Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2018-217
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 16 August 2018

Natural Hazards and Earth System Sciences
Open Access
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Towards Measuring Resilience of Flood Prone Communities: A Conceptual Framework

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Abstract. Community resilience has become an important policy and research concept for understanding and addressing the challenges associated with the interplay of climate change, urbanization, population growth, land use, sustainability, vulnerability and increased frequency of extreme flooding. Although measuring resilience has been identified as a fundamental step toward its understanding and effective management, there is, however, lack of an operational measurement framework due to the difficulty of systematically integrating socio-economic and techno-ecological factors. The study examines the challenges, constraints and construct ramifications that have complicated the development of an operational framework for measuring resilience of flood prone communities. Among others, the study highlights the absence of definitional convergence with its attendant proliferation of conceptual frameworks, challenges of data availability, data variability and data compatibility. The study suggests the adoption of an agreed definitional platform as the basis for developing conceptual constructs across all disciplines dealing with resilience. Using the National Academies' definition of resilience (NRC 2012), a conceptual and mathematical model was developed using the dimensions, quantities and relationships established by the definition. A fuzzy logic equivalent of the model implemented to generate a resilience index for three flood prone communities in the US. It is concluded that the proposed framework offers a viable approach for measuring community flood resilience even when there is a limitation on data availability and compatibility.

Keywords: Hazard, Disaster, Flood, Resilience, Measurement, Fuzzy, Community

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1 Introduction

Developing resilience of communities has become widely recognized as critical for for disaster risk management due to the increased incidents of extreme weather events, such as flooding, which have disrupted economic activities, caused huge losses, displaced people and threatened the sustainability of communities across the world (Cai et al., 2018; Cutter 2018; Mallakpour and Villarini, 2015; Montz, 2009; Oladokun et al., 2017; Su, 2016a; Wing et al., 2018). Major international policy instruments such as the United Nations International Strategy for Disaster Reduction's (UNISDR) 2015 Strategic Framework and the 2005 Hyogo Framework have emphasized and adopted resilience principles in disaster risk management (Cai et al., 2018; Cutter et al., 2016). For instance, the interplay of extreme floods, population growth and rapid urbanization has increased flood hazard risks such that conventional flood risk management (FRM) measures of concrete structures, levees, flood walls and other defenses have become inadequate and unsustainable across various communities (Duy et al., 2018; Guo et al., 2018; Trogrlić et al., 2018; Wing et al., 2018). Building community resilience has therefore emerged as particularly relevant in dealing with flooding, which has become the most widespread and destructive of all natural hazards globally (Jha et al., 2012; Mallakpour and Villarini, 2015; Montz, 2009).

Consequently, there has been a shift from relying solely on large-scale flood defense and structural systems towards an approach that emphasizes the concept of community resilience as a strategic component of flood risk management (Hammond et al., 2015; Park et al., 2013). This shift is being reinforced by a consensus that since floods cannot be all together prevented, FRM must focus more on building the resilience of flood prone communities ((Joseph et al., 2014; Oladokun et al., 2017; Schelfaut et al., 2011). Resilience has gained a lot of attention from both policy and research perspectives with the literature replete with many efforts at using resilience to understand and address the challenges associated with the interplay of climate change, urbanization, population growth, land use, vulnerability and sustainability (Cohen et al., 2016; Cohen et al., 2017; Folke, 2006; Parsons et al., 2016; Sharifi, 2016) .

From a definitional perspective, resilience is a multifaceted and multidimensional concept that has developed from across multiple disciplines and applications over the last few decades. Resilience discourse has attracted multidisciplinary interests from both research and policy perspectives and has

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become a widely accepted platform for dealing with disaster and hazard risk management. While the wide spectrum of multidisciplinary and practice interests that characterize resilience discourse has increased its understanding and generated insights, it has also increased definitional and conceptual confusion and some lack of clarity (Brown and Williams, 2015; Cohen et al., 2016; Cutter 2018). In fact, resilience has been noted to have varied definitions depending on the hazard and disciplinary contexts, with over 70 definitions identified by Fisher (2015). The multiplicity of definitions has led to proliferation of conceptual models, frameworks and interpretations (Costache, 2017). The United Sates National Academies, in a widely cited report (National Research Council, NRC, 2012), describes resilience as the ability of a system to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events (Cai et al., 2018; Cutter, 2018). Essentially, the concept of resilience involves the interactions of several entities each defined by some social, economic, natural, technical and environmental dimensions (Cai, et al., 2018; Norris et al., 2008). According to Cutter (2018), there are also difficulties in operationalizing the definitions, thereby leading to a wide array of measurement approaches. Therefore, there still exists a difficulty in transforming resilience measurement from an abstract concept into an objective operational quantitative template.

Meanwhile, a pre-requisite to having an operational model, in the context of resilience measurement, is the adoption or convergence of definition by the resilience research and policy community. Such a definition should meet the following criteria: i) emanates from or receives the formal endorsement of a widely recognized institutional platform of stakeholders, ii) encompasses a wide spectrum of existing resilience concepts, iii) has some degree of simplicity, and iv) enjoys high acceptance of both the research and policy community. From our extensive review of the literature, it appears that the definition of resilience put forward by the US National Academy of Sciences (NRC, 2012) meets these criteria. Therefore we are adopting this definition as a basis for developing the conceptual framework for the proposed template for measuring the resilience of flood prone communities.

There is a consensus that the first and fundamental step toward understanding and operationalizing resilience for disaster and hazard management is to have an acceptable resilience measuring template (NRC, 2012). For instance, the ability to understand and objectively evaluate the impact of FRM programs, interventions and practices on community flood resilience is needed for making political and business cases for proactive FRM investment from both public and private sectors. Cutter (2018) suggested that an acceptable template is a basic foundation for monitoring baselines and progress in building hazard resilience.

Furthermore a measuring template will be useful as a decision support tool for the efficient deployment of scarce FRM resources and also provides a basis for monitoring resilience changes with respect to resource deployment. For instance, Keating et al. (2017) explained that there is a need for the continued development of measurement frameworks and tools that help in understanding key components of resilience in order to better target resilience-enhancing initiatives and evaluate the changes in resilience as a result of different capacities, actions and hazards. The authors noted that such a template must be theoretically anchored, empirically verified, and practically applicable. Therefore, the search for an acceptable and easy to use framework and empirical model for measuring resilience remains relevant and continues to attract attention (Cutter et al., 2016; Zou et al., 2018). Despite the attention resilience has gained, the concept remains difficult to operationalize in the context of community hazard risk management due to, among other factors, the difficulty in measuring resilience (Cutter, 2018; Fisher, 2015).

The literature is replete with many efforts address to the problem of measuring hazard and disaster resilience with a lot of attention directed at conceptual models for understanding the variables and interactions that define the hazard-resilience system (Cai et al., 2018; Cutter et al., 2016; Keating et al., 2017). In a concise review of literature (Cai et al., 2018) identified and characterized some existing approaches to measuring resilience to include the following: i) the Baseline Resilience Indicators for Communities (BRIC) with six dimensions (social, infrastructural, economic, institutional, community, and environmental) for assessing community resilience), ii) the Resilience Inference Measurement (RIM) framework which attempts to integrate empirical validation into a resilience index, iii) the Coastal Resilience Index created by the National Oceanic and Atmospheric Administration (NOAA 2010), iv) the PEOPLES Resilience Framework, incorporating seven dimensions for measurement, and v) the

Communities Advancing Resilience Toolkit (CART), a publicly available tool for use by stakeholders (NRC 2012).

Despite these efforts, many experts and authors have noted that there is still difficulty in integrating indicators of the natural and human systems as well as socio-environmental factors into resilience by most of the existing frameworks (Cai et al., 2018; Cutter, 2018; Fuchs and Thaler, 2018; Qiang and Lam, 2016). Other challenges relate to issues of data availability, data variability and data compatibility between the natural and human variables, as well as the complexity inherent in community resilience.

From a systems perspective, community-resilience is a collection of socio-ecological, socio-political, techno-ecological and socio-economic entities, each characterized by dynamic and complex spatiotemporal interactions. For instance, the community component was succinctly described by (Cai et al., 2018) as a coupled natural and human system that manifests various complexities such as nonlinearity, feedback, and uncertainty in system components and relationships. Hence, resilience modeling presents some challenges from both conceptual and computational perspectives.

2 Resilience Measuring: A Conceptual Framework

2.1 Definition model

The design objective is to have a conceptual framework and its associated mathematical model with sufficient tractability by minimizing the number of model elements and adopting the barest minimum relationships while maintaining a reasonable level of validity. Therefore, as the theoretical basis for the proposed conceptual model, as mentioned earlier, we are adopting the resilience definition put forward by the US National Academies (NRC 2012). This definition has been widely cited by subsequent publications on hazards and resilience with some considerable level of acceptance among researchers (Cai et al., 2018; Cutter et al., 2016; Cutter, 2018; Zou et al., 2018).

Conceptually this definition implies that a community's resilience is a quantity that reflects the community's capacities, in terms of a threshold of hazard it can absorb as well as its accessible resources, its processes and resource utilization systems. These capacities interact to define its ability to prepare for, absorb, recover from, and more successfully adapt to adverse flooding events. In other words, this

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concept describes a three factor reservoir system consisting of: 1) Hazard Absorption Capacity H, 2) Resource Availability G, and 3) Resource Utilization Processes θ to drive all the phases of recovery on a spectrum of Recovery Quality Q which encompasses both equilibrium and adaptive recovery. We attempt to conceptualize this understanding as shown in Fig. 1.

Each of the dimensions in Fig. 1 is influenced by a number of technical, social, ecological, economic, and political factors. A lot of work has been reported in the literature which sheds light on these factors and how they influence the dimensions (see Cohen et al., 2016; Lee et al., 2013; Rose, 2017). For example, hazard absorbing capacity H is determined by a number of techno-ecological factors such as adequacy, redundant capacity, sophistication and use of infrastructure and technology. It is also determined by socio-ecological and socioeconomic factors that influence both individual and institutional coping capacities. Resource availability is determined by things like community capital, political influence, and economic activities as well as ecological resources accessible to drive the quality and timeliness of recovery. Resource utilization processes are determined by the quality of governance and institutions such as judiciary, police, media, and public service. These processes influence policy formulation and implementation, the ease of doing business and the efficiency of use of resources. A detailed structured and operational rendition of the foregoing is presented in sections 2.2 and 3.3.

2.2 Mathematical model

The next stage is to transform the above conceptual framework into an operational model. This is accomplished by defining a geometric model of the framework as shown in Fig. 2. This model is then used to derive appropriate mathematical relationships for generating resilience indices and provide some insights.

The following explains the components of Fig. 2 in the context of flood hazard.

i. Hazard Absorbing Capacity (H): (H=h: $0 \leq h \leq 1.0$). The resilience of a community depends on the level of the flood hazard the community systems can absorb before totally collapsing or undergoing irreversible disintegration. H=1 is the highest absorbing capacity whereby the

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community can absorb and survive the damages and disturbance of the most severe category of flooding conceivable.

ii. Resource Availability (*G*). This is the quantum of resources available to plan and pursue recovery as well as achieve recovery quality level *Q*. Note that $G=g$ ($0\leq g \leq 1.0$) captures both economic and community capital. It is the measure of resources the community is able to attract as a result of its overall economic and political influence, its natural assets, and human capital.

iii. Resource Utilization Processes (θ): With $0\leq\theta\leq \Pi/2$, we define ρ (ρ = Sin θ) as system efficiency. This is a component of recovery that revolves around the community governance, systems and processes that determine the efficiency and effectiveness of the use of resources for recovery. That is, how *well* resources are utilized is important as how *much* of a set of resources is used in building resilience. It measures the probity, level of accountability, level of waste, corruption, red-tapism, and bureaucracies within the system. A community with strong institutions and a functioning judiciary, for instance, will tend to return high ρ, so an ideal or utopian community will have its *G* deployed at $\theta= \Pi/2$, that is ρ = Sin θ= 1.

iv. Recovery Quality Level (*Q*). This represents the outcome of post hazard conditions in terms of restoration quality and socio-ecological functionality, among others.

2.3 Definitions and terms

We define the following terms with respect to Fig. 2

a_i : Resilience reservoir of a real system i is defined as the area of trapezium ABFE' determined by the hazard absorbing capacity, at $H= h$, of the system, the available quantum of resources ($G=g$), the quality of governance processes and resource utilization systems (Sin θ) and the achievable recovery quality ($Q=q$).

a_u : The resilience reservoir of a utopian (ideal) system, the area of square ACDE . This occurs at ideal FRM conditions: that is, a community system with adequate resources, perfect governance and processes with zero waste of resources and infinite hazard threshold. That is h= AE (at maximum absorbing

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capacity), g=ED (maximum resource adequacy) and θ = Π/2 (perfect or utopian system with efficiency Sin θ=1.0). The utopian system can achieve a perfect recovery index Q= q= 1.0 or Q=AC.

The utopian resilience reservoir is the benchmark for evaluating resilience such that Resilience R can be defined as the ratio of a_i to a_u as indicated in equation 1.

2.4 Resilience modelling

$$R_i = \frac{a_i}{a_u} \quad (1)$$

Using the insights from Figure 1, we attempt to develop the mathematical model implied in equation 1, note R is a dimensionless since both a_i and a_u are areas.

$$a_i = \frac{1}{2}\{AE' + BF\}AB \quad (2)$$

$$a_u = AE \times ED$$

$$a_u = H \cdot G \quad (3)$$

Note: $AE' \equiv h$ (4)

$$BF = AE' - F'E' = h - gCos\theta \quad (5)$$

$$AB = F'F = gSin\theta \quad (6)$$

Putting 4, 5, 6 into 2

$$\Rightarrow\ a_i = \frac{1}{2}\{h + (h - gCos\theta)\}gSin\theta$$

$$a_i = hgSin\theta - \frac{1}{2}g^2Sin\theta Cos\theta$$

$$a_i = hgSin\theta - \frac{1}{2}g^2Sin\theta \pm \sqrt{1 - Sin^2\theta}$$

Recall we define ‘Efficiency of resource utilization system’ as ρ =Sinθ

$$\therefore a_i = hg\rho - \frac{1}{2}g^2\rho\sqrt{(1-\rho^2)} \quad (7)$$

Putting 3 and 7 into 1

$$R_i = \frac{hg\rho - \frac{1}{2}g^2\rho\sqrt{(1-\rho^2)}}{HG} - \quad (8)$$

Without loss of generality, h and g are treated as indices such that

$0 \le h \le 1 \quad and\ 0 \le g \le 1$

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Then H=G=1 in equation 8 which implies

$$R_i = hg\rho - \frac{1}{2}g^2\rho\sqrt{(1-\rho^2)} \tag{9}$$

Equation 9 is a valid expression for resilience.

That is $R_i = f(h, g, \rho)$

This implies that the resilience of a flood prone community is determined by:

1) h: the threshold hazard level that the community can cope with or absorb based on, for example, existing FRM infrastructure, coping capacity, redundancy, and ecological buffers.
2) g: the level and availability of resources to plan and execute recovery
3) ρ: the level of efficiency of the systems, processes, and communal structures that use the resources (linked strongly with quality of governance structures, policies and processes).

The values for these variables are decided by experts and/or stakeholders, varying depending upon the location and scale of application of the model.

2.5 Model insights with some extreme values

This section discusses some example cases of the model output using selected extreme values of the system variables to generate further insights into model structure (with reference to equation 9 and Fig. 1).

Case 1: As $\boldsymbol{\rho \to 0}$ $\boldsymbol{R \to 0}$

In fact, R= 0 when $\rho = 0$. This may be interpreted as the case when the resource utilization processes have zero efficiency (see Fig. 3) or a collapsed governance system such as when a flood disaster occurs in a community ravaged by civil war with breakdown of law and order. In such situations, community resilience is nil as all resources put into recovery will be 'wasted,' irrespective of the level of coping or infrastructure previously in place.

Figure 3

Case 2: As $\boldsymbol{\rho \to 1}$ $\boldsymbol{R \to hg}$

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This implies that θ=Π/2 or Sinθ=1 which depicts an ideal situation when the communal processes, FRM resource administration, and utilization systems are highly efficient and near perfect. Under this scenario, the resources g and community's coping capacities contribute maximally to resilience (see Figure 4).

Case 3: $\boldsymbol{g \to 0}$ $\boldsymbol{R_i \to 0}$ Resilience disappears when resources dry up.

Case 4: h= $\mathbf{1}$ Resilience is determined by resource availability and utilization

Case 5: As $\boldsymbol{h \to 0}$ $\boldsymbol{R \to 0^-}$

From Figure 5, resilience approaches zero from negative values. In fact, R is negative if $\rho < 1\ and\ h = 0$. 'Negative' resilience is another expression for vulnerability, sometimes seen as the flip side of resilience (Folke et al., 2002) or a complementary community-hazard management concept (Cutter, 2018; Fekete and Montz, 2018; Shah et al., 2018). As absorbing capacity h approaches zero, a community enters vulnerability mode because more resilience area lies below the positive plane. In other words, equation 9 suggests that a community without coping or built in absorbing capacities is vulnerable, especially if its governance structure is poor (ie.Sinθ → 0).

3 Toward Model Analysis: An Overview of Fuzzy Logic

The resilience measuring problem with its interplay of definitional ambiguities, multi-dimensionality, and spatiotemporal dynamics invariably results in complex models. Such models, given the level of incompleteness, vagueness, and subjectivity that characterizes the human and socio-political aspects of resilience, offer little tractability with conventional hard computational tools and are difficult to operationalize. Hence, Oladokun et al. (2017) suggested that a resilience measuring model may be more amenable to a soft computing analytical technique such as fuzzy logic. Fuzzy set theory provides a mathematical tool for modeling uncertain, imprecise, vague and subjective data which represents a huge class of data encountered in most real-life situations (Adnan et al., 2015; Lincy and John, 2016). The fuzzy logic (FL) concept, introduced in 1965 by Lot A. Zadeh, is an extension of the classical set theory of crisp sets. FL, like humans, accommodates grey areas where some questions may not have a clear Yes or No answer or black and white categorization. According to (Zadeh, 1996), Fuzzy Logic = Computing with Words. FL logic mimics human reasoning and capability to summarize data and focus on decision-relevant information in problems involving incomplete, vague, imprecise or subjective information (Oladokun and Emmanuel, 2014). This capability to mine expert knowledge and use limited or fuzzy data makes a fuzzy inference system (FIS) a suitable tool for resilience measurement. Therefore, the FIS equivalent of the proposed model will be explored for easy of application.

3.1 Resilience fuzzy inference system design

While the resulting model of equation 9 provides useful insights, its application however is based on the premise that there are adequate data on resilience input factors, described in section 2.2, for estimating dimensions H, G and θ. However, there are issues of data availability and data compatibility between the natural and human variables (Parsons et al., 2016) which make it inefficient to do crisp estimation of these dimensions. Therefore, to operationalize the proposed framework, a (FIS) equivalent has been developed. In particular, the Mamdani FIS will be adopted for mapping the dimensions into resilience (Mamdani and Assilian, 1975). The Mamdani FIS is characterized by the use of linguistic variables and their term sets, the membership functions for the fuzzification and de-defuzzification processes, and the fuzzy rules.

The concept of membership function (MF) is central to FIS. In traditional logic, an element x is either in or out of crisp set A; in other words, its degree of membership of the set is either zero or one. However, in fuzzy logic the element x can be in a fuzzy set B 'partially' by using a MF $\mu_B(x)$ which can return any real value between 0 and 1. This returned value is the degree of membership representing the degree to which the element belongs to a fuzzy set. Therefore, in FL, the truth of any statement becomes a matter of degree.

Thus for crisp set A $\mu_A(x) = \begin{cases} 1 & if\ x \in A \\ 0 & otherwise \end{cases}$

On the other hand, for a fuzzy set, the MF may be represented as follows

$$\mu_B(x) = \begin{cases} f(x) & if\ b_1 \le x \le b_2 \\ g(x) & if\ b_2 < x \le b_3 \\ 0 & otherwise \end{cases}$$

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Actually, the crisp set is a special case fuzzy set whose MF returns only zero or one. There are many functions that are used as MFs. Some widely used MFs are Gaussian, Generalized bell shaped, Gaussian curves, Polynomial curves, Trapezoidal, Triangular and Sigmoid MFs. The Mamdani FIS approach (Mamdani and Assilian, 1975) is made up of a fuzzy inference engine characterized by the use of linguistic variables and carefully selected MFs and a fuzzy rule base. The rule base is a set of 'IF THEN' statements that capture experts' knowledge of logic governing the problem.

3.2 Resilience fuzzy inference system (R-FIS): Computer model

A computer model of the proposed R-FIS (Figure 6) was designed in the Matlab fuzzy logic development environment. The environment was adopted because it supports easy to use GUI tools and has multiple MFs for implementing a FIS. A process consisting of systematic review of the literature, interactions with experts, meetings with community leaders, interviews of other stakeholders and field observations would be used to gain insights for specifying the R-FIS's design and inference engine's elements (Table 1) as well determine appropriate IF THEN statements for the rule base (Table 2). With three input linguistic variables, each with three term sets (or possible values), there can be up to 27 explicit input variable combinations, or 27 explicit fuzzy rules combinations. Table 2 is a sample extract from the 27 'IF THEN' statements of the rule base.

Figure 7 shows the 3D surface plot resulting from an infinite combination of input factors. The shape of the resilience surface is determined by the rules (Table 2) and the selected membership functions (Table 1) used to express the term sets. This shape can be varied by modifying the membership functions, the term sets, the rules and their weights to reflect new realities and understandings about the resilience systems. This gives flexibility to simulate various combinations of parameters in order to arrive at an optimum design.

3.3 Model expert scoring framework

The objective of the FL implementation of the model is to have a framework that can use limited or fuzzy data and subjective estimates by experts of Hazard Absorbing Capacity (H), Resource Availability (G) and the Resource Utilization Processes (θ) of a target community as input for analysis. To realize this objective, extensive review of the literature was carried out to provide an informed basis for mapping FRM factors and inputs to the dimensions of resilience. This is summarized as shown in Table 3. Theoretically, the values of the dimensions H, G, θ can be estimated from adequate data on these input factors and appropriate functions.

Although information and explanations in Table 3, in principle, give a general guide for evaluating and quantifying these dimensional inputs of the resilience model, there is still the need for an easy to use operational template for capturing experts' input into the FIS in relatively standardized fashion. Table 4 is an example of such an input template designed for this study. Its application is described below with the case study communities.

4 Model Application: Study Location

The following describes the application of the model using three flood prone communities in the United State (U.S.). Following decades of experience in dealing with hazards and disasters, cities and institutions in the U.S. offer considerable information and insights in community resilience systems management Su, 2016b. Two coastal states of North Carolina and Virginia are home to many flood prone communities of various sizes with diverse socio-economic and techno-ecological characteristics that readily lend themselves to a study of resilience. Both states have adopted a number of FRM programs, policies, and strategies for building flood resilience across many rural and urban communities. Specifically, Norfolk, VA a coastal city in Virginia with a massive naval base, Greenville, NC, a large university town, and Windsor, NC a small riverine rural town were selected (Figure 8). Table 5 summarizes some vital socio-economic features of these communities.

Norfolk, located on the Chesapeake Bay and near several rivers, experiences precipitation flooding, when the intensity of rainfall exceeds stormwater drainage capacity, storm flooding from hurricanes and nor'easters, and tidal flooding due to its elevation and coastal location. Greenville, with relatively flat topography is located on the Tar River and is traversed by a number of small streams. Besides riverine flooding, the relatively flat topography of its coastal plain location leads to flooding from intense or longlasting rain events such that the stormwater system is incapable of handling the overland flow. Located on the meandering Cashie River in eastern North Carolina, Windsor has experienced four major floods since 1999, all from tropical storms. Thus, not only are the communities different demographically, but they have rather different flood regimes and histories.

4.2 Model application: results

For the purpose of illustration, hypothetical input scores were developed using the template shown in Table 4, the scoring guidelines summarized in Table 3, and the communities' information captured in Table 5. Table 6 shows the results. Norfolk and Greenville both have relatively high hazard absorbing capacities, with Norfolk rated as slightly lower owing to problems associated with the disruption that regularly occurs from overland flooding combined with tidal flooding. Windsor's is lower that Norfolk and Greenville but still moderate because of how the community has adapted to its flood risk. Not surprisingly, Norfolk has the highest resource availability and Windsor the lowest based on their size and relative wealth. At the same time, for the illustrative purposes here, size and diversity of the communities are seen to be inversely related to resource utilization processes. The model output, Resilience Index R, indicates that, based on the input values, Grenville's resilience is slightly greater than Norfolk's while, not surprisingly, Windsor lags rather far behind.

The input to output mapping implemented in Matlab fuzzy toolbox allows for infinite combinations of input factors either by sliding or inputting the respective input variable axis on the fuzzy rule interface. Figure 9 is a snapshot of the input combinations for Greenville, using the scores from Table 6. The vertical bar (red line on each) can be moved to indicate how resilience changes with a change in one or another (or all) of the three variables. The yellow shapes indicate the rules (see the subset in Table 2) that contribute to each variable's score. All of the output, in both Table 6 and Figure 6, is based on expert insights and understandings and thus provides a dynamic template to measure resilience under different conditions.

5 Discussion and Conclusions

This study discusses the need for an acceptable template to measure flood resilience. As such, it examines the challenges, conceptual constraints and construct ramifications that have complicated the development of an operational framework for measuring the resilience of communities prone to flood hazard.

Although the proliferation of conceptual models and frameworks for understanding resilience has indeed posed some challenges for development of an acceptable scenario-based measurement framework, there has been evidence of rich multidisciplinary insights resulting from the continuously evolving collaborative platforms for driving resilience research, policy and discourse. The review of literature and existing policy instruments reveals the emergence of definitional and conceptual convergence. Hence towards achieving definitional clarity, the study recommends and adopts the National Academies' definition of resilience (NRC, 2012) as a robust and viable basis for developing a measurement model. Non-linearity, multiple feedbacks and complexity have made achieving computationally tractability and model validity major challenges. Complexity has been identified as a hindrance to achieving computational and operational practicality in many models. Therefore, the resulting conceptual framework was built using a minimum number of components and interactions in order to reduce model complexity.

There has also been the challenge of compatibility between the natural and human variables due to the well recognized complexity inherent in community resilience. The integration of both technical and non technical communal resiliency factors has been well documented in the literature. This study developed mathematical functions to establish logical relationships among key socio-technical parameters and quantities that characterize the community resilience system, thus infusing a theoretical basis into the framework.

In terms of insights, the resulting models provide some explanations into the relationships existing among resilience factors and dimensions. For instance, the importance of good community governance, processes and resource utilization systems becomes obvious in the various scenario analyses. For instance, the model was able to document the relative contributions of variables that contribute to or detract from resilience. Although only hypothetical values are used in the model tested here, it illustrates the relative impacts that varying levels of institutional strength and resource availability, for example, have on progress toward resilience at a place. Use of the model can then confirm the need to establish a minimum level of infrastructure and ecological defenses and buffers for any flood prone community before recovery efforts and investments can be effective.

While the study developed a template for data collection and illustrated its application, the template still relies on subjective opinions of experts which may be seen as a drawback of the model. Hence further research is suggested to explore the automation and standardization of the R-FIS input process by integrating with web based socio-economic and ecological rankings or indices of communities. Yet, from computational and operational perspectives, the adoption of a fuzzy inference system as an analytical tool is presented as a viable approach for harnessing the opinions and experiences of experts and residents. The R-FIS provides a pathway for dealing with challenges of data issues such as missing data, spatiotemporal variations, and the use of subjective information because the critical input variables are locally and/or contextually defined. Thus, the proposed framework offers a viable approach for measuring flood resilience even when there are limitations of data availability and compatibility.

Acknowledgements

This work is part of research carried out under the Fulbright African Research Scholar Program Award (2017/18) funded by the United States Government.

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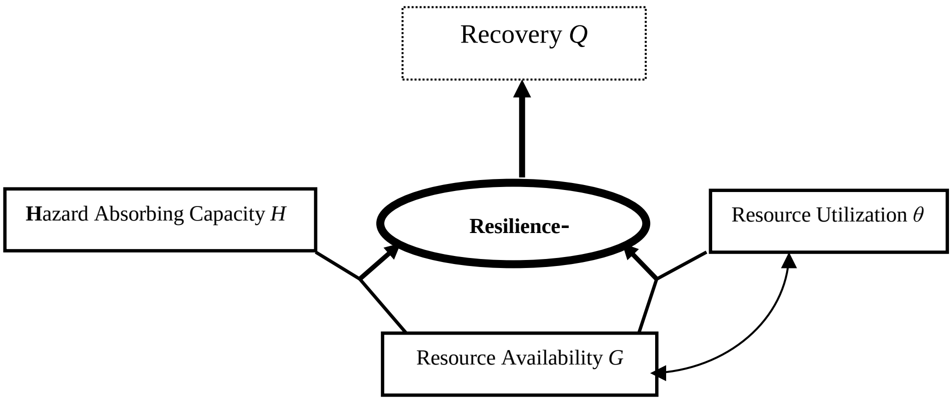

Figure 1: Resilience measuring conceptual framework

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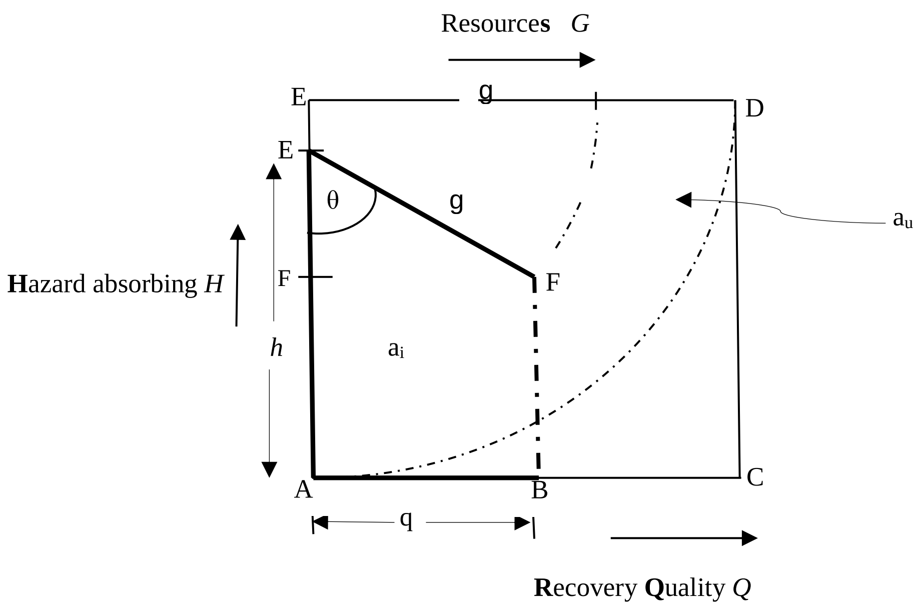

Figure 2: Resilience conceptual model

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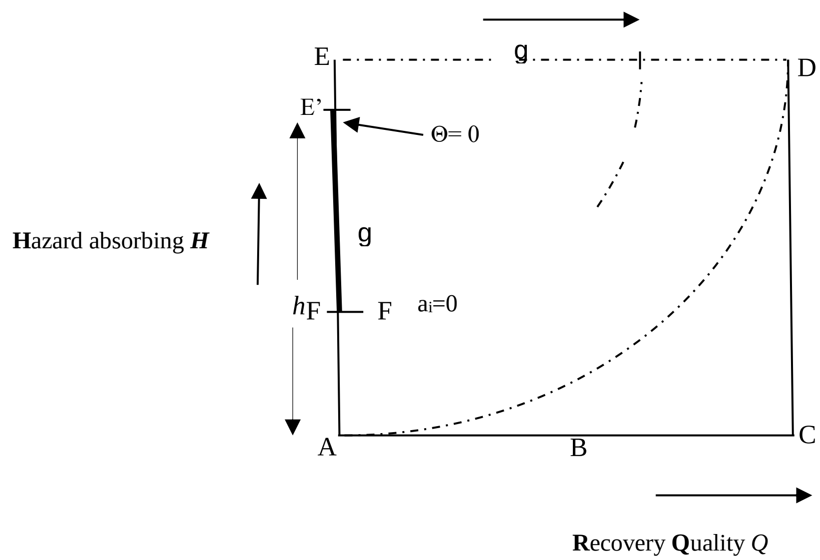

Figure 3: Resilience area = 0 when ρ= Sin Θ= 0

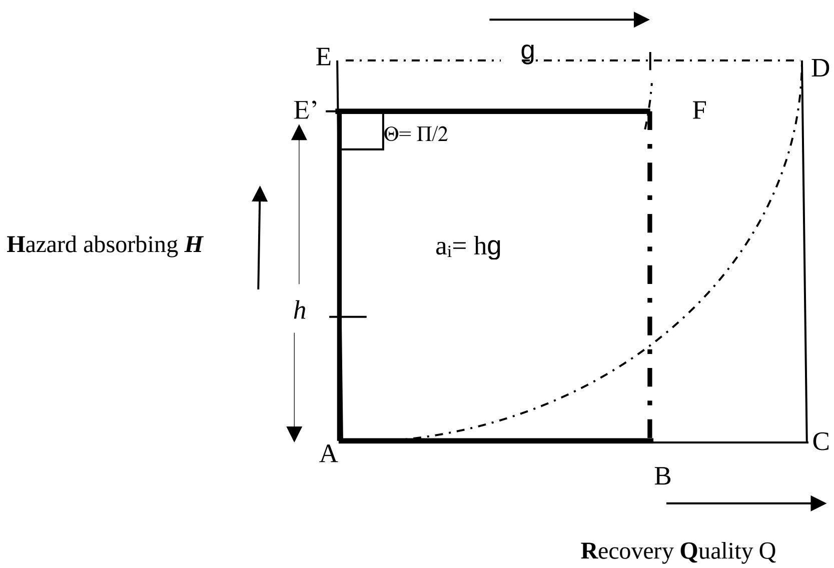

Figure 4: Resilience area (a_i = hg) maximizes recovery resources' g on absorbing capacity h

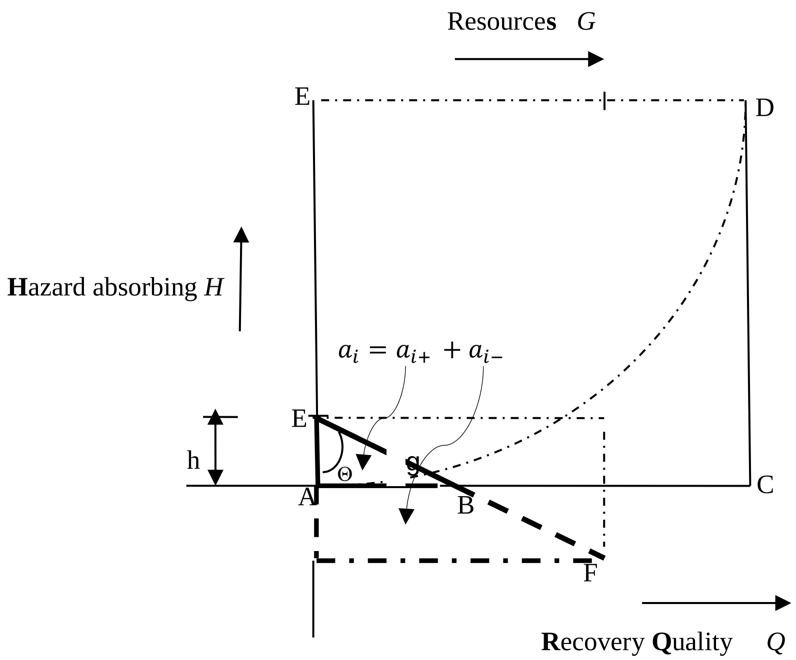

Figure 5: Resilience as Absorbing capacity approaches zero

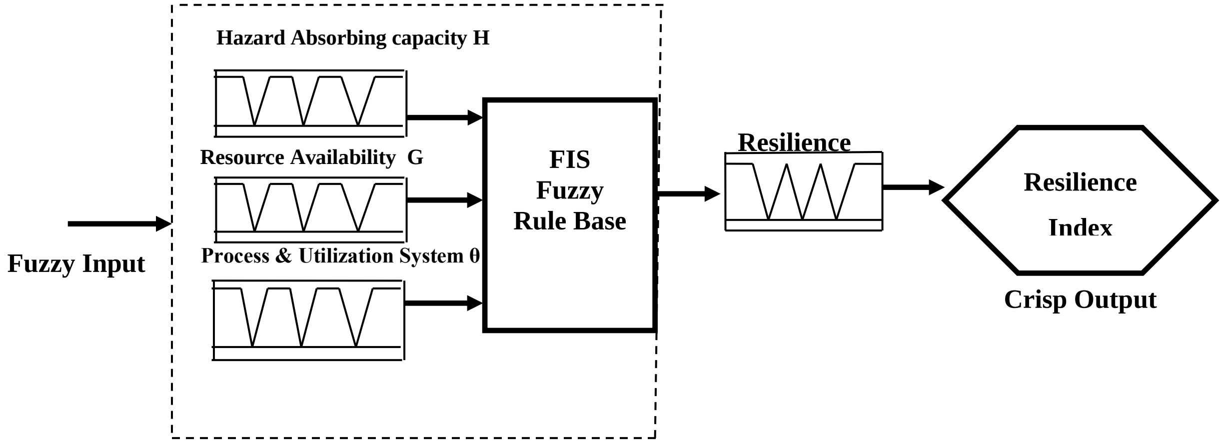

Figure 6 Resilience fuzzy inference systems

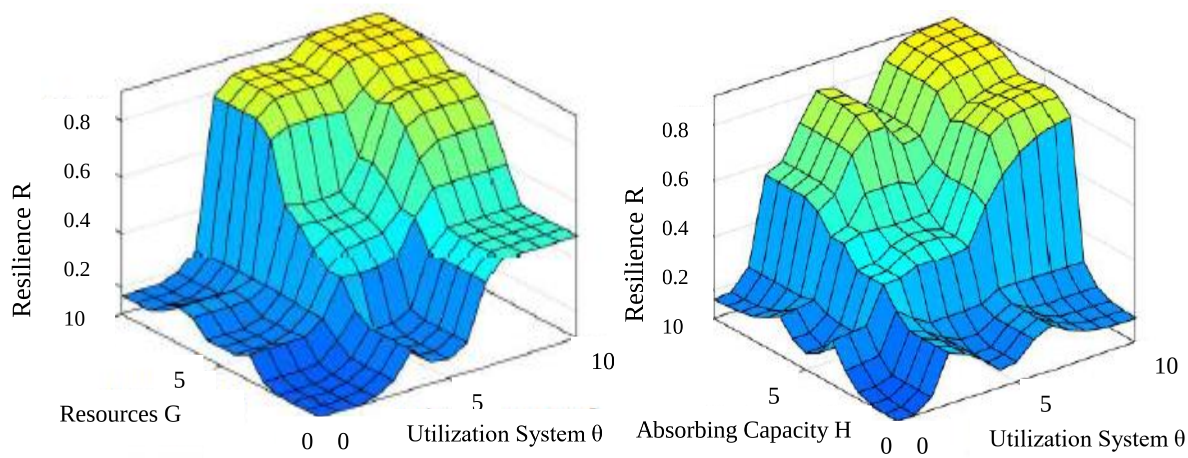

Figure 7 Resilience output surface plots

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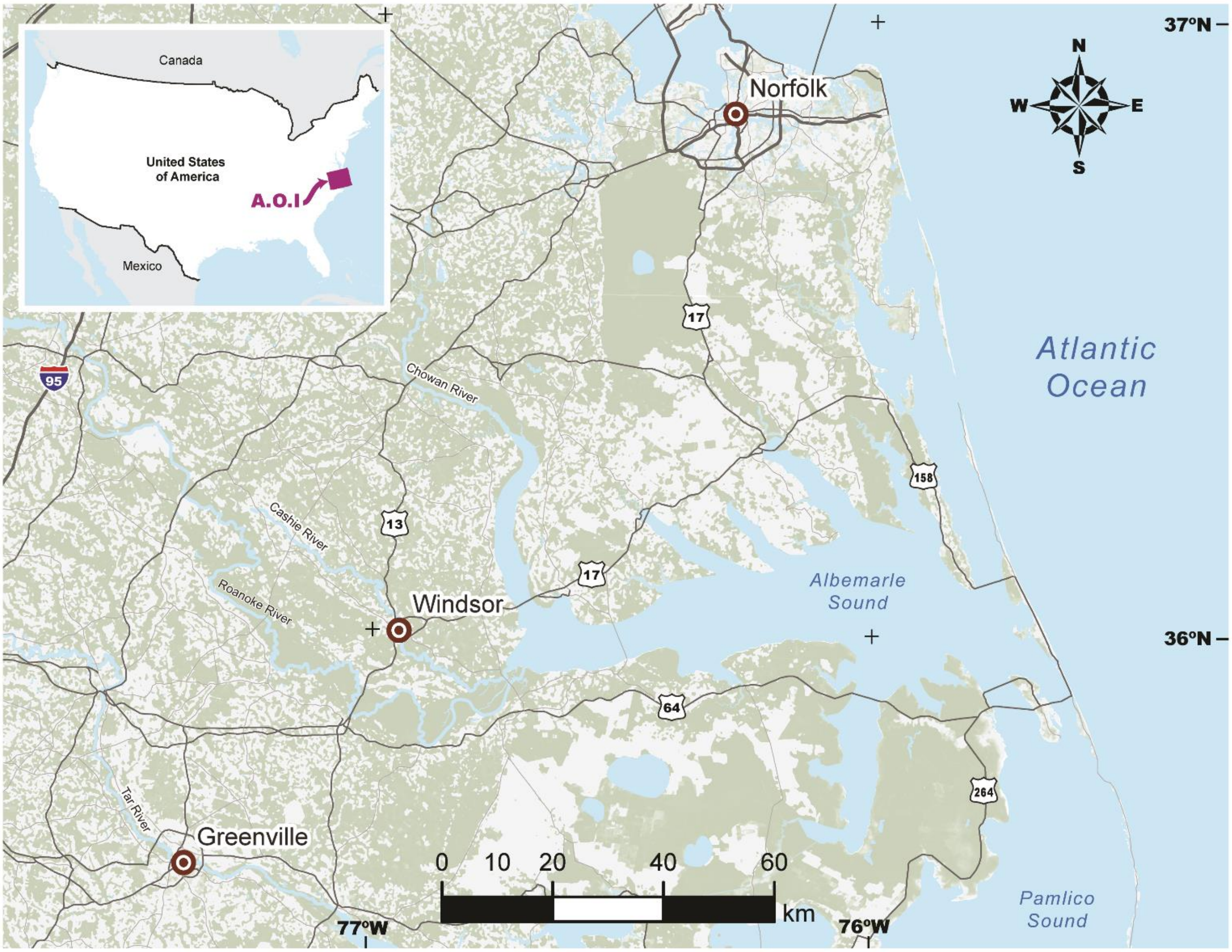

Figure 8. The study area

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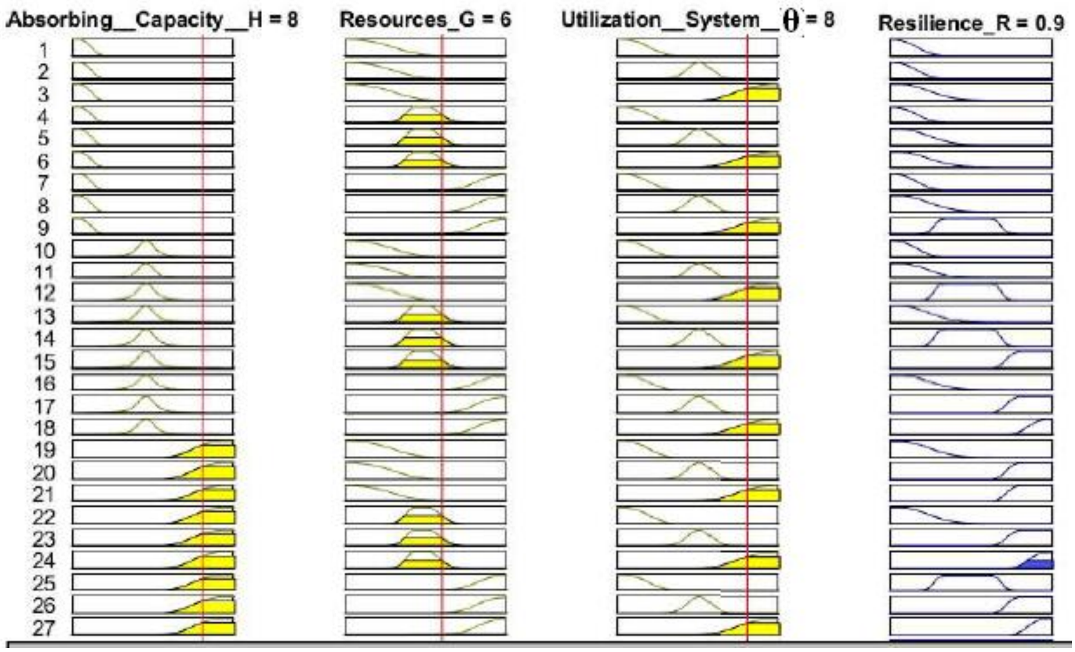

Figure 9: Rule setting and output for Greenville, NC

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Linguistic Variables	Term sets	Membership function
Hazard Absorbing Capacity H **Input 1**	Low	PiMfunction
	High	GbellMf
	Very High	SMfunction
Resource Availability G. **Input 2**	Very Low	ZMfunction
	Low	GaussianMfunction
	High	SigMfunction
Resource Utilization Processes θ. **Input 3**	Poor	PiMfunction
	Good	GaussianMfunction
	Excellent	PiMfunction
Resilience R_i **Output**	Very Low	Zmfunction
	Low	Gauss2Mfunction
	Moderate	GbellMfunction
	High	PiMfunction
	Very High	PiMfunction

Table 1 Fuzzy Inference Linguistic Variables Term set and Membership Functions

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Rules premise	Rules Consequence	Weight
If (**H** is Low) & (**G** is Very Low) & (θ is Poor) THEN	(Resilience is very low)	1
If (**H** is Low) & (**G** is Low) & (θ is Excellent) THEN	(Resilience is Low)	0.8
If (**H** is Low) & (**G** is High) & (θ is Excellent) THEN	(Resilience is moderate)	0.8
If (**H** is High) & (**G** is High) & (θ is Excellent) THEN	(Resilience is Moderate)	1
If (**H** is Very High) & (**G** is Very Low) & (θ is Good) THEN	(Resilience is High)	0.7
If (**H** is Very High) & (**G** is High) & (θ is Good) THEN	(Resilience is High)	1
If (**H** is Very High) & (**G** is High) & (θ is Excellent) THEN	(Resilience is Very High)	1

Table 2: Sample rules of the R-FIS 27 Rule Base*

*Rules and weights to be determined by experts and/or stakeholders

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Resilience Dimensions	Resilience input factors
1. Hazard Absorbing capacity **H**	1. Level of infrastructure in terms of sophistication and adequacy. Effectiveness of FRM measures such as flood and shoreline defenses, forecast and warning system, 2. Redundant capacities. Evidence of alternatives in critical utilities, evacuation routes, communication and energy infrastructures, hospitals, police posts, supermarkets. 3. Evidence of redundant housing capacity. 4. Ecological defenses and buffer. Evidence of complementary use of nature to improve threshold, e.g. using landscaping and topography, natural drainage and canals, vegetation cover, rain/storm water harvesting, permeable pavements, etc. 5. Residents coping capacity. Evidence of large portion of populace with previous flood experience, awareness, cohesion and place attachment 6. Evidence of stable or growing population in spite of past events. 7. Educational and literary level of populace 8. Evidence of social and communal clusters to enhance coping through support, meaning, avoidance etc., e.g. church, local sport team, ethnic clusters. 9. Presence of critical and strategic institutions of national importance, e.g. university, military base, major ports, etc. 10. Evidence of technology driven information dissemination. Eg social media, sms (Ashraf and Routray, 2013; Cohen et al., 2017; Esteban et al., 2013; Ibanez et al., 2004; Lee et al., 2013; Mavhura et al., 2013)
2. Resource Availability **G**	1. Evidence of budgetary provision for, or commitment to, flood risk management. 2. Evidence of thriving economic activities in the community, e.g. size of local GDP 3. Evidence of economic strength of residents, e.g. per capita income, income level, housing value, savings, cooperative societies, etc. 4. Evidence of political, institutional and economic influence that can attract grants and funds from national or regional sources, e.g. population 5. Evidence of adoption of flood insurance plans. 6. Availability of land for relocation development beyond or outside the flood plains. 7. Evidence of community capital and community natural assets accessible for reconstruction, e.g. forest resources, granite and quarry deposits. 8. Economic status of the ‘parent’ entity, e.g. the state’s or country’s GDP (Filion and Sands, 2016; Rose, 2017; Swalheim and Dodman, 2008; Thomas and Mora, 2014)
3. Community Processes and Resource Utilization **θ**	1. Evidence of good governance 2. Level of ease of doing business 3. Evidence of strong institutions such as judiciary, police, media, and public service 4. Evidence of culture of law and order. 5. Ranking of internationally recognized bodies like Transparency International, World Bank, UN, CIA, etc. on the above (Begg et al., 2015; Brown and Williams, 2015; Cohen et al., 2016; Rose, 2017; Tompkins et al., 2004)

Table 3 Resilience Dimensions Input Factors

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Linguistic Variables Dimension	Tick the grey box next to your linguistic rating		Tick the grey box that best reflect your score of your linguistic rating						
Hazard Absorbing Capacity **(H)**	Low		1		2		3		
	Moderate		4		5		6		
	High		7		8				
	Very High		9		10				
Resource Availability **(G)**	Low		1		2		3		
	Moderate		4		5		6		
	High		7		8				
	Very High		9		10				
Resource Utilization Processes **(θ)**	Poor		1		2		3		
	Good		4		5		6		
	Very Good		7		8				
	Excellent		9		10				
Location/city									
Date of assessment									
Assessors' name									

Table 4 Linguistic Variables Input Template (Use attached explanations as guide in rating)*

*Table 3 can be attached to this scoring template as a guide

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	Windsor NC	Greenville NC	Norfolk VA
Location type	Small town	City	Large city
Types flood	River/storm/ rain	River /storm/ Rain	Coastal /river rain/storm
Total Population	3,630	84,554	242,803
%Male	59.3	45.8	51.8
%Female	40.7	54.2	48.2
Median income *	29,063	34,435	44,480
Poverty rate *	27.8	32.5	21
Median Age	38.6	26.0	29.7
%Under 14	12.4	15.9	17.7
%75 above	8.7	4.3	4.6
US Citizenship *	97.9	96.8	96.6
Non English speaking *	5.83	6.74	10.3
No of Households	1088	36071	85485
%Family household	61.2	46.3	58.7
Average household size	2.29	2.18	2.43
%Household with individuals above 65	34.1	14	20.3
No of Housing units	1193	40564	95018
% of housing units occupied	91.2	88.9	91.0
Mean property Value*	93800	147100	193400

Table 5 Study Locations: Demographic Summary

*Source http:// census.gov

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Experts Scoring / Community	**Model Input**						**Model Output**
	Hazard Absorbing Capacity **(H)**		Resource Availability **(G)**		Resource Utilization Processes **(θ)**		Resilience Index **R**
	Linguistic Score	Score	Linguistic Score	Score	Linguistic Score	Score	
Norfolk, VA	High	7.0	High	8.0	Good	6.0	**0.836**
Greenville, NC	High	8.0	Moderate	6.0	Very Good	8.0	**0.9**
Windsor, NC	Moderate	4.0	Low	2.0	Very Good	8.0	**0.477**

Table 6 Input Scoring and R-FIS Resilience Index Output