Modeling Social Resilience in Communities

Eunice E. Santos, *Senior Member, IEEE*, Eugene Santos, Jr., *Fellow, IEEE*, John Korah, *Senior Member, IEEE*, Jeremy E. Thompson, *Graduate Student Member, IEEE*, Yan Zhao, *Graduate Student Member, IEEE*, Vairavan Murugappan, *Graduate Student Member, IEEE*, and Jacob A. Russell

***Abstract*— One of the primary challenges of modeling the social resilience of communities is that resilience may depend on a number of multidomain factors, ranging from ecological to political. In addition, the impacts and interactions of the relevant factors may not be fully understood. There is also the challenge of representing the intricate behaviors of the social actors, both individuals and groups, in order to model their responses to perturbations in the environment and to internal changes. In light of these challenges, current works tend to make a number of simplifying assumptions. In this paper, we propose a computational framework to formulate multiple resilience functions, each modeling a particular hypothesis about the system's resilience. One of our key contributions is the ability to use social theories to compose these individual resilience functions into an umbrella resilience function, while providing qualitative analysis. We validate our framework by modeling the resilience of a fishing community in Somalia over the period of 1999–2012, as it underwent a series of dramatic ecological, political, and economic changes. We formulated resilience functions to computationally model the competing support for the community's traditional occupation of fishing and alternatively for taking up piracy on the high seas. We then provide an overall resilience function by combining these individual resilience functions using social theories such as the social norm theory and risk theory.**

***Index Terms*— Bayesian knowledge bases (BKBs), community resilience, computational modeling, resilience function, social norms, social resilience.**

I. Introduction

SOCIAL resilience is defined by Adger [1] as the "ability of groups or communities to cope with external stresses and disturbances as a result of social, political, and environmental change." Social resilience can provide important insights into problems of great interest in the field of computational social systems, including understanding how communities respond to natural disasters and changes in ecology [2], [3]. Incorporating social resilience into existing methodologies for well-studied problems such as group formation [4] can also provide more realistic models for scenarios, where individuals contend with myriad centrifugal and centripetal social forces that form part of a social group's resilience. However, current work on social resilience has been mostly conceptual [5], aiming to provide qualitative explanations for factors and processes that impact social resilience. What is lacking is a generic modeling methodology for social resilience incorporating a wide variety of relevant factors and system information, while dealing with the dynamism seen in real-world scenarios, and simultaneously providing quantitative analysis and, notably, explanations.

An overarching computational framework for social resilience must tackle inherently complex and unique modeling challenges. First, resilience within a social system may be the result of multidomain factors (including economic, political, and ecological factors). Mathematically, the overall resilience exhibited by a system could be represented as a combination of interacting resilience functions. Although there are conceptual models that represent resilience as a set of interacting processes [6], little work has been completed in incorporating these into computational models without simplifying assumptions. Second, there may be competing hypotheses or assumptions (born out of observed data or an applicable social theory) about the relevance of factors and their interactions. Thus, we suggest an overarching framework must define and computationally represent multiple resilience functions based on specific hypotheses, and utilize them to construct an overall resilience function. In addition, factors impacting social resilience may switch between active and inactive states over time, and also change how they interact with each other. Finally, there are difficulties imposed by the uncertainty in individual and group behaviors, and by incomplete social information.

In this paper, we present an overarching computational framework for social resilience composed of multiple resilience functions, where each function represents a specific aspect of resilience. To manage the uncertainty of social behavior and the incompleteness of modeling data, we represent available sociocultural information, applicable constraints in social behaviors, relationships provided by relevant social theories, insights provided by subject matter experts (SMEs), and/or other key information using a probabilistic framework, such as a Bayesian knowledge base (BKB) [7]. The resilience of the social system is a result of the interactions of various entities, in the forms of individuals and groups, represented with BKBs. The interactions between these entities can be implemented in our modeling framework by using BKB fusion algorithms [8], which combine fragments to reflect aggregate behaviors.

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E. E. Santos, J. Korah, and V. Murugappan are with the Department of Computer Science, Illinois Institute of Technology, Chicago, IL 60616 USA (e-mail: Eunice.Santos@iit.edu; john.korah@iit.edu; vmuruga1@hawk.iit.edu).

E. Santos, Jr., J. E. Thompson, Y. Zhao, and J. A. Russell are with the Thayer School of Engineering, Dartmouth College, Hanover, NH 03755 USA (e-mail: Eugene.Santos.Jr@dartmouth.edu; jeremy.e.thompson.th@dartmouth.edu; Yan.Zhao.TH@dartmouth.edu; Jacob.A.Russell.TH@dartmouth.edu).

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At this juncture, it is prudent to mention the contributions of this paper. In short, the contributions are as follows.

1) The capability to integrate multiple hypotheses about the resilience of a system as one or more resilience functions and their compositions, by employing social theories is demonstrated. A more detailed discussion is provided in Section IV-E, after sufficient details of the framework have been discussed. Note that for this effort, theories on social norms and risk analysis were employed, but, as conceived, the framework could integrate any theories deemed relevant to the scenario.
2) We demonstrated how resilience values can be computed using our framework.
3) Key aspects of the social resilience model, including the selection of social theories to tie the individual resilience functions together, are demonstrated.
4) The validation resulted in an initial set of resilience functions and measures (see Section V-C), which provides a foundation for more sophisticated resilience models.

Details of the framework and experimental validation are described in the following sections.

II. Current Work

The concept of resilience has been used in many disciplines to model the robustness of a system. In this section, we provide examples of models and metrics that were formulated for studying resilience in systems ranging from engineering systems to more complex social systems.

Engineering systems are designed to operate around one or more equilibrium points and, as such, their resilience measures are qualitatively defined as the ability to absorb perturbations and subsequently return to the previous stable state or equilibrium [5], [9]. One quantitative metric commonly used to measure engineering resilience is the magnitude of the force absorbed while still recovering [10], another is the magnitude of the resulting deformation, and a third is the recovery rate [9]. In social systems, researchers have applied engineering resilience by looking at resilience in social networks. One statistic used is minimum m-degree [11], the minimum number of edges that must be removed to separate the network into two components with exactly m vertices.

However, engineering resilience measures cannot capture the resilience seen in complex systems, where a system's reaction to change can involve a transformation of form and function. Complex systems are highly adaptive and can have fitness landscapes with multiple equilibrium points [12]. Dynamic system theory has been used to define the concept of resilience in complex systems, commonly termed adaptive resilience, in terms of stability landscapes and basins of attraction [12]. A stability landscape is determined by the values of state variables which change over time. The landscape is characterized by basins and their attractors. Resilience metrics that are qualitatively related to the depth and width of the basins were identified. In a related work, Bruneau *et al.* [13] propose quantitative measures based on four properties of resilience—robustness, rapidity, resourcefulness, and redundancy. They also identify analytical steps for measuring the performance of these properties. Ayyub [14] proposes a measure for the resilience of a multihazard environment using a performance-based approach. However, this model only provides a static resilience measure. Chang and Shinozuka [15] proposed a methodology where they measure the performance of a system during a disaster event versus during normal operations, and quantify the difference and the recovery time as the resilience measure. Similarly, Cimellaro *et al.* [16] provide an analytical method for representing resilience during natural and man-made disasters as mathematical functions. These functions consider the loss in functionality caused by the disasters. However, when modeling complex scenarios, required data are often incomplete and uncertain. Thus, defining loss and recovery functions according to the above methodology is challenging. Finally, Gao *et al.* [17] present an analytical methodology for representing the resilience of multidimensional systems where the components interact through a complex network. Here the resilience of interlinked networks is collapsed into a single universal function that is independent of the network topology and is determined by the system's dynamics. However, each system or scenario requires the formulation of unique mathematical equations and analysis techniques to represent the relevant actors, forces, and networks within that situation. A similar approach is taken by Bozza *et al.* [18], who use multiple networks, multiple reward functions (figures of merit), and agent-based simulation to estimate resilience.

Following the work from Gunderson [19], who pointed out that uncertainty is a critical aspect to modeling resilience, many works in ecology have striven to overcome this challenge while modeling resilience. Marshall and Marshall [20] model the resilience of fisheries using questionnaires, and reduce dimensionality via principal component analysis, identifying four major domain-dependent components. They followed this paper with a case study to validate their model. However, responses to survey questions are taken as ground truth as to whether a stakeholder is resilient [21], and the work does not make an effort to generalize beyond formulation of resilience policy. Machine learning and statistical methods have been applied in ecology as well. For example, Frey and Rusch [22] applied neural networks to analyzing the relationships between common pool resource lists of factors that were found to be significant from inventories; however, this paper only identifies how factors might be related and any predictions that the system gives are difficult to interpret and have high error rates (36%). In related work, Weirich *et al.* [23] used generalized linear models over time series to assess the resilience of wastewater treatment plants. These approaches are useful in identifying key factors and how the factors relate to each other. Our approach differs in that we use available (quantitative and qualitative) data and SMEs to model how factors interact with each other. Moreover, when SMEs disagree, we combine their opinions via a process called fusion [24]. Factors from these other approaches can also form variables within our model. The goal is not only prediction of when the system is resilient, but more importantly to understand and explain why the system is resilient. Resilience models, we have found, focus on one or the other.

Researchers have also studied the psychological resilience of individuals. For example, Ungar [25] studied the impact of social and physical ecologies on personal psychological resilience. Ungar presented four basic principles for an ecological interpretation of the resilience construct: decentrality, complexity, atypicality, and cultural relativity. These factors informed a definition of resilience that emphasizes the environmental antecedents of positive growth for individuals. Bonanno *et al.* [26] applied multivariate models to examine potential predictors of psychological resilience using large-scale survey data after the 9/11 terrorist attack. They found that several factors, including demographics, depression and substance use, resources, and additional trauma exposure and life stressors, are significantly associated with psychological resilience. Another important approach is the study of stress within individuals caused by the presence or absence of resources. Resources are broadly defined as factors, including social, economic, and personal factors that have an influence on an individual's stress. For example, Hobfoll's [27] conservation of resource (COR) theory postulates that loss of resources leads to an increase in stress. COR theory also states that individuals take steps to reduce or reverse the loss by recouping the resources or acquiring alternative resources. Recent works in the allostatic theory [28] have looked at integrating such social theories in modeling the brain's role in regulating emotions to deal with stress. Although psychological resilience models have provided significant insights in understanding behaviors, they focus on individual resilience, even while incorporating social factors [25] and not on the resilience of social groups. In the current version of our model, we did not focus on these individual level factors for several reasons. Most significantly, surveys of individuals in the community are required to identify factors critical for modeling psychological resilience. This is not possible or practical in real-world scenarios from troubled parts of the world, such as that used in our work. In contrast to the objectives of the many works in the psychological resilience domain, our work focuses on understanding how social and cultural influences impact the overall resilience of a social system. Resilience in social systems is especially complex due to the interactions of social actors and their autonomy in decision-making. Analyzing community resilience requires modeling the social system, which is dynamic and multilayered [29]. Social systems can be highly dynamic, resulting from pressures to change from both endogenous and exogenous factors. Endogenously, the beliefs and goals of individuals can change over time, leading to changes in the social system. Likewise, tribes, communities, and organizations can be exogenously affected [30] due to political, economic, or ecological forces, among others, which in turn affect the behavior of individuals or groups, which can subsequently translate to societal changes. Such are the considerations to be weighed when modeling social resilience.

III. Technical Background

Before we discuss our resilience framework, we introduce key mathematical methods that we use to represent the sociocultural information of the scenario and to analyze the resilience. We represent the sociocultural information using (BKBs) [7]. A BKB is an established probabilistic reasoning structure used to represent uncertain behaviors. BKBs are particularly well-suited because they provide the ability to explain which factors, or which arguments, were important to the conclusions reached during analysis. BKB reasoning algorithms [7] also help in quantifying resilience measures in our framework.

A. Bayesian Knowledge Bases

The following background discussions on BKBs have also appeared in a work by Santos and Santos [7]. A BKB is a directed, bipartite graph G consisting of instantiation nodes (I-nodes) and support nodes (S-nodes). Each I-node is an instantiation of a random variable written as $R = v$, where R is the random variable and v is the value of the variable in that instantiation. Each S-node q in the correlation graph G is assigned a weight $w(q)$, which represents the conditional probability of the I-node following q, given the preceding I-node. BKBs can also be described as "if-then" rules, where each S-node q in a BKB $K = (G, w)$ corresponds to a conditional probability rule. We can fuse several related BKBs into a single BKB through a process called BKB fusion, as described by Santos *et al.* [24]. Belief updating is used to perform posterior analysis. Belief updating calculates the probability of a random variable in the BKB having a certain state, given the evidence. A detailed description of the Bayesian updating algorithm for BKBs is provided by Santos and Santos [7].

B. Cultural Fragments

A key factor that characterizes actor behaviors and interactions is culture. We define culture as any behavior learned, or knowledge gained, from our environment [31]. Culture influences the intent, decisions, and actions of actors. Hence, having the capability to systematically incorporate relevant cultural information is essential to effectively model and analyze social organizations. Incorporating cultural information is a challenging task, since available information is often incomplete and uncertain.

We address this challenge by using BKBs to represent cultural fragments. BKBs model cultural factors of actors and organizations as causal chains between the variables that represent axioms, beliefs, goals, and actions. Axioms represent the actors' perceptions about themselves. Beliefs refer to the perceptions one actor has toward other actors and the environment. Goals denote the end states an actor would like to attain. Actions indicate the choices and activities available to achieve an actor's goals. Intent [32] is used to map relevant cultural factors to an individual's or a group's behavior. The intent model prescribes the set of rules for interconnecting axioms, beliefs, goals, and actions. It also aids in understanding the observed behavior. Cultural factors and their relevance to actors' behaviors vary based on the scenario. To incorporate the effects of these diverse factors, the Bayesian fusion algorithm is used to combine several cultural fragments into a single BKB.

Consider Fig. 1, for example. Fig. 1 illustrates a simple cultural fragment designed for a fictional, aspiring graduate

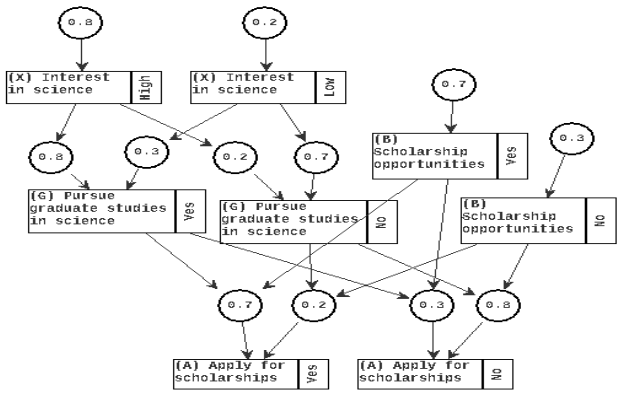

Fig. 1. Sample cultural fragment.

student scenario. As a standard, we prefix belief random variables with "(B)," axioms with "(X)," goals with "(G)," and actions with "(A)." According to Fig. 1, if this student possesses a self-belief (axiom) that indicates a keen interest in science, then he or she is highly likely to have a goal to pursue graduate studies in science. Conversely, if the student has a low interest in science, then he or she is unlikely to pursue graduate studies in science. Similarly, if the student has a goal to pursue graduate studies and believes scholarship are available for a graduate program, then the student is likely to apply for scholarships.

IV. Social Resilience Modeling Framework

Social systems represent one of the most challenging domains for computational resilience modeling. We quantify social resilience using a set of resilience functions. A resilience function is defined as a mapping from a set of states of social-economic factors to a continuous variable ranging from 0 to 1, where 0 indicates least resilient and 1 indicates most resilient. Each resilience function describes a community's resilience from a different perspective. To model a community's overall resilience, we group multiple resilience functions into a single umbrella function by considering the interactions of predictor variables in each aspect of resilience. This umbrella resilience function collectively determines a community's overall resilience. As complex adaptive systems [33], social systems consist of entities, each with distinct behavioral characteristics, interacting with each other and responding to changes in the environment. Consequently, it is possible there are multiple resilience functions operating within the systems, and it is the interaction between these functions that gives rise to the overall resilience of the systems. The key research questions then become what needs to be represented in these individual resilience functions and, even more critically, how to compose these functions to form an umbrella resilience function.

To model social resilience for complex real-world scenarios, it is vital to overcome several modeling challenges. These include the following.

1) *Multidomain Factors:* Case studies [3], [30] have shown that resilience in social systems can be dependent on a large number of multidomain factors, whose impacts and interactions may not be well-understood. These interactions and behaviors may, in turn, reinforce or weaken system resilience. A team of SMEs may thus be required to understand their impacts, which adds subjectivity to the modeling process.
2) *Multiple Resilience Functions:* Current computational models for social resilience are restrictive and may not provide adequate explanations for all aspects of resilience in a system. Moreover, creating an overarching resilience function from the ground up may not be feasible due to numerous underlying factors and their interactions. Therefore, a modeling framework that can integrate individual resilience functions into an overarching resilience function is desired.
3) *Incomplete Information:* Sociocultural information on scenarios is often incomplete, missing information on factors relevant to the resilience being measured. Extensive quantitative studies may not be available, and so modelers may need to employ qualitative or anecdotal information. The social group under study may also not be accessible for extensive field studies. In such cases, approximations of factors must suffice.

In this section, we present a modeling framework that overcomes these challenges. Our key insight behind this framework is to utilize social theories to compose multiple resilience functions into a single overarching resilience function. The framework is generic and can support various mathematical and computational methods to represent resilience information. In addition, our framework provides formalism on defining resilience functions and directions on how to use social theories to compose an umbrella resilience function. In the remainder of this section, we provide a description of our modeling framework, and detail our method for computing the resilience values.

As stated previously, one strength of our framework is the capability to design new computational models while also leveraging the existing work. To achieve this level of flexibility, our framework has four components, each encapsulating key capabilities. Our framework accommodates the fact that multiple models, based on different collections of sociocultural information, social theories, and system constraints, can be constructed for the same social system and scenario. For each of these models, a set of resilience functions, based on varying hypotheses about resilience, can be formulated. The framework provides the capability for the system model to expose relevant factors and interactions for utilization in the resilience functions. A collection of relevant social theories is presented and serves to provide the critical underpinnings for composing multiple resilience functions into an overall resilience function. We allow for the incorporation of social and/or resilience theories at different points in the framework to provide broader capabilities for modeling, testing, and evaluation. For example, if a particular resilience concept that does not vary with different resilience formulations is used, our framework allows for the possibility to incorporate it within the system model itself. On the other hand, if we are testing the utility of a resilience concept for a given scenario, then it may be incorporated during the formulation of a resilience function.

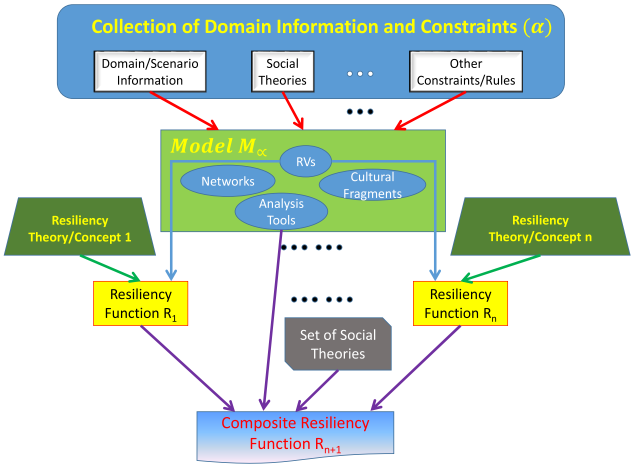

Fig. 2. Social resilience modeling framework.

A detailed account of the key components of our framework architecture (see Fig. 2) is provided below.

A. Collection of Domain Information and Constraints α

This collection represents the available relevant information for modeling a social system S in a selected scenario. We denote this collection as α. Collection α encapsulates a variety of behaviors of individuals, groups, and other social entities within the system, both under broad and specific contexts. It also includes their responses to disturbances in the environment. For example, the behaviors of the system may be either considered under broad contexts, such as its resilience to changes in the national economy, or under specific contexts, such as its resilience to fluctuations in specific local real estate values. Naturally, this affects the scale and detail of the information that must be collected. The information in the collection may be represented in a variety of formats. The domain information for a scenario may be directly retrieved from field studies conducted on location, or derived from other forms of data, such as census information. The data may also be qualitative, in the form of opinions from SMEs, which can help to inform the impact of certain factors on the resilience of the system. Collection α also contains constraint information that aids formulating more realistic models. This might be in the form of qualitative or quantitative relationships between factors that help to filter out implausible behaviors. Constraint information will also assist in identifying the regions or ranges for relevant factors. Social theories that provide additional insights into behaviors or fill in gaps in our information also form part of the collection. Note that information can be gathered from multiple sources with varying reliability. Moreover, the information could be fragmentary and incomplete. The challenges of reliability and incompleteness need to be considered, as α is used to build the model for the scenario. Since social systems are also dynamic, and the impacts of factors and their interactions can change over time, α should include data that will help to model these changes.

B. Model M_α

Model M_α, denoting a computational model of the social system, is formulated using the information and constraints provided in collection α. M_α can contain multiple knowledge representations and submodels. Although different models, of varying complexity and detail, can be potentially built using collection α, its utility toward the formulation of resilience functions should be the guiding principle behind model formulation. Focusing on those factors and behaviors that have an impact on how the social entities within the system respond to both internal changes and external disturbances will help to guide the modeling process. The events in the scenario also shape the model, as they point to response behaviors to be included. As such, in our experimental validation involving the Somali fishing community, we focused on those factors within the community, such as fishing infrastructure and religious values, which were impacted due to the changing conditions.

The framework can support a wide variety of knowledge representations, including semantic networks to represent relationships between concepts and Bayesian approaches to represent causal relations. Moreover, our framework also supports the utilization of both existing modeling techniques, such as agent-based models and social network models, and new modeling techniques, to represent the relevant actors and their behaviors. Although the framework can support a wide variety of submodels and knowledge representations, clearly there are certain desired characteristics of M_α that are particularly useful for designing effective resilience functions. For example, the utility of M_α is enhanced by the use of knowledge representations and submodels that allow variables and relationships to be easily identified and mapped to resilience functions. Another desirable characteristic for M_α is the ability to represent and model social behaviors, at relevant temporal and spatial scales, which are useful in the formulation of resilience functions. In addition, employing methodologies in M_α amenable to appropriate reasoning and analysis methods will also aid in the formulation of useful resilience measures.

For instance, in our experimental validation, we selected cultural fragments, described in Section III-B, and BKBs, described in Section III-A, to represent complex and dynamic social behaviors in the form of an entity's beliefs, goals, and actions, and to connect them to their underlying sociocultural factors. We decided to utilize BKBs and cultural fragments, as they allow for the application of probabilistic reasoning algorithms within our model M_α, and to in turn allow for quantitative measures of resilience.

C. Resilience Functions $\{R_1, \ldots, R_n\}$

Using computational representations and submodels within M_α, our framework supports the formulation of multiple resilience functions which may be based on varying hypotheses about which factors and interactions impact the system's resilience. Our framework also supports a broad set of methodologies, ranging from a weighting system to more sophisticated statistical techniques, to formulate and refine resilience functions. We present below one possible design for resilience functions that provide measures which can be used to perform analysis, such as comparative and explanatory analysis, of the system's resilience.

1) In this design, which is also used in our experimental validation, we leverage BKB methodology to define

TABLE I
EXAMPLE OF A METHOD FOR COMPUTING VALUES OF RESILIENCE FUNCTION R_i

RESILIENCE-COMPUTE($K, \mathbb{E}, F_i, C_i$)
$F_i^{in} = \Phi$, // Set of target variables satisfying constraints
$F_i^{out} = \Phi$, // Set of target variables not satisfying constraints
FOR each factor $f_{i,l} \in F_i$
If CHECK-CONSTRAINT($K, \mathbb{E}, f_{i,l}, c_{i,l}$) is TRUE
$F_i^{in} \leftarrow f_{i,l}$
ELSE
$F_i^{out} \leftarrow f_{i,l}$
END FOR
IF $\lvert F_i^{in} \rvert == \lvert F_i \rvert$ // all constraints have been satisfied; system is resilient
Resilience value=RESILIENCE-VALUE($K, \mathbb{E}, C_i, F_i^{in}$)
ELSE //system is not resilient
Non-resilience value=RESILIENCE-VALUE($K, \mathbb{E}, C_i, F_i^{out}$)

a resilience function $R_i : (K, \mathbb{E}, F_i, C_i) \to [0, 1]$, where K is a set of BKBs, $\mathbb{E}$ is its corresponding set of evidence variable instantiations [7], F_i is the set of target variable instantiations (factors relevant to the resilience function), and C_i is a set of constraint functions. The evidence variable instantiations set $\mathbb{E}$ contains information that is known with high certainty, thus pruning possible states in the BKB K. The target set $F_i = \{f_{i,0}, \ldots, f_{i,l}, \ldots, f_{i,|F_i|-1}\}$ represents factors that we selected based on available information, initial assumptions, and/or recommendations from SMEs, and which are considered to have an impact on resilience. Similar concepts of constraint functions have been used in the dynamic systems area based on the idea of resilience basins or wells, which are regions within which the system is considered resilient [12]. We define the set of constraint functions $C_i = \{c_{i,0}, \ldots, c_{i,l}, \ldots, c_{i,|F_i|-1}\}$, where $c_{i,l} : (\mathbb{E}, K, W_l) \to \{0, 1\}$ is the constraint function for a target variable $f_{i,l} \in F_i$. Here, W_l represent the relative importance of the target variable. The constraint function C_i is said to be satisfied if $\forall c_{i,l} \in C_i, c_{i,l} \to 1$. As shown in Table I, a system is considered resilient with respect to a resilience function if all its factors satisfy their respective constraints.

As mentioned before, the design described above is only one of the many possibilities within our framework. Different types of complex resilience functions, including those that incorporate other types of information such as factors varying over time, etc., can be formulated within our social resilience framework.

D. Composite Resilience Function R_{n+1}

The key insight in our resilience framework is to use social theories to formulate a composite resilience function from individual resilience functions. When constructing such a composite function, it is necessary to select relevant social theories. Social theories are good at explaining interactions among factors in human behavior; as such, they can help formulate modeling frameworks for social resilience. In short, social theories provide the theoretical foundations to calibrate our model so that it matches reality and provides reasonable explanations. One of the challenges of using a social theory is that it may only provide descriptive analysis, limiting its direct application in a computational framework. For example, social norm theory [34] tells us how social norms form and evolve, but it does not define a mathematical function to describe how the procedure happens; therefore, it is hard to quantitatively determine the influence of social norms on social resilience. Some of the ways in which social theories can be used to formulate the composite function include the following.

1) *Factor Selection:* Social theories can be used to select the set of factors F_{n+1} from the set of factors $\bigcup_{i=1}^{n} F_i$ of the underlying resilience functions. Descriptive social theories may be useful to determine relative importance to aid factor selection.
2) *Factor Masking:* In a dynamic scenario where the influence of a factor may vary over time, social theories can provide insights into when a factor contributes to system resilience and when it does not.
3) *Factor Weights:* The weighting of relevant factors can also change with time, depending on relative importance. Social theories can help determine dynamic weights in resilience models.

In Section V-B, we will demonstrate how to apply the modeling framework to a real-world scenario. We will explain a process that can be followed to represent sociocultural behaviors of the individuals and groups that impact the resilience of a social system, and then formulate resilience functions based on these factors and their constraints.

E. Contributions of the Framework

One key contribution of our framework is its capability to model each of the hypotheses about the resilience of the system as one or more resilience functions. For instance, a particular hypothesis about resilience may correspond to a subset of the factors and their interactions represented within the aforementioned cultural fragments, and can be utilized to formulate a specific resilience function. The framework also has the capability to compose a global or umbrella resilience function from individual resilience functions using select social theories. In some cases, the information on how factors of different resilience functions interact may not be available. Social theories can help to fill in these gaps while providing important insights into how individual resilience functions interact, when one or more resilience functions dominate, and when they only have a minor influence. However, note that our overall modeling framework is not tied to any particular social theory or knowledge representation. Relevant social theories are selected based on the scenario to be modeled. In the scenario for this investigation, the experimenters have utilized theories related to social norms and risk analysis to inform the model.

This initial effort focuses on key aspects of the social resilience model, including the application of social theories to tie the individual resilience functions together. To accomplish this, we defined resilience functions for both fishing and piracy. An overall resilience function was then defined by employing select social theories related to social norms and risk analysis. In the experimental validation, we leverage sociocultural modeling methods previously explored as part of our earlier work with computational sociocultural modeling [35]–[37].

V. Experimental Validation

While selecting a suitable scenario for our simulation, we had several criteria in mind. Perhaps the most critical was finding a situation with enough complexity to require the application of multiple views of resilience, as previously discussed in the introduction. We also selected a scenario to highlight other strengths of our framework, namely, its ability to represent diverse types of information and to leverage existing representations and modeling techniques, if applicable. In addition, to demonstrate the capability of our system to handle not only uncertainty, but also incomplete information, we were interested in finding a setting which had copious information, yet was not so well documented and studied that it was essentially a completely known entity. Thus, we required a real-world scenario that exhibited complex forms of resilience and yielded detailed information for incorporation into the model, while still retaining some unknowns and uncertainties. In Section V-A, we describe the selected scenario, and then review details of the experiment configuration and execution.

A. Scenario

To validate our resilience framework, we chose to model a fishing community along the coastal regions of Somalia from 1991 to 2012 [38]–[41]. With the fall of the Barre regime in 1991, Somalia devolved into civil strife among its clans. The absence of a central government led to damaging illegal activities in Somali coastal waters. Excessive fishing by illegal international vessels and disposal of toxic waste, followed by the destruction caused by a tsunami, led to depletion of fish resources and loss of livelihood for Somali fishermen [42]. The impacts of these environmental factors are captured in our model using BKBs. For instance, the effects of the tsunami are reflected in the BKB in Fig. 3, represented by the random variable "(B) Tsunami is destructive," which leads to a reduction in the availability of boats and fishing equipment. Similarly, the impact of other factors, such as illegal fishing and illegal waste dumping, was included in the scenario during the initial stages (T_1 and T_2 of Table II). As the economic situation of the fishermen worsened, such hardships eventually gave rise to piracy. Piracy in the Somali waters reached its peak in 2008 and 2009 [38]. The events surrounding the rise and fall of piracy in Somalia which we incorporated into our simulation are detailed in Table II. The specific modeling question we asked was: "How did the livelihood provided by two competing occupations, namely, fishing and illegal piracy, contribute toward the resilience of the community?" Considering the economic hardships the fishing community endured during these years, this scenario provided the complexity, dynamism, and information that we desired to validate our framework. We also leveraged information from [35] and [36] on Somalia, which focused on modeling the instability in Somalia during the fall of the Islamic Courts Union (ICU) in 2006.

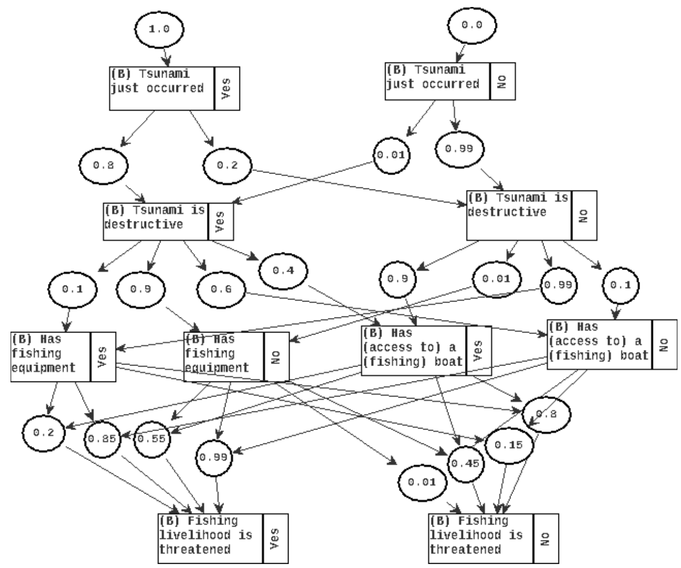

Fig. 3. BKB representing the tsunami event in Somalia.

TABLE II
Timeline of Events Used to Model Resilience

Time Step	Time Period	Description
T_0	1991	Somalia experienced civil strife since 1991, leading to the collapse of fishing industry [38].
T_1	1991-2004	The absence of a coast guard allowed foreign fishing companies to illegally fish in Somali waters [56].
T_2	1993-2004	Foreign companies began dumping hazardous waste in unpatrolled Somali waters. Fishermen start to take matters into their own hands which leads to piracy [56].
T_3	Dec. 2004	A tsunami severely effects the fishing industry[57]. This led to a surge in piracy [58].
T_4	Jun. 2006	During their brief reign, the ICU) enforced strict rules to control piracy, virtually wiping out piracy [38].
T_5	Dec. 2006	The sudden fall of the ICU leads to revival of piracy flourished in Puntland and southern Somalia [38].
T_6	Sep. 2008	Hijack of MV Faina by Somali pirates cements the reputation of Somalia coast as world's most piracy-prone area [38].
T_7	Nov. 2008	The pirate attacks reached their peak and are seen as an international threat [38][40].
T_8	Jun. 2009	UN approved countries to protect against Somali pirates in Oct 2008, but the first publicized interception by an international warship was in June 2009 [58].
T_9	Mar. 2010	Corporations started arming ships with private security guards, and implementing anti-piracy tactics [39][58].
T_{10}	Jan. 2012	Piracy and lack of a proper central government led to high inflation rates by 2008. This increased in the later years, leading to frustration and anger [59].
T_{11}	Mar. 2012	Anti-piracy forces, such as the Puntland Marine Police, deployed on the shore, reducing piracy significantly [60].

B. Experimental Setup

In this section, we first describe the general construction of the Somali fishing community model, so that it follows the general scenario just described. After highlighting the events central to the simulation, we then review the formulation of

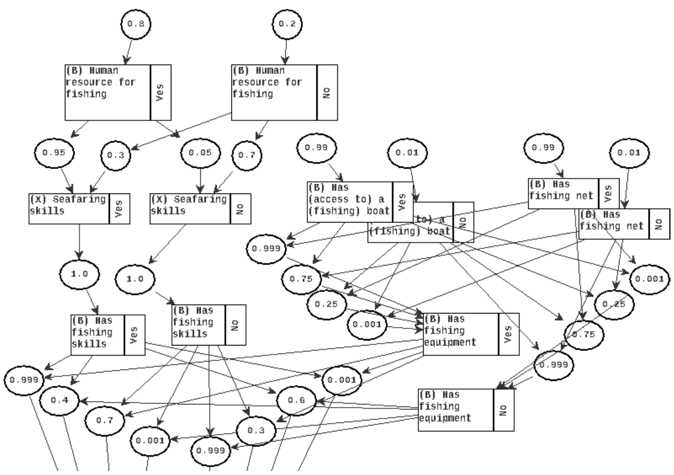

Fig. 4. Partial BKB representing fishermen.

our individual resilience functions for two distinct types of livelihood for that region, namely, fishing and piracy. Next, we describe the social theories we employed to identify relevant factors to be applied to our general resilience function. In concert with the applicable social theories, in the following section we discuss the process used to determine which resilience target variables were masked to produce an overarching resilience function. We also describe the rationale behind the dynamic weights in the overall resilience function for the selected resilience target variables.

1) Scenario Simulation: We used information on fishing communities in Somalia to validate our resilience model. As the initial step, BKBs were constructed based on factors that could affect the fishermen's decisions regarding fishing or piracy as a means of livelihood. These BKBs were considered as a baseline from which the simulation was conducted. An example of the fisherman BKB is shown in Fig. 4. Due to the large size of the fisherman BKB, only a portion of the BKB is shown. Next, we identified relevant events from public media sources that could have affected the resilience of the fishing community. As the information was gathered from public sources, there are no privacy issues to be considered, nor any actual human participants in our experiment. Our results and analysis are based wholly on our computational model.

The resilience of the community was measured and analyzed over the time period from 1991 to 2012. In order to focus on the most critical factors, only major events which could influence the resilience of the fishing community were considered while modeling the scenario. The scenario was extensively researched, and information was gathered from various resources, including journals, news articles, websites, and open sources. The 11 major events selected by the SMEs for this time period are depicted in Table II. These events include initial circumstances that then drove actions and reactions which spiraled into the failure of the fishing industry in Somalia, a growth of piracy as a response to lost income, and then eventually the suppression of piracy and a resurgence of fishing for livelihood. All of these actions and reactions originate from forces, both internal and external, on the Somali village, which are captured by the application of risk theory and social norms, and by economic, religious, political, and social pressures within the local and international community. All of these factors contribute to the overall resilience of fishing and piracy in the village. Each event is represented in the model using BKBs. An example of an event BKB representing the tsunami that occurred during December 2004 can be seen in Fig. 3. Overall, the model consisted of 14 BKBs with 45 random variables.

2) Individual Resilience Functions: Two major aspects of the fishing community that contributed to its resilience were analyzed. They were: 1) R_1—resilience with fishing as a livelihood and 2) R_2—resilience with piracy as a livelihood. To gauge the resilience measures R_1 and R_2, a portion of the team selected factors central to the resilience of fishing and piracy, then designed functions for resilience based upon conditional probabilities for variable instantiations. The resilience random variables for R_1 and R_2 are found in Table IV.

We define resilience functions for each of the livelihoods, a fishing resilience, $R_1 : (K, \mathbb{E}_1, F_1, C_1,) \rightarrow [0, 1]$, and a piracy resilience, $R_2 : (K, \mathbb{E}_2, F_2, C_2,) \rightarrow [0, 1]$, where the modeling information represented as BKBs is the same, but the evidence, targets, and constraints vary. It should be noted that these two survival methodologies were not presumed to be either more or less viable (or preferred) than the other by the experimenters. The longevity and effectiveness of each would be determined by social pressures, both internal and external, placed upon the community.

It may also be noted that we selected the social theories based on the need to model factors and social processes that we deemed to be relevant for the Somali scenario. For instance, the decision to adopt piracy is fraught with social and economic risks from various sources, including risk of social ostracization within the community and the danger of armed retaliation from foreign navies. This can be adequately represented by risk theories [43], [44]. However, risk theories do not capture the complex and dynamic sentiments of the community toward piracy. We utilized social norms theories [45]–[47] to represent community sentiments that have their roots in the religious and cultural beliefs of the people. However, note that our resilience framework is not tied to specific theories. As such, the social resilience results, analysis, and explanations provided by our framework are driven by the specific social theories utilized.

Our framework does not prescribe a specific method to compute resilience values. For the experimental validation presented here, we use the posterior probability of each factor to determine if it satisfies its corresponding constraint. Clearly, the constraints for the factors can be modeled within our framework in several ways. For our validation experiment, we use thresholds and weights within the constraints to represent the range within which the factor contributes toward the system's resilience, and to represent their relative importance, respectively. Based on available scenario information and recommendations by SMEs, we select a set of weights $W_i = \{w_{i,0}, \ldots, w_{i,l}, \ldots w_{i,|F|-1}\}$ and a set of threshold values $Q_i = \{q_{i,0}, \ldots, q_{i,l}, \ldots q_{i,|F|-1}\}$, where $q_{i,l}$ is the threshold for factor $f_{i,l}$. Note that our framework is flexible and allows for inclusion of diverse types of quantitative and

TABLE III
METHODOLOGY USED IN EXPERIMENTAL VALIDATION FOR CHECKING RESILIENCE CONSTRAINTS

CHECK-CONSTRAINT($K, \mathbb{E}, f_{i,l}, c_{i,l}$)
Note: the constraint function $c_{i,l}$ for a factor $f_{i,l}$ is based on its weight $w_{i,l}$ and threshold $q_{i,l}$
Calculate posterior probability $P_{i,l}$ of factor $f_{i,l}$ using belief updating on BKB K under evidence set $\mathbb{E}$.
IF $P_{i,l} < q_{i,l}$
    constraint $c_{i,l}$ is satisfied
ELSE
    constraint $c_{i,l}$ is not satisfied

TABLE IV
TARGET VARIABLES AND THRESHOLDS

	Target Variable		Target State	Operation	Threshold
R_1	(B) Fish supply is sufficient		Yes	>	0.75
	(B) Has (access to) a (fishing) boat		Yes	>	0.9
	(B) Has fishing equipment		Yes	>	0.8
R_2	(B) Attitude towards piracy		Positive	>	0.2
	(B) Piracy benefit is ok		Yes	>	0.6
	(B) Piracy cost is ok		Yes	>	0.4

TABLE V
EXAMPLE OF A METHODOLOGY FOR COMPUTING RESILIENCE VALUES

RESILIENCE-VALUE ($K, \mathbb{E}, C_i$, F)
Note: the constraint function $c_{i,l}$ for a factor $f_{i,l}$ is based on its weight $w_{i,l}$ and threshold $q_{i,l}$; F is either the complete set of factors, all of which are resilient, or the set of factors which are not resilient
$D = 0$, // set of euclidean distance of target variables either satisfying (resilient) or not satisfying (non-resilient) the constraints
FOR each factor $f_{i,l} \in$ F
    Calculate posterior probability $P_{i,l}$ of factor $f_{i,l}$ using belief updating on BKB K under evidence set $\mathbb{E}$.
    $$D = D + w_{i,l}^2 * \left(\frac{P_{i,l} - q_{i,l}}{1 - q_{i,l}}\right)^2$$
END FOR
Resilience value $= \sqrt{D}$

qualitative information. For each factor, we determine if it satisfies its constraint using the procedure in Table III. If all the factors satisfy their constraints, the system is said to be resilient. Note that the weights and thresholds (see Table IV) for R_1 and R_2 factors are based on the scenario information. As this is the initial validation of the framework, we chose to keep the factor weights and thresholds static, and then use the L_2-norm as the basis for the distance of the operating point of the system from the basin (as represented by the thresholds), and thus compute how resilient or nonresilient the system is (see Table V). Note that our framework is not tied to this methodology of using the L_2-norm, and other measures can be used in its place.

The simulation is initiated using the BKBs representing the fundamental behaviors of fishermen and pirates as mentioned before, followed by the 11 time steps depicting the major events. At every time step, changes are incorporated into the model by fusing an event BKB corresponding to that time step and/or by setting evidence in the BKBs. Belief updating is performed on the fused BKB during each time step, and the posterior probabilities of random variables used to measure resilience are calculated. For example, during the simulation runs for measuring R_1, at each time step the posterior probabilities of all the states of random variables selected for R_1 are noted. As time progresses, prior events may not have the same effect at the current point in time. Therefore, a fading effect is introduced by reducing the reliability index of previous event BKBs when fused in later time steps. Lowering the reliability index of the preceding BKBs will reduce their impact within the current fused BKB. The fading effects varied across time steps and were based on factors such as time interval between events and the effect of BKBs at the time of the events.

3) Composite Resilience Function (R_3): This section describes the computation of R_3 from individual resilience functions R_1 and R_2. Recall that R_3 is not computed by directly combining R_1 and R_2 with weights. Instead, we break down R_1 and R_2 at the variable level and recombine relevant variables according to select social theories. The challenge of formulating an umbrella resilience function is to understand how to model the interactions between its constituent functions. Take for instance our scenario, where the central challenge faced by the Somali fishing community is earning a livelihood under the pressures of illegal fishing, environmental change, and the collapse of the Somali government. The fishing community must compete with better equipped foreign fishing companies invading their fishing grounds if they are to continue fishing. If switching careers, they must consider the risks associated with rampant unemployment during civil war. To properly incorporate such considerations when developing a composite resilience function for the community, we explore the use of various social theories to help determine the relevance of the individual resilience factors throughout the scenario. Specifically, we use social theories related to social norms and risk analysis to determine weights to model the relative importance of the factors in the scenario. For each time step of our scenario, we apply relevant social theories to determine pertinent factors and their weights. The procedure for computing R_3 at each time step includes the following operations.

1) Select social theories that can best describe the major driving force of community behavior at the time.
2) Based on these social theories and time-step related events, pick relevant factors from R_1 and R_2 to form the key factors of R_3, and assign their weights, denoting their relative importance during the time step, based on feedback from SMEs.
3) According to chosen factors and their weights, calculate R_3 on that time step. In the following sections, we provide examples of the weights and masking factors for selected time steps.

a) Social norms and risk analysis: When constructing the composite resilience function, two social theories were determined to be well-suited for the scenario of interest: social norms and risk analysis.

Social norm theories are a group of social theories describing human behavior under complex social and economic conditions. According to Cialdini and Trost [34], "social norms are rules and standards that are understood by members of a group, and that guide and/or constrain social behavior without the force of laws." Social norms divide into two groups: descriptive norms [45] and injunctive norms [46], [47]. Descriptive norms describe human behaviors in specific situations and injunctive norms focus on the social acceptability of specific behaviors.

Social norms have in fact been employed in resilience research in the past. Adger *et al.* [3] briefly mention social norms in the context of adjusting management behaviors to implement recommended measures to limit the hazards of coastal disasters. In contrast, Poortinga [48] employs social norms when addressing community resilience, but notes that "unhealthy" social norms can result in less desirable outcomes, and thus applies social norms to the analysis of the dynamics within a community. This is somewhat akin to our use of social norms here, where the pressures exerted upon villagers' choices of livelihood are identified by examining social norms.

The conjunction of resilience and risk is common, as illustrated by the plethora of studies in numerous areas of research [49]–[54]. The extant approach to incorporating risk into social resilience has been focused on evaluating risk of outcomes when considering resilience of systems to possible events. For instance, Coaffee [50] applies risk analysis to the concerns of environmental resilience, evaluating the different possible disruptions environmental change might cause, and then assesses the resilience of possible solutions to the identified risks. Another example of risk and resilience, closer in subject matter to this project, is found in [54]. Masten [54] is concerned with social resilience, admittedly in a smaller context, that of the military family. Here, the focus is on using risk analysis to identify perceived risks, for the analyst to evaluate the resilience of military families to those risks.

In contrast, we incorporate risk analysis as one of the tools the actors within the Somali scenario use to evaluate their situation and decide on beliefs to hold and actions to take. Risk theory is applied to evaluate likely actions taken within the scenario in the simulation. In this way, the theories of perceived risk and risk amplification are especially relevant to the fluctuation of the social acceptability of piracy and fishing. Perceived risk [43] describes subjective evaluation of risk. Risk amplification [44] describes how subjective risk responds when new information arrives.

b) Application to resilience: Both social norm and risk theories play roles in our resilience framework. When determining the relevance of resilience factors to the overall resilience of the community, many issues come into play. There are the pressures from the community or society in general to conform to certain accepted behaviors. These pressures are well represented through the application of social norm theories.

On the other hand, actions and behaviors are also frequently governed by cost and benefit analysis, which is where the risk theories are utilized. In each time step, we apply at least one theory to explain the community's behavior and determine which resilience target variables apply to the community's overall resilience. Social norms and risk theory may interact with one another. Consequently, one must at times balance two contradictory theories for certain time steps. For instance, in the time step where the tsunami occurred, social norms dictate that the community members remain fishermen and reject piracy. On the other hand, risk theory takes into account the threat to fishermen's livelihood due to the destruction of their fishing boats. In order to survive, they may thus be willing to take higher risks than before, namely, through piracy. In short, when a particular theory dominates a time step, it is chosen to explain behaviors; otherwise, a set of relevant interacting theories are used.

TABLE VI
MASKING FACTORS AND WEIGHTS IN R_3

Time step	Social Theory[1]	Fish supply is sufficient [Yes][2]	Has a fishing boat [Yes][2]	Has fishing equipment [Yes][2]	Attitude towards piracy [Pos][2]	Piracy benefit is ok [Yes][2]	Piracy cost is ok [Yes][2]
T_0	DN	-	0.06	0.02	-	-	-
T_1	CC	0.05	0.08	0.02	-	-	-
T_2	CC	0.14	0.07	0.02	-	-	-
T_3	SG	-	0.15	0.03	-	0.27	-
T_4	PR	-	0.15	0.01	-	-	-
T_5	PR	-	-	-	0.04	-	0.41
T_6	DN, PR, RA	-	-	-	0.04	0.29	0.44
T_7	DN, PR, RA	-	-	-	0.04	0.29	0.44
T_8	PR, RA	-	0.06	-	-	-	0.37
T_9	PR, RA	-	0.06	-	-	-	0.37
T_{10}	DN, PR	0.11	0.06	0.02	-	-	-
T_{11}	PR, IJ	0.11	0.06	0.02	-	-	-

[1]DN = descriptive norm; CC = conditional cooperation; SG = survival of group; PR = perceived risk; RA = risk amplification; IJ = injunctive norm.
[2] "-" indicates the random variable not utilized in resilience calculation for that step; values indicate dynamic weight for that variable.

c) Masking factors and dynamic weights: A composite resilience function depends on model factors, interactions among factors, and events or external influences. Events in a time step T_i influence factors and their interactions. Even more, events' impacts can also evolve across time steps. Certain events may also require multiple theories to explain their specific influences in the model.

In the fused scenario, we consider both fishing and piracy factors. In addition, due to factor interactions, some factors become increasingly important while others fade out, which is captured by factor masking and dynamic weights calculated from pertinent posterior probabilities within the model. Table VI provides a complete breakdown of the social theories, masking, and weights used for each time step, where a "–" indicates this variable was not utilized for calculation of the resilience values during this time step due to social theories indicating that it does not have an impact on the system's resilience. On the other hand, any other values indicate the dynamic weight used for that variable in that time step.

For example, in T_0, we apply the descriptive norms theory [45]. Initially fishing was the major career in this community, indicating the majority followed this norm in career choice. Therefore, the negative attitude toward piracy was obvious, and nobody would consider piracy-related activity. Only the availability of a boat and fishing equipment are constraints, because fish are plentiful.

TABLE VII
RESILIENCE OF FISHING (R_1), PIRACY (R_2), AND COMPOSITE (R_3)

Time step	# variables in-bounds / total # variables			Resilience values () Indicates non-resilience		
	R_1	R_2	R_3	R_1	R_2	R_3
T_0	3/3	0/3	2/2	0.3664	(0.3809)	0.0579
T_1	2/3	2/3	2/3	(0.1911)	(0.0250)	(0.0182)
T_2	2/3	2/3	2/3	(0.2741)	(0.0250)	(0.0742)
T_3	0/3	2/3	0/3	(0.2331)	(0.0250)	(0.0497)
T_4	0/3	1/3	0/2	(0.0299)	(0.2191)	(0.0033)
T_5	0/3	2/3	2/2	(0.1031)	(0.0250)	0.1032
T_6	0/3	3/3	3/3	(0.2465)	0.1863	0.2395
T_7	0/3	3/3	3/3	(0.3849)	0.1829	0.2186
T_8	3/3	2/3	2/2	0.1199	(0.1248)	0.1413
T_9	3/3	2/3	2/2	0.2569	(0.1446)	0.0681
T_{10}	3/3	1/3	3/3	0.2977	(0.1639)	0.0564
T_{11}	3/3	1/3	3/3	0.3143	(0.1459)	0.0580

In T_1 and T_2, we apply the social norm of conditional cooperation [55]. Before the Somali government collapsed, both the local and international fishing industry cooperated by fishing in separate areas, which fulfilled the public good requirement. However, the foreign fishing industry began fishing illegally once the Somali government collapsed. Since the foreigners no longer maintained the public good, Somali fishermen reacted by collecting fees from commercial fishing vessels, at first stopping short of hijacking and ransoming ships. They believed their reaction was fulfilling social justice rather than piracy, so the acceptability of piracy is not considered.

As a final example, in T_6 and T_7, we applied three theories: descriptive norms, perceived risk, and risk amplification. Based on risk amplification, news of successful hijackings convinced the community that piracy was easy and safe. Descriptive norms regarding piracy changed in favor of it, since many community members had joined. Accordingly, a perception that many worked for piracy reversed the attitude toward piracy as well. Suddenly, all piracy-related factors seemed attractive to the local community. This resulted in the fishing-related variables becoming largely irrelevant, and so were masked out.

C. Results and Analysis

In this section, we provide results and analysis for the resilience of the community from the perspectives of fishing (R_1) and piracy (R_2) as a source of income, verifying that our individual computations for fishing and piracy resilience track well with the events in the scenario. We then review the resilience of the community as a whole (R_3), considering both fishing and piracy, and discuss the merits of our findings.

1) Fishing Resilience R_1: For the fishing resilience R_1, the results are listed in Table VII. The first column denotes each time step ranging from T_0 to T_{11}. The second major column represents the number of target variables that are inside the resilience bounds, with three subcolumns with values for R_1, R_2, and R_3. Likewise, the third major column provides our numerical calculation of resilience, again divided into R_1, R_2, and R_3 subcolumns. Keep in mind that we apply different formulas to compute a time step's value if it is resilient, versus one that is nonresilient, so we cannot directly compare the value of a resilient time step with that of a nonresilient one. Here, only in the time steps with all three target variables in bounds or within the threshold values is fishing considered resilient.

Overall, the fishing resilience measurements follow what would be expected from the scenario. Early on, specifically T_0, fishing is found to be resilient. The T_0 resilience value is the weighted sum of the three target variables' squared distance to their corresponding bounds. This is a measure of how much total tolerance to perturbation this community has at that time.

In later time steps, however, the onset of various difficulties has pushed the community out of resilience, and the associated resilience measurement is an indicator of the minimum effort required to return this community to a resilient state. We see that fishing remains nonresilient for an extended period, from T_1 until T_7, to begin with because of hardships such as the tsunami and illegal activities resulting from the fall of the Somali government, and later due to the vibrancy of piracy detracting from efforts at a traditional fishing livelihood.

One notable exception occurs in T_4, where the nonresilience value of 0.0299 is significantly closer to the resilience bounds than the surrounding time steps because the ICU has come into power, and it enforces law and order on shore, while forbidding piracy. Under more stable political rule, the fishing community finds it easier to recover from the natural disaster and to compete with the illegal fishing in their waters.

From T_8 to the end of the simulation in T_{11}, we see a steady increase in the resilience of fishing, as increasing antipiracy actions at the national and international levels take effect. By the end of T_{11}, the resilience of fishing has recovered to around 90 percent of the baseline resilience. However, we do observe a drop in the resilience distance of the $\langle$fish supply is sufficient $=$ Yes$\rangle$ target alone, due to the gradual return of illegal fishing vessels from other countries. This is not as severe as before, so the fishing community remains resilient.

2) Piracy Resilience R_2: For piracy resilience R_2, again consult Table VII. The R_2 columns have the same meaning as for R_1, except that they refer to different target variables. As we would expect, piracy starts out in a nonresilient state, and remains so through T_5. In general, though, there is a softening of attitude toward piracy as fishing becomes more difficult, with the exception of T_4, when the ICU penalizes piracy with death. The resilience value of 0.2191, indicating the required force to reach resilience for piracy, is much larger than the surrounding time steps, for few people are willing to risk their lives due to this harsh penalty.

For both T_6 and T_7, all three targets finally fall into the resilience bounds, yielding similar resilience values of 0.1863 and 0.1829 for piracy. This community is now quite resilient regarding piracy, because they can earn vast sums of money with little cost, as there is very little resistance against them. The pirates are also very generous toward local citizens, so they have earned support from the populace, receiving benefits such as food and shelter for hostages.

In T_8 and onward, piracy falls further away from resilience, as both domestic and international efforts to combat piracy have increasing success. The resilience value in the final time step is slightly lower than the previous step, because the target ⟨attitude toward piracy=Yes⟩ is closer to its bound in this last time step than in the previous one. This is because most pirates have returned to a fishing career, and the hostility toward piracy has reduced slightly.

3) Composite Resilience R_3: For the community's combined resilience value R_3 in Table VII, the analysis is different than in the previous ones, since we apply masking and dynamic weights on the target variables in each time step. The key point to this is that the composite measure is not simply a union of the separate resilience calculations. This is most clearly illustrated with T_5, which is not resilient in either of the individual resilience measurements, yet is resilient when the two livelihoods are considered together. The resilience is a result of considering the net effect of a struggling fishing industry and a growing piracy strategy which, in effect, allow the community to survive, despite neither livelihood being effective enough alone. Of course, subtler indications of the composite resilience calculation can be found in other time steps, such as the stronger overall measures of resilience in T_6 and T_7 when compared to R_2, where fishing contributes positively to R_3, despite it not being resilient when considered alone in R_1.

By producing an overall resilience measure for a domain in this manner, we endeavor to forge a reliable method for composing a single umbrella resilience function from a variety of specialized approaches. Our functions for fishing resilience, R_1, and piracy resilience, R_2, were indeed specialized, and our method for composing them into a single resilience function, R_3, is a successful demonstration of the value of our general framework for measuring social resilience.

VI. Conclusion

Capturing, measuring, and modeling social resilience remain challenging endeavors. Beyond the general idea of determining how much stress or distortion a physical system can take before breaking, social resilience adds many challenging factors, including multidomain factors, multiple hypotheses on what social factors apply, the interactions between sometimes unobservable factors, incomplete social data, transformational adaptability of social entities, and the dynamism of multiple actors. Given a complex social scenario, rather than trying to identify a single resilience function that defines the strength of the social group, we instead proposed that multiple resilience functions may be defined, with each one focused on a specific hypothesis about its resilience. A composite resilience function may then be constructed through the judicious application of select social theories. By producing an overarching framework for tying resilience functions together through the application of social theories, we broaden the applicability of our resilience framework to larger and more complex situations.

To demonstrate this concept, we modeled a fishing community in Somalia during the rise and fall of the Somali pirates. This scenario is rich in economic, ecological, political, and military influences, thus providing the complexity and multiple resilience considerations we required for validating our thesis. By defining a resilience function for fishing, and another for piracy, we were able to observe the periods when fishing was vibrant, when piracy was vibrant, and when both struggled. More importantly, we constructed a composite resilience function, which leveraged aspects of both fishing and piracy, to indicate how the community managed to survive this exceptionally difficult period in their history. This composite function relied on social norm and risk theories to define the relevance of factors at each step in the dynamic timeline. The composite function not only identified when the community was resilient due to either fishing or piracy, it revealed resilience for the overall community where both fishing and piracy were struggling. More importantly, the composite resilience function demonstrated a capability to bridge the gap between different measures of resilience, and integrate them into a single framework to reflect the complex interplay between sometimes opposing, sometimes synergistic functions.

This proof of concept has yielded several areas where additional research may be explored. Certainly, as other scenarios are explored in future work, the selection of pertinent social theories to employ will likely vary, thus validating the expectation that the overall framework can exploit the rich variety of social theories found in the literature. Another possible extension is including dynamic (rather than static) thresholds. The inclusion of social networks, to provide not only further complexity and realism to the simulation, but also to bring the abundant social network tools to bear, is an additional option. The resilience functions presented in this paper could also be extended. While certainly versatile and well-understood, the L_2 norm may be limited in its applicability to complex resilience landscapes. Ultimately, we aim to find a measure to remove the discontinuity between the resilient and nonresilient measurements, and thus allow for direct comparisons between them. Finally, as with many complex simulations, as the number of variables increase, the computation time significantly increases. We will explore new computational approaches, including parallel methodologies, for reducing computational load while maintaining accuracy.

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Eunice E. Santos (M'94–SM'05) received the B.S. degree in mathematics and computer science and the M.S. degree in mathematics from Youngstown State University, Youngstown, OH, USA, in 1989 and 1990, respectively, and the M.S. and Ph.D. degrees in computer science from the University of California, Berkeley, USA, in 1993 and 1995, respectively.

She is currently the Ron Hochsprung Endowed Chair of computer science with the Illinois Institute of Technology, Chicago, IL, USA. Her current research interests include large-scale distributed processing, computational modeling, complex adaptive systems, computational sciences, computational social sciences, and human modeling with applications to the biological, physical, and social sciences.

Prof. Santos is a fellow of the American Association for the Advancement of Science. She was a recipient of numerous awards, including the IEEE-CS Technical Achievement Award. She was the founding Co-Editor-in-Chief of the IEEE TRANSACTIONS ON COMPUTATIONAL SOCIAL SYSTEMS. She has been a member of several U.S. Department of Defense Senior Technical Advisory Committees and has also been a past member of the Institute for Defense Analyses/Defense Advanced Research Projects Agency Defense Science Study Group.

Eugene Santos, Jr. (M'93–SM'04–F'12) received the B.S. degree in mathematics and computer science and the M.S. degree in mathematics with a specialization in numerical analysis from Youngstown State University, Youngstown, OH, USA, in 1985 and 1986, respectively, and the Sc.M. and Ph.D. degrees in computer science from Brown University, Providence, RI, USA, in 1988 and 1992, respectively.

He is currently a Professor of engineering with the Thayer School of Engineering, Dartmouth College, Hanover, NH, USA. His current research interests include information, cognition, human factors, mathematics, dynamic human behavior, intent inferencing, and decision-making with an emphasis on learning nonlinear, emergent behaviors and decisions, cybersecurity—insider threat and deception detection, intelligence assessment, and adversarial intent and course of action analysis.

Dr. Santos is a fellow of the AAAS. He was formerly an Editor-in-Chief of the IEEE TRANSACTIONS ON CYBERNETICS (formerly IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS: Part B) from 2008 to 2013.

John Korah (SM'15) received the M.S. degree in electrical engineering and the Ph.D. degree in computer science from the Virginia Polytechnic Institute and State University, Blacksburg, VA, USA, in 2002 and 2010, respectively.

He is currently a Research Assistant Professor with the Illinois Institute of Technology, Chicago, IL, USA. His current research interests include parallel/distributed computing, parallel graph algorithms, computational social systems, large-scale network modeling/simulation, and information retrievals.

Dr. Korah is the founding Co-Chair of the IEEE ParSocial Workshop and served as a technical reviewer for journals such as the IEEE TRANSACTIONS OF COMPUTATIONAL SOCIAL SYSTEMS and the *Journal of Computational Intelligence*.

Jeremy E. Thompson (GS'11) received the B.S. degree in electrical engineering from the Missouri University of Science and Technology, Rolla, MO, USA, in 1991, and the M.S. degree in computer systems from the Air Force Institute of Technology, Dayton, OH, USA, in 1996. He is currently pursuing the Ph.D. degree with the Thayer School of Engineering, Dartmouth College, Hanover, NH, USA.

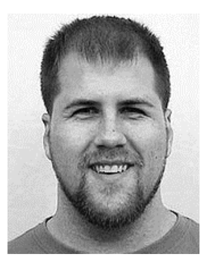
His current research interests include artificial intelligence in general (more specifically social and cultural modeling), including opinion diversity.

Yan Zhao (GS'16) received the B.E. degree in electrical engineering from the Dalian University of Technology, Dalian, China, in 2012. He is currently pursuing the Ph.D. degree with the Thayer School of Engineering, Dartmouth College, Hanover, NH, USA.

His current research interests include supervised learning from multiple information sources, modeling emergence in dynamic complex systems and modeling emergence in multistep multisource decision-making processes.

Vairavan Murugappan (GS'16) received the B.E. degree in computer science engineering from Anna University, Chennai, India, in 2008, and the M.Sc. degree in high performance computing from the University of Edinburgh, Edinburgh, U.K., in 2010. He is currently pursuing the Ph.D. degree with the Illinois Institute of Technology, Chicago, IL, USA.

His current research interests include parallel/distributed computing, social networks, and large-scale computational modeling.



Jacob A. Russell received the B.A. degree in management computer systems and mathematics with computer emphasis from the University of Wisconsin–Whitewater, Whitewater, WI, USA, in 2009. He is currently pursuing the Ph.D. degree with the Thayer School of Engineering, Dartmouth College, Hanover, NH, USA.

His current research interests include artificial intelligence, machine learning, natural language processing, and decision-making.