Delta (Cai *et al*., 2016), and the 142 counties impacted by Hurricane Sandy in the northeastern USA (Wang *et al*., 2023). RIM model has also been applied to measure county resilience after the 2008 Wenchuan earthquake in China (Li *et al*., 2016), and the drought resilience in South-Central USA (Mihunov *et al*., 2018; 2019).

More assessment studies using RIM for different hazard types and at various spatial and temporal resolutions could lead to a core set of generalized resilience attributes for resilience building. Table 1 compares the lists of predictor variables extracted from using RIM for measuring coastal resilience in the Mississippi River Delta (Cai *et al*., 2016) and drought resilience in South-Central USA (Mihunov et al., 2018). Three of the variables are the same from both studies (in italic-bold font); The other variables, though not having the same name, have similar meaning/property. This finding is encouraging; it shows that activities aimed at improving resilience capacity for one natural hazard will also benefit the resilience to other natural hazards. It also shows that developing a generalized set of resilience indicators is possible.

To make the results from discriminant analysis more interpretable, an ordinary least squares (OLS) regression analysis between the $RIMScore$ and the set of extracted variables is conducted. If the regression model yields a high R^2 value, then the importance of the variables can be evaluated more directly through their regression coefficients. In Cai *et al*. (2016), regression between the *RIMscore* and the 10 predictor variables yielded an R^2 of 0.79, which is reasonable. The variables and their coefficients in the regression can then be used to explore how increasing the value of one variable affects the final *RIMscore*.

Although the regression technique is straightforward, it does not show how the predictors interact as a system that will affect the final resilience. This **dynamic resilience analysis** is crucial to a better understanding of the interdependency of predictors and building more accurate simulation scenarios for decision making. In the Mississippi River Delta study, Cai *et al*. (2018) developed a Bayesian Network (BN) to illustrate how population change was affected by the ten resilience predictors. Mihunov and Lam (2020) also used the BN method to model the dynamics of drought resilience in South-Central USA.

Table 1. *Major predictor variables of community resilience to flood vs. drought hazards extracted from the RIM analysis.*

Category	Flood resilience (Cai *et al*., 2016)
Social	• ***% female-headed households*** • % housing units with telephone service available
Economic	• ***% population employed in construction, transportation, material moving*** • ***% population living in poverty***
Infrastructure	• % housing units built after 2000 • Total housing units per square mile • Total length of roads per sq. km
Community	• % population that was native born and also lives in the same house or same county
Environmental	• Mean subsidence rate • % area in an inundation zone

Category	Drought resilience (Mihunov *et al*., 2016)
Social	• ***% female-headed households*** • % population over 65 years
Economic	• ***% employed in agriculture, forestry, fishery*** • ***% population living in poverty*** • Median value of owner-occupied housing • Median rent*
Infrastructure	• Mobile homes per square mile
Community	• Disabled and not working labor force per 10,000
Environmental	None

CONCLUSIONS

The RIM model meets several of the challenges in resilience measurement. First, the model uses empirical data for the three elements to derive the index, thus the resultant RIM index has already been validated by empirical observable outcomes. Second, the equations derived from the discriminant analysis can be used to predict resilience of other similar communities if the assumptions hold, thus the RIM method has inferential power. Third, the model can incorporate resilience predictors from multiple sectors, and at the same time, the stepwise option can be employed to extract major variables and avoid collinearity. Fourth, the model provides not only the final RIM scores but also the weights associated with the major variables. When the model is further extended into a dynamic mode using Bayesian Network or other system dynamic methods, we can identify the interdependency of the variables and their associated probabilities for a better understanding of the resilience process and more accurate scenario simulations.

However, as expected in any type of spatial-temporal models, the RIM model results are subject to uncertainty, depending on the temporal and spatial scales used and other factors. More application studies are needed to examine how the predictors and their weights change with spatial and temporal scales, the hazard type, and the selection of predictor variables. Furthermore, incorporating input from local communities, experimenting with rural versus urban setting, comparing with rapid vs. slow-moving hazards, and testing with the AI/machine learning algorithms would help improve the science and practice of resilience measurement. We argue that through more experimental studies, it is possible to develop a set of high-level standards of resilience capacity to help advance the science and practice of resilience measurement to benefit society.

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