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Extending Resilience Assessment to Dynamic System Modeling: Perspectives on Human Dynamics and Climate Change Research

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ABSTRACT

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It is widely known that the same type and strength of hazard could lead to very uneven impacts on different communities due to their varying vulnerability and resilience capacity. Hence, identifying the factors that make a community more resilient to hazards is critical to its sustainability and is central to climate change research and planning. This paper addresses three questions: what is the best way to measure community resilience to disasters and how to identify the key indicators? How do the resilience indicators dynamically interact in a quantitative manner that would lead to long-term resilience? And how can we translate the scientific results into practical tools for decision making? Using the population change pattern in the Mississippi River Delta as a case study, this paper demonstrates the use of a relatively new resilience assessment method called the Resilience Inference Measurement (RIM) method to measure resilience. Then, a newly developed spatial dynamic model is used to simulate population changes in the study area. The results show that without any changes in the current condition, the coastal portion of the study area will continue to suffer population loss and the region is unlikely to sustain in the future.

ADDITIONAL INDEX WORDS: *Community resilience assessment, coupled natural-human system modeling, Mississippi River Delta, population changes, coastal resilience and sustainability.*

INTRODUCTION

Climate change is inevitable. The 2014 Inter-governmental Panel on Climate Change Report reveals that extreme weather and climate conditions in the future are very likely (IPCC, 2014). These weather extremes include a decrease in cold temperature extremes, an increase in warm temperature extremes, an increase in extreme high sea levels, and an increase in the number of heavy precipitation events in a number of regions. These extremes increase the likelihood of catastrophic events, including more and stronger hurricanes, storm surge, flooding, and drought (Emanuel, 2013), causing enormous impacts and revealing significant vulnerability of many ecosystems and human systems around the world. There is an urgent need to improve community resilience to disasters so that we can find ways to better protect communities and cope with these hazards in a changing climate world (Lam *et al.*, 2015, 2016).

Humans play a pivotal role in climate change because they are both a casual and an impact agent. In general, we know more about the effects of human activities on climate change and have developed strategies to mitigate such effects. We also know how human activities can worsen the impacts from climate-related events, but we are less certain on the best adaptation strategies. For instance, despite the danger of flood risk, people may still choose to live in coastal areas due to many economic and other considerations. Dense population living in flood-prone areas, inadequate infrastructure planning and investment, and unwise land-use decisions have all made some communities more vulnerable to disasters and difficult to recover than others (Qiang *et al.* 2017). Understanding the interactions and feedback mechanisms between the natural and the human systems is critical to the development of effective strategies to lessen the impacts of climate change.

The objective of this paper is to introduce new approaches to modeling and understanding human dynamics in the context of climate change. Specifically, this paper focuses on the issues of

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community resilience assessment and how it is linked to coupled natural-human (CNH) system modeling. The Mississippi Delta is used as a case study to illustrate the complex problems of low-lying coastal regions in the world are facing and how the proposed methods can be applied to address the coastal resilience problem. The paper addresses three questions: what is the best way to measure community resilience to disasters and how to identify the key indicators? How do the resilience indicators dynamically interact in a quantitative manner that would lead to long-term resilience (i.e., sustainability)? And how can we translate the scientific results into tools for decision making.

METHODS

The methods developed by this research team for resilience measurement and coupled natural-human system modeling are summarized below.

Community Resilience Analysis

There is extensive literature in the broad field of disaster resilience, vulnerability, hazards, risk assessments, and sustainability, which spans across many disciplines (Cutter, 2015; Cutter *et al.*, 2010; Norris *et al.*, 2008). Among the various issues, developing tools or metrics for measuring and monitoring progress of resilience is considered vital to building resilience (National Research Council (NRC), 2012).

However, there are major challenges in developing useful resilience indices. First, there is no consensus on the definition of resilience, especially its relations with other similar concepts such as vulnerability, recovery, adaptability, and sustainability. This major disagreement among researchers on the definition of resilience has affected the measurement approaches and the choice of indicators to measure resilience. Second, many existing resilience indices were developed without objective empirical validation. Without empirical validation of the derived indices, it is difficult to justify them as a credible decision-making tool to monitor progress in resilience across space, time, and hazard type. Third, existing resilience or vulnerability assessment methods seldom have an inferential ability, thus the indices developed are only applicable to the specific study and study area. Fourth, existing indices seldom incorporate both social and environmental variables and their feedback mechanisms, which is necessary for understanding and evaluating long-term sustainability (Liu *et al.*, 2007a, 2007b).

This research team recently developed the Resilience Inference Measurement (RIM) model to overcome the aforementioned problems. The RIM model uses three dimensions (hazard threat, damage, and recovery) to denote two relationships (vulnerability and adaptability) (Figure 1). If a community has high hazard threat but sustains low damage, then the community is considered to have low vulnerability. Similarly, if a community sustains high damage but has a favorable recovery (e.g., return of population), then the community is considered to have high adaptability. Resilience is measured based on the two relationships. K-means clustering is used to group the communities into four *a prior* resilience groups (usurper, resistant, recovery, susceptible) according to the two relationships. Discriminant analysis is then applied to identify the key social-environmental variables that best characterize each group. Discriminant analysis produces discriminant functions which can be used to calculate the posterior group membership of each community (Figure 2). If the predicted group memberships agree closely with the *a prior* group memberships, then the discriminant classification accuracy is high, meaning that the set of social-environmental variables used in the discriminant analysis are good predictors of the resilience rank of communities.

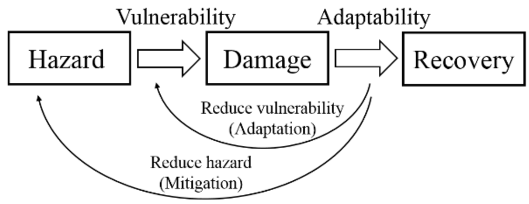


Figure 1. The Resilience Inference Measurement (RIM) model.

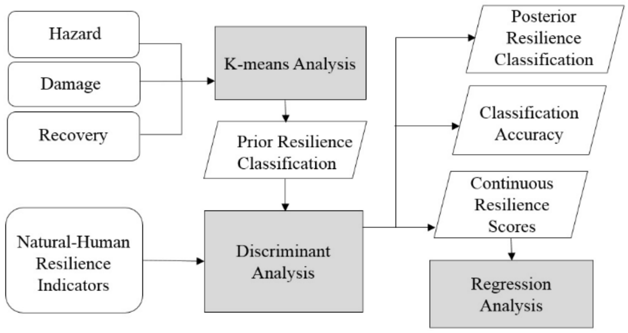


Figure 2. Flowchart of the RIM procedure (source: Cai *et al.*, 2016).

Tweaking Science into Practice

To make the RIM model results easier to use and understand, two extensions can be conducted. First, we can convert the discrete resilience categories into continuous resilience scores using Equation 1 (Cai *et al.*, 2016; Mihunov *et al.*, 2017):

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

where m is the number of resilience groups from k-means clustering, i refers to the resilience group, and $Prob(i)$ denotes the posterior probability of a community belonging to resilience group i. For example, if a community's probabilities of belonging to group 1 to 4 are 0.7, 0.2, 0.1, and 0.0, respectively, then its *ReScore* is (1x0.7)+(2x0.2)+(3x0.1)+(4x0.0)=1.4.

Second, an ordinary least squares (OLS) regression analysis between the RIM scores and the social-environmental variables identified by discriminant analysis can be conducted. If the regression model yields a high R^2 value, then it can be used as a simplified policy tool to evaluate the importance of the variables in contributing to the resilience scores based on their regression coefficients.

The RIM model provides a methodological framework where individual dimensions can be modified to fit into different problem settings. The model has been successfully applied to assess community resilience to various hazards (coastal, drought, earthquake) and in different regions to extract key socioeconomic variables that affect resilience (Cai *et al.*, 2016; Lam *et al.*, 2015, 2016; Li K *et al.* 2015; Li X *et al.* 2016; Mihunov *et al.*, 2017).

Coupled Natural-Human Dynamic Modeling

The community resilience assessment discussed above focuses on what is the best way to *measure* community resilience, and it is a snapshot, static assessment of the condition of resilience. To *understand* how the various resilience variables interact that would lead to resilience, we need to model the dynamics of resilience, and using a coupled natural-human system approach is necessary (Liu *et al.*, 2007a, 2007b). Two commonly used spatial modeling tools to model system complexity are cellular automata (CA) (Clarke & Gaydos, 1998; Qiang and Lam, 2015) and agent-based modeling (ABM) (An, 2012).

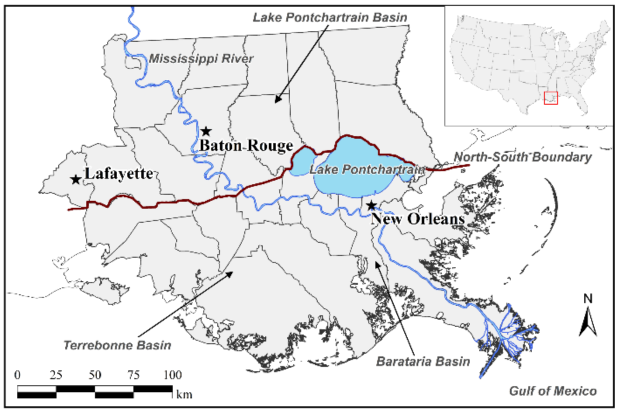
A CA model uses cells with different states as the modeling units, and defines the rules for updating the states over time with consideration of the neighborhood effects. In a CA model, each cell has a size, state, space, and neighborhood. The dynamics is controlled by a set of CA rules according to its previous state and its neighbor cells' previous states. In some CA models, the cells can have mobility with certain defined site-exchange rules (Li and Lam, 2018).

ABM uses agents to simulate the behavior of a complex system. There is no universal agreement of the definition of the term "agent" in ABM, but some common characteristics of ABMs are: agents have the ability to change their physical locations and modify their attributes, agents can actively sense the environment conditions and respond accordingly, and agents can interact with other agents within their perspectives. A recent review of ABM for CNH modeling shows that there are indeed a variety of ABMs developed by different researchers, making cross-fertilization between models difficult (An, 2012). While ABMs are most applicable to model individual decisions, their application to large-scale system modeling is limited due to the lack of individual-level data. In the following, we demonstrate a spatial dynamics model which incorporates CA and some properties of ABM to model population changes in a vulnerable coastal environment such as the Mississippi River Delta.

Study Area

The study area, broadly recognized as the Lower Mississippi River Basin (LMRB), is located in southeastern Louisiana and extends from the parishes (*i.e.,* counties) north of Lake Pontchartrain to the coast (Figure 3). We consider Lake Pontchartrain as an approximate boundary where areas north of it are called the "North" (inland areas), whereas areas south of it are labeled as the "South" (coastal areas). Over the years, the South has endured multiple threats such as land loss, subsidence, sea-level rise, flooding, hurricanes, and oil spills. The disappearing land is a critical problem, and drowning of the Mississippi Delta is plausible due to insufficient sediment supply and high rate of regional sea level rise (> 9mm/year) (Blum and Roberts, 2009). At the same time, we observe a trend of steady population growth in the North since 1990s, in contrast with a steady decline in the South surrounding New Orleans. The trend seems to accelerate after Hurricane Katrina (Qiang and Lam, 2016). Thus a pressing question facing the communities is: *has southern coastal Louisiana reached the tipping point where it may be too costly to sustain?* Can we capture, quantify, and explain these changes using a CNH system model? And, what are the implications for mitigation and adaptation planning?

Figure 3. The study area – the Lower Mississippi River Basin (LMRB).



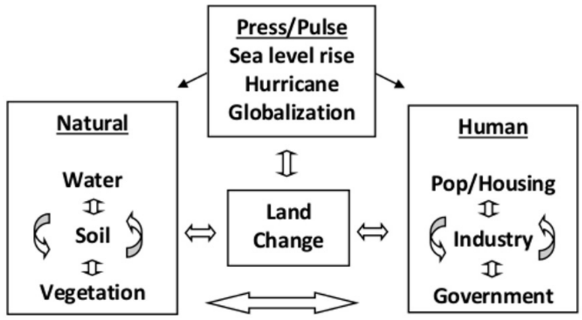


Figure 4. The coupled natural-human system framework for the LMRB.

Because of its economic, social, and cultural significance, many researchers and agencies have conducted studies on the region using various approaches (CPRA, 2017). However, surprisingly a system-level study that incorporates both natural and human systems has yet to be conducted. With funding from the U.S National Science Foundation, this research team launched a project to examine the coastal sustainability problem in the study area using a CNH approach. Figure 4 shows the CNH framework for the entire project, which includes components from both the natural and the human systems and their feedback links. This paper summarizes the results of a resilience assessment and a spatial dynamic modeling study to illustrate the extension of community resilience assessment from static to dynamic. The data period was 2000-2010.

RESULTS

The RIM model was applied to assess the community resilience level of LMRB using census block group as the unit of analysis (Cai *et al.*, 2016). There were 2,086 block groups in 2010. A total of 25 variables were selected to represent the social, economic, infrastructure, cultural, and environmental sectors for the discriminant analysis. Results show that during 2000-2010, a total of 420 coastal hazard events severely affected the study area, causing over 50 billion dollars of property damages. Population change was chosen as an indicator of recovery. Block groups with the highest population increase were mostly in the North, while several block groups in the South (Plaquemines Parish) along the coastline lost all the population in 2010. This area also suffered the highest level of hazard threat and had high land subsidence and land loss.

Stepwise discriminant analysis yielded a classification accuracy of 73.1% and selected 11 variables that best characterized the 4 resilient groups. The 11 variables were: percent housing units with telephone service, percent female-headed households, percent population living in poverty, median household income, percent population employed in construction and transportation, percent housing units built after 2000, housing density, road density, percent population native born, mean subsidence rate, and percent area in inundation zone. In terms of geographical pattern, block groups with higher resilience were found generally in the North, whereas lower-resilience communities were located mostly along the coastline and in lower-elevation area (Figure 5). The regression between the continuous RIM scores and the 11 variables yielded a R^2 value of 0.89, suggesting that the final regression model could be used as a simplified decision-making tool to evaluate the relative importance of the 11 variables in the final resilience scores.

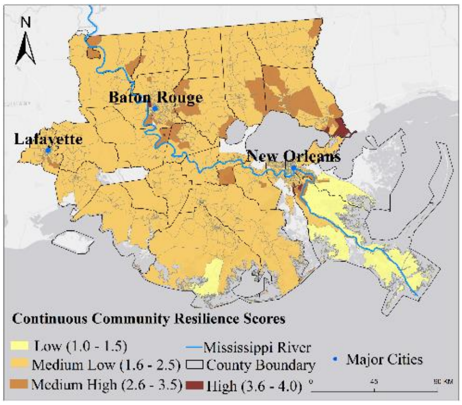


Figure 5. Continuous RIM scores map, the higher the scores, the more resilience (source: Cai *et al.*, 2016).

Extending static resilience analysis to dynamic modeling of resilience requires many new steps (Li and Lam, 2018). First, the study area was converted into 3 km x 3 km grids as the modeling units (a total of 5,890 grids). Second, a volume-preserving areal interpolation technique was used to transform all the data into the same grid platform. A total of 33 variables were selected for the analysis, many of which were the same as those used in the previous resilience assessment study. Third, an Elastic Net model was applied to extract 12 variables from the set of 33 to develop a utility function to capture the major social-environmental variables that affected population changes. Fourth, a genetic algorithm was applied to calibrate the neighborhood effects. Finally, a system dynamic model was built to simulate population changes in the study area.

The resultant system dynamic model is governed by three equations, each specifying a state variable (population count, developed area percentage, and utility) in time *t*+1 as a function of the same variable in time *t* plus other influencing variables. Due to space limitation here, only the final model is shown in Figure 6. A Monte Carlo simulation was used to analyze the uncertainty of the model outcome. The accuracy assessment shows that the model slightly over-predicts the population count and developed area in 2010. A simulation of population change from 2010 to 2050 was conducted, and their trajectories was evaluated using the resilience framework. It was found that areas in the South continue to suffer population loss whereas areas in the North continue to have steady population growth. In other words, without mitigation and adaptation or any changes in the current condition, the areas in the South will unlikely be sustainable.

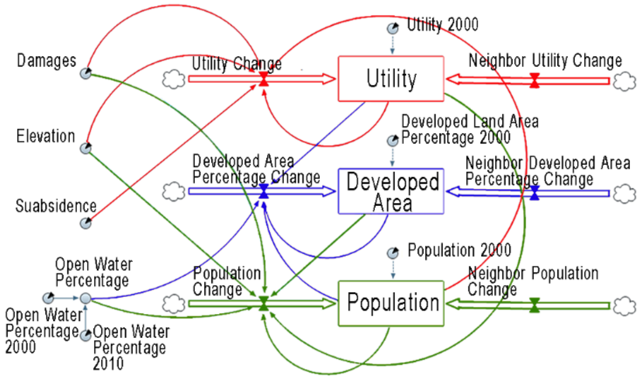


Figure 6. The spatial dynamic model of LMRB (source: Li and Lam, 2018).

DISCUSSION

Despite many investigations on coupled natural and human systems, few studies have actually attempted in quantifying the feedback relationships in a real-world setting. Modeling the dynamics of a real CNH system is complex and challenging. First, incorporating all the major components from both natural and human systems is difficult, thus the system models developed are seldom able to replicate the real condition. Second, modeling the dynamics require data collected at multiple spatial and temporal scales, validation of the model results is difficult without appropriate fine-scale subsystem analysis to support the validation. Third, the scales of operation of the natural and the human processes are very different, incorporating them into a single system requires assumptions, interpolation, and manipulation that often lead to errors and uncertainties.

CONCLUSIONS

Disaster resilience is a pressing global concern, and solution of which undoubtedly requires collaboration across a wide spectrum of society, including researchers from various disciplines, policy makers, community stakeholders, first responders, and citizens. Through studying the population change pattern in the Lower

Mississippi River Basin, this paper has demonstrated that the Resilience Inference Measurement (RIM) model can assess resilience and extract key resilience variables. Unlike many existing resilience assessment methods, the RIM method has the validation and inferential properties. The RIM model can further be tweaked and simplified through a regression analysis so that it can be used as a practical science-based decision-making tool.

A spatial dynamic model was developed to examine how the resilience indicators interact dynamically that would lead to population changes and ultimately sustainability in the study area. Extending static resilience assessment analysis to dynamic resilience analysis is necessary to understand the underlying processes leading to resilience. Based on the model simulation results from 2010-2050, this paper shows that without any changes in the current condition, the lower Mississippi River Delta region will continue to suffer population loss and the region is likely to sustain.

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