Parameterization Framework and Quantification Approach for Integrated Risk and Resilience Assessments

Mariana Goodall Cains*† and Diane Henshel†
‡O’Neill School of Public and Environmental Affairs, Indiana University, Bloomington, Indiana, USA

ABSTRACT
A growing challenge for risk, vulnerability, and resilience assessment is the ability to understand, characterize, and model the complexities of our joint socioecological systems, often delineated with differing natural (e.g., watershed) and imposed (e.g., political) boundaries at the landscape scale. To effectively manage such systems in the increasingly dynamic, adaptive context of environmental change, we need to understand not just food web interactions of contaminants or the flooding impacts of sea level rise and storm surges, but rather the interplay between social and ecological components within the inherent and induced feedforward and feedback system mechanisms. Risk assessment, in its traditional implementation, is a simplification of a complex problem to understand the basic cause-and-effect relationships within a system. This approach allows risk assessors to distill a complex issue into a manageable model that quantifies, or semiquantifies, the effects of an adverse stressor. Alternatively, an integrated risk and resilience assessment moves toward a solution-based assessment with the incorporation of adaptive management practices as 1 of 4 parts of system resilience (i.e., prepare, absorb, recover, and adapt), and directly considers the complexities of the systems being modeled. We present the Multilevel Risk and Resilience Assessment Parameterization framework for the systematic parameterization and deconstruction of management objectives and goals into assessment metrics and quantifiable risk measurement metrics and complementary resilience measurement metrics. As a proof-of-concept, the presented framework is paired with the Bayesian Network–Relative Risk Model for a human-focused subset of a larger risk and resilience assessment of climate change impacts within the Charleston Harbor Watershed of South Carolina. This new parameterization framework goes beyond traditional simplification and embraces the complexity of the system as a whole, which is necessary for a more representative analysis of an open, dynamic complex system. Integr Environ Assess Manag 2021;17:131–146. © 2020 The Authors. Integrated Environmental Assessment and Management published by Wiley Periodicals LLC on behalf of Society of Environmental Toxicology & Chemistry (SETAC)

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INTRODUCTION
Watersheds, airsheds, and other landscape-scale ecosystems—especially those including humans—are complex systems. These systems, depending on spatial and temporal scale, contain multiple interacting ecosystems, human activities, ecosystem services, and feedback mechanisms between humans and ecosystems, that is, socioecological systems. Additionally, these socioecological systems are governed by various levels of policies and regulations that affect humans and their uses of, and interactions within, a given region. When assessing at landscape or system scale, the impact of active processes on metrics must be taken into account through data collection, modeling, or both, and models need to integrate the interactions and influences between metrics (Schröder and
The key to modeling complex and dynamic systems, as indicated by John Boyd’s conceptualized Destruction and Creation, is first parameterization and second metric integration (Boyd 1987). The process of parameterization deconstructs the system into its representative components to identify system critical assessment and measurement metrics and interactions. The subsequent integration of the metrics and models of their interactions produces a single, iterative, dynamic model.

Little formal guidance exists to help the practitioner with the parameterization and integration of multiple metrics of dissimilar sources that enable a quantitative integration of multidomain, multistressor, and multiendpoint risk assessment metrics (Suter 2007). Although cumulative and integrated risk assessment models recognize and allow for multi-metric integration, the frameworks provide a way to conceptualize, rather than calculate, cumulative or multi-stressor risk (USEPA 2003). Efforts to advance multistressor, cumulative, and holistic assessments are exemplified by the Ecosystem Based Management-Driven, Pressure, State, Ecosystem service, and Response (EBM-DPSER) conceptual model (Kelble et al. 2013); the Chesapeake Bay oyster restoration study (Richkus and Menzie 2013); Common International Classification of Ecosystem Services framework (ECC 2017); and the Bayesian Network—Relative Risk Model (Ayre and Landis 2012; Landis et al. 2017). The Bayesian network analytical approach paired with the Relative Risk Model conceptualization enables the quantitative integration of dissimilar measurement metrics and data for multistressor, multiendpoint risk assessments, which is necessary for the assessment of socioecological systems.

Purpose and motivation

We present a framework for the systematic parameterization and deconstruction of management objectives and goals into assessment metrics and quantifiable risk measurement metrics and complementary resilience measurement metrics. In contribution to the field of integrated (i.e., holistic) socioecological risk assessments, the presented multilevel risk and resilience parameterization framework facilitates operationalization within the problem formulation phase for complex systems. Operationalization is the “process of defining the measurements of a phenomenon that is not directly measurable, though its existence is inferred by other phenomena” (Wikipedia 2020).

Risk is the probability of an effect (i.e., consequence) on an endpoint resulting from exposure to a stressor (i.e., hazard; NRC 2009). Risk assessment, in its traditional implementation, is a simplification of a complex problem to understand the basic cause-and-effect relationships within a system. Such an approach allows risk assessors to distill a complex issue into a manageable model that quantifies, or semiquantifies, the effect of an adverse stressor. Resilience is the ability of a system to plan and prepare for the stressor, absorb the perturbations induced by the stressor, recover from damage created by the stressor, and adapt to prevent future severe effects from the same stressor (NRC 2012). Risk and resilience are clearly related concepts but are not solely inverse measures of each other (Cains and Henshel 2019). In a simplified framing of the difference, risk assessment characterizes the potential impacts of stressors on the system; resilience assessment characterizes the response and plasticity of the system to stressors that reflect the homeostatic mechanisms of the system (Carpenter et al. 2001).

An integrated risk and resilience assessment moves toward a solution-based assessment with the incorporation of adaptive management practices as 1 of 4 parts of system resilience (i.e., prepare, absorb, recover, and adapt), and directly considers the complexities of the system(s) being modeled. The presented risk and resilience parameterization framework paired with Bayesian network analysis embraces the complexity of the system as a whole, which is necessary for a more representative analysis of an open and dynamic complex system.

Paper structure

In this paper, we first discuss and compare the problem formulation stage of select assessment frameworks relevant to the integrated assessment of risk and resilience of socioecological systems. We then examine the role of parameterization within risk assessment problem formulation and review resilience assessment scoping. Next, we introduce the expanded Multilevel Risk and Resilience Assessment Parameterization (MulRRAP) framework for the systematic deconstruction of assessment metrics into quantifiable measurement metrics as a critical process within problem formulation. The utility of the presented parameterization framework is exemplified through a case study focused on the Charleston Harbor Watershed region of South Carolina, USA. The case study uses a Bayesian network analysis approach to quantify the risk of regional climate change impacts within the context of managing for increased resilience to climate change (e.g., advanced warning systems for flood events, reinforced sea walls). Last, the parameterization framework is placed within the current body of environmental risk assessment research and complex system modeling.

THE ROLE OF PROBLEM FORMULATION

Across multiple disciplines, the problem formulation step is noted as the most critical step and foundation of the risk management and risk assessment process (Dai et al. 2002; Suter et al. 2003; Zavadskas et al. 2010; Oltramari et al. 2015). Although the specific vocabulary and components of the problem formulation step have evolved with each domain ideation and application of the risk management and risk assessment process, problem formulation establishes the scope, context, and criteria specific to the assessed management questions and goals through conceptual models and analysis plan development (USEPA 1989, 1998, 2003; Suter et al. 2003; ISO 2018).

Risk analysis, especially the assessment and management of risk, has been practiced for millennia (Bernstein 1996;
Aven 2016). In 1983, the National Research Council (NRC) established the foundation of environmental and human health risk assessment as the construction of a single stressor risk characterization through the process of hazard identification, release and exposure assessments, and a dose–response curve (i.e., an exposure–response relationship; NRC 1983). The hazard identification lays out the beginnings of problem formulation. In 1989, the USEPA promulgated the Risk Assessment Guidance for Superfund (RAGS), which adapted the NRC framework into a formalized process for human health risk assessment of hazardous substances. The RAGS framework renames and repurposes the hazard identification phase to data collection and data evaluation, which includes guidance on the development of a site-specific conceptual model and analysis plan (USEPA 1989). The NRC and RAGS frameworks were developed for the assessment of one risk agent (e.g., chemical, stressor) at a time and the qualitative aggregation of assessment results at the end.

The problem formulation step, formally named such in the USEPA Guidelines for Ecological Risk Assessment (ERA), (1) identifies assessment endpoints (i.e., quantifiable attribute of a specified entity) relevant to the risk management goals; (2) builds conceptual models illustrating the relationships between stressors and assessment endpoints; and (3) develops an analysis plan appropriate for the selected assessment endpoints and available data (USEPA 1998). The USEPA ERA guidelines presented the first risk assessment framework that acknowledged and attempted to address the system-level effects within the risk assessment process and provided a foundational framework for the contemporary development of the Framework for the Integration of Health and Ecological Risk Assessment (Suter et al. 2003), USEPA Framework for Cumulative Risk Assessment (USEPA 2003), and USEPA Framework for Human Health Risk Assessment to Inform Decision Making (USEPA 2014a).

Cumulative and integrated risk assessments examine and integrate, within a system, either multiple stressors from a single domain or multiple similar stressors from multiple domains. A simple risk assessment only examines one domain (e.g., human health, environment) of risk within a system, which forces the result of that risk assessment to reside within the predetermined domain of risk. A cumulative risk assessment is the “analysis, characterization, and possible quantification of the combined risks to health or the environment from multiple agents or stressors” (USEPA 2003), whereas an integrated risk assessment “combines the processes of risk estimation for humans, biota, and natural resources in one assessment” (Suter et al. 2003). The problem formulation phase of a cumulative risk assessment and an integrated risk assessment share the same structure and output (i.e., assessment endpoints, conceptual model, and analysis plan) but differ in the scope used to inform the problem formulation phase. The integrated risk assessment scope explicitly integrates human, ecological, and natural resource endpoints, whereas the cumulative risk assessment assesses human health and/or the environment (i.e., “ecological targets”; Suter et al. 2003; USEPA 2003).

The existing traditional risk assessment guidance is not sufficient for complex systems as it was developed for simplified systems analysis (e.g., baseline of single stressor to single endpoint). Integrated multistressor risk assessments move beyond system simplification and embrace the complexity of the system as a whole, which more accurately reflects the complexity of interacting stressors on interacting nodes of a system.

**Problem (re)formulation for complex systems**

The assessment of complex systems at a regional scale can be overwhelming because of (1) a lack of problem formulation guidance relevant to complex systems; and (2) the layered complexity of socioecological systems with internal and external interactions and processes that cannot always be directly measured or modeled (e.g., Bristol Bay, Alaska ecological risk assessment; USEPA 2014b). Conceptual models are developed during the problem formulation phase of risk assessment (Figure 1A and B) to identify relevant parameters and relationships within the system for a given space and time. Conceptual models serve as the foundation for the quantitative model built during the analysis phase of problem formulation. Figure 1 is an example of the systematic development from a generic regional conceptual model (Figure 1C) to a parameterized conceptual model (Figure 1D) with an elaboration of the relationships between those parameters leading to a specific endpoint (e.g., ‘Human Health’; Figure 1E).

Conceptual models organize and visualize the connections between the sources of stress in the system, the location and habitats affected by the stress, the effects of the stress on the system, and the subsequent impacts on assessment endpoints (van den Brink et al. 2016). Conceptual models also enable integration of the models characterizing the interactions between system nodes (i.e., entities), thus visualizing dynamic system states. The specific structure and content of the conceptual model are dependent on the assessment management objectives and the system in question. The components of the conceptual model can be generalized into sources, stressors, exposure, effect, and impact on endpoints of interest (USEPA 1989, 1998, 2003, 2014a; Landsik and Wiegers 1997). Definitions of each term can be found in Table 1.

The analysis plan is the last step of the problem formulation phase of risk assessment and is specific to the risk management question being assessed. Where the conceptual model visualizes the flow of information and subsequent risk propagation within a system, the analysis plan identifies the measures used to quantify the sources, stressors, exposure, effect, and impact on the endpoints of interest (USEPA 1998, 2003, 2014a). Although research and formal documentation on the development of conceptual models and selection of assessment metrics do exist, there is currently no framework that explicitly guides the parameterization of measurement metrics and their interrelationships.
The expanded multilevel risk and resilience assessment parameterization framework (Figure 2) introduced in this paper outlines a systematic approach to operationalize conceptual models into risk and resilience metrics (Figure 3), and their respective interactions (Figure 4), for quantification during the analysis phase of risk assessment (Figure 5).

**MULTILEVEL RISK AND RESILIENCE ASSESSMENT PARAMETERIZATION FRAMEWORK**

Resilience frameworks have been developed across multiple disciplines in an effort to establish a method for deconstructing and quantifying the resilience of a system through the use of resilience indicators and scenario...
analysis (Frazier et al. 2014; Cutter 2016; Quinlan et al.
2016). Although there are no regulatory-based standards for conducting a socioecological resilience assessment, research organizations have published practitioner-focused guides and workbooks for assessing resilience in socioecological systems (Resilience Alliance 2010; Mahmoudi et al. 2018; IEMA 2020). Analogous to the problem formulation phase within risk assessment, the initial phase of the socioecological resilience assessment framework addresses the question “resilience of what to what?” and determines if general or shock-specific resilience is being assessed (Carpenter et al. 2001). This phase describes the system of analysis (e.g., spatial boundaries, stakeholders) with a conceptual model and then identifies external system shocks (i.e., stressors; e.g., climate change) and management alternatives to alleviate the impact of system shocks (Walker et al. 2002; Resilience Alliance 2010; IEMA 2020).

Just as with risk, resilience cannot be captured in a single metric; resilience is an emergent property of the system as a whole. Measuring resilience for a quantitative resilience assessment requires the identification of proxy variables to serve as resilience indicators (Quinlan et al. 2016). The identification of resilience indicators is a relatively recent endeavor within the fields of geography (Cutter et al. 2010), policy analysis (Hinkel 2011), and environmental science (Nelson et al. 2007). The identification of risk measurement metrics and resilience indicators must be specific to the modeled complex system and the sources of risk represented in that system. The presented MulRRAP framework (Figure 2) explicitly includes the parameterization of resilience indicators that influence how vulnerability (i.e., sensitivity to a hazard) and ultimately risk (i.e., probability of effect from stressor exposure) propagate through the modeled system throughout the 4 phases of resilience. The 4 phases of resilience are (1) preparation and planning for system stress; (2) absorption of stress; (3) recovery from impact; and (4) adaptation to new and changed system state to inform the next preparation and planning phase (NRC 2012). The inclusion of resilience indicators allows for the parameterization of a management practice to be quantified within the modeled risk (e.g., for the 4th phase of resilience—hard and soft adaptation practices; Sovacool 2011; NRC 2012).

The MulRRAP framework is an expansion of the multilevel risk assessment parameterization framework, originally developed to operationalize cybersecurity risk management via the parameterization of risk metrics for cyber, social, and sociotechnical systems of varying complexity (Oltramari et al. 2015; Henshel et al. 2016).

Structure of MulRRAP framework

The MulRRAP framework facilitates the systematic evaluation of the conceptual model parameters and the identification of representative and quantifiable risk measurement metrics and correlative resilience measurement metrics relevant to selected assessment endpoints and system stressors (see Figure 2). At the highest level, the MulRRAP framework consists of the parameterization of (1) risk assessment objectives and risk management goals; (2) risk measurement metrics; and (3) complementary resilience indicators (e.g., management actions, societal characteristics) for a given phase of resilience.

The hierarchical structure of the MulRRAP framework begins with the assessment domains (AD), which frame the assessment metrics and represent the management goal domains of the system and the high-level organization of disciplines that have traditionally conducted singular risk

Table 1. Risk assessment terminology resulting from the integration and modification of terminology used by numerous environmental risk assessment efforts*

| Source                          | Any system input or activity that produces stressor(s) in the system of interest. |
|--------------------------------|----------------------------------------------------------------------------------|
| Stressor                       | Any entity or process (e.g., physical, chemical, or biological) that causes or can cause an effect, either positive or negative, to, on, or in an entity. |
| Entity                         | An organism, resource, or service of the natural or built system that has the potential to be affected by a stressor. It is the attributes of an entity that provide value to a system. |
| Habitat                        | The type(s) of environment and/or location in which the entity is found. |
| Exposure                       | When there is an interaction between an entity with a stressor within a defined space and time, which results in an effect to, on, or in an entity. |
| Effect                         | A change in the state or dynamics of or in the entity resulting from exposure to a stressor. |
| Response                       | The effect of exposure to a stressor to, on, or in an entity. |
| Assessment endpoint or impact  | An entity or characteristic of the natural or built system that is of value to society, the local community, and the ecology of the system. |
| Measurement endpoint or metric | An effect or response that is measurable in or for an entity and, ideally, causally links the effects of a stressor to an assessment endpoint. |

*For example, human health, ecological, cumulative, integrative, and regional (Landis and Wiegers 1997; USEPA 1998, 2003, 2014a, 2014b, 2019; Suter et al. 2003; Suter 2007, NRC 2009).
assessments (Figure 2). For each managed domain the MulRRAP framework follows the subsequent levels of hierarchical deconstruction for risk measurement metrics: assessment subdomain (AS, as needed), assessment endpoint (AE), assessment metric (AM), measurement metric (MM), and data quality & uncertainty (DQU), as illustrated in Figure 2 and detailed in Table 2. The interconnections between the AD are represented in the parameters of the subsequent levels and interacting measurement metrics.

Resilience measurement metrics are identified by following the causal pathway and connecting the primary system stressor to a previously parameterized assessment endpoint. The primary stressor is identified from the assessment objective based on the management goal and can be iteratively redefined when given new information. From the assessment endpoint, from which the assessment metrics are derived, the MulRRAP framework logically links the following levels: primary stressor (PS), secondary stressor (SS), stressor measurement metric (SMM), exposure (Ex), exposure measurement metric (EMM), effect (Ef), resilience goal (RG), resilience indicator (RI), and data quality & uncertainty (DQU), as illustrated in Figure 2 and detailed in Table 3.

For integrated risk and resilience, the managed domains are human health and well-being, environment, and societal context (Figure 3). The human health and well-being domain captures adverse health impacts and quality of life. The environment domain captures biological, chemical, and physical entities and processes within the natural environment in addition to ecosystem services. The societal context domain captures the demographic, geographic, economic, policy, and regulatory aspects of the system that influence the human health and well-being domain.

Figure 3B and Table 2 in the following case study illustrate the deconstruction (i.e., parameterization) of a risk assessment objective (e.g., risk to human health from flood events) and risk management goal (e.g., minimize risk to human health) into relevant and representative assessment and measurement metrics. Figure 3C and Table 3 illustrate how resilience indicators, such as management options, are parameterized to complement the assessment endpoint identified in Table 2.
Table 2. Organizational levels and taxonomy (with examples) within the multilevel risk and resilience parameterization framework to identify assessment metric and measurement metric.

| Organizational level                | Purpose of level                                                                 | Example                                                                 |
|------------------------------------|----------------------------------------------------------------------------------|-------------------------------------------------------------------------|
| Assessment objective               | What is the objective of the risk assessment?                                    | Determine risk to human health from climate change-compounded flood events |
| Management goal                    | What is the management goal of the system being assessed?                        | Minimize human health risk from climate change-compounded flood events  |
| Assessment domain (AD)             | What domains within the management goal are being assessed?                      | Human health and well-being Environment Society                           |
| Assessment subdomain (AS)          | What subdomains, if any, of that domain are being assessed?                      | Acute adverse health impact Physical stressor Geography                  |
| Assessment endpoint (AE)           | What domain attribute(s) is/are being evaluated?                                | Mortality Flooding Population distribution                               |
| Measurement metric (MM)            | What is the actual metric and unit used to quantify the assessment metric?       | Flood mortality rates, population living within flood-prone areas, extent and depth of flooding |
| Data quality & uncertainty (DU)    | Do the metric data exist? How reliable is the measurement method? How robust is the dataset? |                                                                         |

Note: Figure 3B is a parallel visualization of this taxonomy.

**PROOF-OF-CONCEPT: CASE STUDY OF REGIONAL CLIMATE CHANGE IMPACTS IN CHARLESTON HARBOR WATERSHED, SOUTH CAROLINA, USA**

The greater Charleston Harbor region of South Carolina is highly susceptible to the current and projected impacts of climate change because of its low-lying geography, a disparate socioeconomic spectrum, and invaluable ecosystem services (Carter et al. 2018; Del Giudice and Wei 2018; Moore 2018). This case study highlights the application of the MuRRAP and Bayesian network–relative risk model (BN-RRM) as a means of quantifying climate change risk and resilience beyond the vulnerability assessment approach (Cutter et al. 2003; Chakraborty et al. 2005; Flanagan et al. 2011). The presented approach and application of an integrated risk and resilience assessment are used to assess the risk posed to a defined system by climate change and the ability of that system to absorb, recover from, adapt to, and plan for current and future climate change stressors.

*Bayesian network–relative risk model*

The BN-RRM assesses the relative risk of assessment endpoints through causal pathways visualized with conceptual models and quantified with Bayesian network analysis (Ayre and Landis 2012; Landis et al. 2017). The RRM was developed to use spatial data to causally determine risk posed by multiple stressors to multiple endpoints at the regional or landscape scale (Landis and Wiegars et al. 1998). The RRM divides the region of interest into spatially distinct subregions to geographically organize causal relationships and data. The RRM then uses a conceptual model to identify the spatially explicit links between system stressors, impacts, and endpoints (Figure 1C). Exposure–response (i.e., dose–response) data are discretized into a ranking scheme as a means of combining data of dissimilar units. The BN-RRM uses Bayesian network analysis to probabilistically quantify risk and dynamic interactions, rather than hazard quotients and risk quotients typically used in risk assessments. There are numerous examples of the RRM and BN-RRM being successfully used to calculate the risk of multiple stressors to multiple ecological endpoints (Herring et al. 2015; Harris et al. 2017; Johns et al. 2017; Landis et al. 2017). Figure 1 illustrates the rendering of a general RRM conceptual model (Figure 1C) into a region-specific conceptual model (Figure 1D) and then to an endpoint-specific conceptual model (Figure 1E). Once parameterized (Figures 3 and 4), the endpoint-specific conceptual model serves as the structural foundation for the Bayesian network (Figure 5).

Bayesian networks (BN) are acyclic graphical models that quantitatively visualize direct and indirect relationships via conditional probability (Woodberry et al. 2004), such as those linking climate change stressors and impacts on endpoints of value. Moe et al. (this issue) and Kaikkonen et al. (this issue) provide detailed descriptions of BNs and their properties. Additionally, Landis (this issue) details the
Table 3. Organizational levels and taxonomy (with examples) within the multilevel risk and resilience parameterization framework to develop the conceptual model and identify an absorption phase resilience indicator

| Organizational level       | Purpose of level                                                                 | Example                                                                 |
|----------------------------|----------------------------------------------------------------------------------|------------------------------------------------------------------------|
| Management Goal            | What is the management goal of the system being assessed?                        | Minimize human health risk from climate change-compounded flood events |
| Primary Stressor           | What is the source of the stress in the system relevant to the management goal? | Global climate change                                                  |
| Secondary Stressor         | What is/are the consequence(s) of the primary stressor?                         | ACUTE Hurricane intensity                                             |
| Tertiary Stressor          | What is/are the consequence(s) of the secondary stressor? (optional)            | CHRONIC Sea level rise                                                |
| Stressor measurement metric| How is the stressor quantified?                                                 | Extent and depth of flooding                                           |
| Exposure                   | How do the assessment endpoints (i.e., entities) interact with the stressor?    | Floodplains, riparian zones, and low-lying coastal regions             |
| Exposure Measurement Metric| How is/are exposure(s) of the assessment endpoints to the stressor quantified? | Flood-prone areas populated with endpoints of value (e.g., residences, businesses, vulnerable populations, ecosystem services) |
| Effect                     | How are the assessment endpoints effected by stressor exposure?                 | Ability to evacuate flooded areas; drowning mortality                  |
| Resilience goal (i.e., assessment metric) | What system or endpoint characteristics enhance planning/preparing, absorption, recovery, and/or adaptation? | System governance: governing rules and policies of the system (i.e., soft adaptation) |
| Resilience indicator (i.e., measurement metric) | What control factors reduce exposure to, and the effect of, the stressor for the assessment endpoint? | Systemic actions for greenhouse gas emission reductions |
| Data quality & uncertainty (DQU) | Do the metric data exist? How reliable is the measurement method? How robust is the dataset? | |

Note: Figure 3C is a parallel visualization of this taxonomy.
history of the RRM and integration of BNs into the RRM and the resulting BN-RRM methodology, which produces a risk score (in relative risk units) for each subregion of the system.

Application of BN-RRM and MulRRAP

As a proof-of-concept, the MulRRAP framework and the BN-RRM were used sequentially to parameterize and quantify risk to human health resulting from climate change-compounded flooding in 3 representative regions of the Charleston Harbor Watershed using historical and projected climate data, sea level rise projections, and hurricane storm surge model output (NOAA 2017, 2018, 2019). The 3 representative regions are Region 1 with a coastline in a high-risk flood zone, for example, the historic and heavily developed peninsula; Region 2 with coastline in a medium-risk flood zone, for example, residential development on James Island; and Region 3 with no coastline and a low-risk flood zone, for example, the industrial area around Cooper River (Figure S1).

Parameterization. The MulRRAP framework breaks down the primary stressor of climate change into secondary (e.g., sea level rise, extreme precipitation) and tertiary (e.g., nuisance flooding, habitat alteration) stressors, a process exemplified in Table 2. Tertiary climate change stressors are consequences of the secondary stressors. For this case study, the secondary stressors are regional consequences of global climate change. The multistressor model, illustrated in Figure 1E, is an adaptation of the BN-RRM and incorporates resilience parameters as control factors that modulate how risk is carried through the model (e.g., physical flood protection). These control factors modify the degree of exposure to stressors and intensity of effects. The control factors represent resilience characteristics (i.e., plan and/or prepare, absorb, recover, and adapt), management practices, and/or personal actions that, when implemented, reduce risk to the assessed endpoints by reducing exposure to a stressor or the impact of an effect or both. From left to right in Figure 4, the 1st control factor represents the system governance needed to reduce the source of stress, the 2nd represents local government-level hard adaptations (i.e., physical entities, e.g., infrastructure) that control the degree of exposure experience by a location or habitat, the 3rd represents individual-level hard or soft adaptations (i.e., behaviors) that control the degree of impact of effects, and the 4th and last control factor represents the forward-thinking hard and soft adaptations needed at the local level to further reduce risk in the future.

The risk measurement metrics of Charleston residents living within floodplains, the extent and depth of flooding, and the mortality rates for drowning in flood waters were identified using the MulRRAP framework for the evaluation of the assessment endpoint “death due to flood events” (see Table 2 and Figure 3B). The resilience goals (i.e., assessment metrics) related to climate change-compounded flooding include CO₂ emissions regulations, storm surge protection (e.g., oyster reefs as a measurement metric), physical flood protection (e.g., wetlands, flood walls, dam maintenance, directed drainage system as measurement metrics), flood preparedness, and updated floodplain maps that incorporate projected sea level rise (see Table 2 and Figure 3C). Data quality and uncertainty for each measurement metric were evaluated for existence, reliability, and robustness. For example, flood drowning mortality rates were not available for site-specific flooding events, so rates from the primary literature were used instead (Ashley and Ashley 2008; Doocy et al. 2013). The distributions within the respective conditional probability tables were widened to incorporate the estimated uncertainty because the mortality rates were not site specific (see Netica files [.neta] in the Supplemental Data).

The regional governments of the Charleston Harbor Watershed cannot directly affect international governance on the causes of climate change. For this proof-of-concept, only the 2nd and 3rd control factors (e.g., exposure and impact control) are integrated into the parameterized conceptual model as resilience indicators because the assessment is quantifying the hard and soft adaptations at the local level. The identified resilience indicators (i.e., measurement metrics) are incorporated into the conceptual model as a means to reduce exposure to stressors (physical flood and storm surge protections) and the intensity of stressor effects (flood preparedness and access to a personal vehicle). The primary stressor organization level corresponds to the “Source” category of the RRM conceptual model, secondary and tertiary stressor to “Stressor,” exposure to “Habitat/Location,” and effect to “Effect” (Figures 4 and 1, respectively).

Analysis. Figure 5 is a Bayesian network representation from Netica of the endpoint-specific conceptual model (Figure 1E) parameterized using the MulRRAP framework (Norsys Software Corporation 2020). These Bayesian network parameters (i.e., nodes) and relationships (i.e., edges) create a causal pathway between secondary climate change stressors and selected human health risk endpoints. Control factors are the dash-bordered nodes (Figure 5) in ‘Exposure and Effect’ and represent adaptive management practices as resilience indicators (e.g., percent of coastline with physical storm surge protection; percent of population with personal vehicle for evacuation).

The case study input node risk parameter states are discretized into the following relative risk states and corresponding relative numeric values: zero (0), low (2), medium (4), and high (6). The higher the numerical risk state the more adverse the state; so, within each risk node, risk increases when read top (low) to bottom (high). Resilience parameter states are “no,” that is, lack of resilience indicator and unfiltered propagation of risk, and “yes,” that is, presence of resilience indicator and reduction of propagated risk. The current representation of resilience-only models is the ability of the system to “absorb” risk (i.e., the 2nd resilience phase in response to adverse effects). The model currently does
Figure 3. The problem formulation structure expanded to include the multilevel risk and resilience assessment parameterization (MulRRAP) framework and parameterized conceptual model (A). Hierarchical taxonomy of the MulRRAP framework to identify risk assessment metric and measurement metrics (B) and resilience goals and indicators (the 5 black dotted rounded rectangles within C) represent the control factors for the management objective and goal of “Determine and minimize risk to human health due to climate change compounded flood events.” The bracketed numbers in the upper left corner of the MulRRAP components signify the parameterization sequence outlined in Figure 2 and detailed in Figure 4. The gray dash-dotted boundaries encompassed the risk and resilience parameters whose data quality and uncertainty must be quantified. AD = assessment domain; AS = assessment subdomain; AM = assessment endpoint; AM = assessment metric; DQU = data quality & uncertainty; Ef = effects; EMM = exposure measurement; Ex = exposure; MM = measurement metric; PS = primary stressor; SMM = stressor measurement metric; SS = secondary stressor; TS = tertiary stressor.
Figure 4. (A) The problem formulation structure expanded to include the multilevel risk and resilience assessment parameterization (MulRRAP) framework and parameterized conceptual model. (B) Overlay of the MulRRAP framework (gray-outlined and numbered boxes) and relative risk model (rectangle, arrow, and rounded rectangle) produces the parameterized conceptual model (gray-filled shapes) which provides the structural foundation of the Bayesian network in Figure 5.
Figure 5. (A) The problem formulation structure expanded to include the multilevel risk and resilience assessment parameterization (MuRRAP) framework and parameterized conceptual model. (B) Example parameterized Bayesian network for risk to human health from climate change-compounded coastal flooding. Network overlaid with the MuRRAP framework categories. The black dash-bordered nodes denote model control factors, that is, resilience indicators.
not quantitatively reflect the other attributes of resilience (i.e., plan and/or prepare, recover, and adapt), but these are captured in the fourth control factor in the conceptual model (Figure 1). The conditional probability tables (Tables S1 to S24) were populated by establishing the probability of the extreme states. When all the input nodes were zero or high risk, the intermediary or child node would be 100% zero or 100% high risk, respectively. The remaining cells of the conditional probability table were conservatively interpolated using observational and projected data (Marcot et al. 2006). The output node of the analysis produces a continuous endpoint relative risk score between 0 and 6. Detailed explanations of the parameters, discretization schemes, data sources, and Netica files (.neta) are available in the Supplemental Data.

Results. The expected value for risk to human health was calculated using projected and estimated input data producing the following relative risk scores: Region 1 (e.g., peninsula), 2.42; Region 2 (e.g., coast), 3.54; and Region 3 (e.g., no coastline), 1.56 (Table 4). The higher the relative risk score, the more at-risk the region. When all resilience parameters were set to 100% “no,” that is, low resilience, the risk to all 3 regions increased compared to the expected values: Region 1, 4.63; Region 2, 4.55; and Region 3, 1.86. Region 1 was most sensitive to the decreased resilience with a risk increase of 91%. Conversely, when all resilience parameters were set to 100% “yes,” that is, high resilience, the risk to all 3 regions decreased compared to the expected values: Region 1, 1.70; Region 2, 1.87; and Region 3, 1.20. Region 2, with more populated floodplains than the other regions, was most sensitive to the increased resilience with a risk decrease of 47%. Region 3, with fewer floodplains, was the least influenced by resilience scenarios, varying approximately 20% in either direction.

The current configuration of the Bayesian network embodies dynamic changes (e.g., “what if” scenarios) to risk and resilience through the automatic recalculation of relative risk whenever evidence (e.g., “Hurricane Category” at 100% medium risk) is set for a scenario occurring during a specific time point. The generation of a “what if” scenario allows managers to identify worst- and best-case scenarios that can inform current and future management decisions.

### DISCUSSION

This paper presents the MulRRAP framework applied to a subsystem of a complex socioecological system (e.g., Charleston Harbor Watershed) using the Bayesian Network—Relative Risk Model (BN-RRM) as the integrating quantitative method (Ayre and Landis 2012; Landis et al. 2017). The MulRRAP approach unfolds the problem formulation step, allowing for systematic analysis of a complex system within the risk and resilience management framework. The application of the MulRRAP framework facilitates the hierarchical organization and characterization of system components within a complex system across ecological, spatial, and temporal scales, thus enabling the identification of system entities and relationships from which potential measurement metrics and indicators are derived from management-focused assessment goals (Angeler et al. 2016).

The MulRRAP framework is a logical extension of early biomarker frameworks (Burger 2006), parallels the Adverse Outcome Pathway (AOP) framework (Ankley et al. 2010), systematizes the parameterization process for both risk and resilience, and integrates a quantitative approach to resilience assessment. However, models resulting from any assessment framework, even the MulRRAP framework, are abstractions of complex systems and their properties (e.g., socioecological resilience indicators). Socioecological systems are open systems despite the spatial and temporal boundaries defined during the assessment process. Therefore, the parameterization and assessment of any open system will always be incomplete. Two of the strengths of Bayesian network analysis are the ability to incorporate uncertainty (e.g., probability distribution) and to account for a lack of data, typically addressed by using a uniform distribution. Additionally, assessment parameter values can be readily updated with new data for rapid recalculation.

The MulRRAP framework also explicitly identifies where data quality and data uncertainty should be quantified within the parameterization process and further characterizes data uncertainty before quantification. Parameterization is critical to reach the point of measurement and quantification. Ideally, data for each parameterized metric and indicator should (1) exist; (2) have reliable measurement methods; and (3) have robust datasets. Although the existence of data is an obvious criterion (that is not always met), an underappreciated aspect of data uncertainty, especially in the social component of socioecological systems,

### Table 4. Relative risk output table for changes in scenario risk scores caused by varying levels of resilience as affected by control factors.

| Scenario | Risk region | 1 (e.g., peninsula) | 2 (e.g., coast) | 3 (e.g., no coastline) |
|----------|-------------|---------------------|----------------|-----------------------|
| Expected values | Relative risk score | 2.42 | 3.54 | 1.56 |
| Low resilience | Relative risk score | 4.63 | 4.55 | 1.86 |
| Difference | 2.21 | 1.01 | 0.30 |
| Relative risk score | 91% | 29% | 19% |
| High resilience | Relative risk score | 1.70 | 1.87 | 1.20 |
| Difference | −0.70 | −1.67 | −0.36 |
| Relative risk score | −29% | −47% | −23% |

Note: The “Relative Risk Score” is the output of the Bayesian network analysis within the Relative Risk Model. The “Difference” is the percent change of the “Relative Risk Score” when modeled with “Low Resilience” and “High Resilience” compared to the “Expected Values” state. Bolded numbers indicate largest magnitude of change. The higher the “Relative Risk Score,” the more at-risk the region. A negative difference between relative risk scores results from increased resilience.
is the logistical difficulty in obtaining data theoretically suitable as a metric or indicator. Therefore, 1 key metric for data uncertainty must include an attribute for whether the data exists, and not just a qualitative or quantitative estimate of the size of the uncertainty relative to the values used (i.e., data robustness) or the measurement methodology (i.e., data reliability).

The overall approach we have proposed enables the quantification of a complex metasystem, such as a socioecological system, to be systematically analyzed using the equivalent of a systems engineering approach. The systems engineering perspective evaluates all likely aspects of a system, which are then integrated to create a system that is greater than the sum of its components (Holstein and Bode 2015). For example, increased flooding events and adverse health impacts caused by water contamination may well be synergistic. Thus, the socioecological watershed system should be examined as a whole when characterizing and modeling such a relationship. Additionally, the impact of sea level rise on storm surge flooding (e.g., extent, intensity, and duration) can be predicted using hydrodynamic models (Castrucci and Tahvildari 2018). However, the storm surge models produced by the National Hurricane Center do not account for sea level rise, thus adding calculation uncertainty by modeling the predictions for each phenomenon separately. Extrapolating from modeled predictions is only a start to the analysis. Future modeling scenarios must include synergistic impacts across critical infrastructure. For example, although the direct impacts of Hurricane Sandy affected the eastern coastal states, indirect infrastructure impacts reached as far west as Ohio and Michigan (NERC 2014).

A benefit of the BN-RRM is that inherent node and internode mechanisms and interactions can be integrated in the same model, even when internode interaction mechanisms require very different assumptions to be built into the node dynamics models. The current discretization scheme used within the BN-RRM approach simplifies a continuous probability distribution into a 4-bin approach (i.e., zero, low, medium, high). However, the scheme can be modified for tipping point analysis, such as “points of no return” when too many critical infrastructure systems fail and the dependent socioecological system follows (Costanza 1999; Fortna n.d.).

As we strive to assess the true complexity of complex systems, it becomes more important to build into our models the interactions and dynamics of the system parameters (i.e., nodes). The MuIRRAPR process makes complex and dynamic systems more approachable and feeds easily into Bayesian network analysis. Characterization of node interactions is understudied but critical (Kellble et al. 2013; Landis et al. 2013), especially when evaluating multistressor phenomena such as those associated with climate change. Resilience is a dynamic, multithread process (e.g., preparing and hardening, resisting and absorbing stressors, recovery from induced damages, and adaptation for future protections) that influences the node states and interactions while amplifying the complexity of analysis (Holling 2001; Linkov and Trump 2019). Future dynamic complex risk and resilience analysis must also include the ability to quantify the influence of both feedforward (as per Bayesian network analysis) and feedback processes inherent to large-scale, highly complex, evolving metasystems, such as the socioecological-physical systems as found in any human-populated watershed.

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Data Availability Statement—All data sources are public government dataset available via the links provided in the References and Supplemental Data. Bayesian network analysis files are available by contacting corresponding author Mariana Goodall Cains (cainsmg@gmail.com).

SUPPLEMENTAL DATA
The Supplemental Data files contain: 1) supplemental image of the case study site, Charleston Harbor Watershed, SC; 2) the discretization scheme for the Bayesian network; 3) the conditional probability tables for Region 3 of the case study site; and 4) Bayesian network analysis files (Netica; .neta).

ORCID
Mariana Goodall Cains http://orcid.org/0000-0002-6729-6729

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