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Decision-Making Analytics Using Plural Resilience Parameters for Adaptive Management of Complex Systems

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It is critical for complex systems to effectively recover, adapt, and reorganize after system disruptions. Common approaches for evaluating system resilience typically study single measures of performance at one time, such as with a single resilience curve. However, multiple measures of performance are needed for complex systems that involve many components, functions, and noncommensurate valuations of performance. Hence, this article presents a framework for: (1) modeling resilience for complex systems with competing measures of performance, and (2) modeling decision making for investing in these systems using multiple stakeholder perspectives and multicriteria decision analysis. This resilience framework, which is described and demonstrated in this article via a real-world case study, will be of interest to managers of complex systems, such as supply chains and large-scale infrastructure networks.

KEY WORDS: Decision support; resilience; risk management

1. INTRODUCTION

The study of resilience commonly involves analyzing a system's ability to absorb, recover, and adapt after a disruption (Aven, 2011; Haimes, 2009a; Linkov et al., 2014). Methods for studying resilience often involve the analysis of some performance indicator or figure of merit (Henry & Ramirez-Marquez, 2012) for the system, then measuring aspects of the system recovery process (Ayyub, 2014). This recovery process can be studied in relation to specific scenarios or disruptive events, though broader goals for resilience management also involve the assessment of strategies to protect against unforeseen or surprise events (Aven, 2015). There is need to expand the study of resilience to consider complex systems that may involve multiple performance indicators and system uses. In addition, there is need to understand how to invest in resilience initiatives for systems that are both complex and adaptive. For example, a supply chain system is a complex adaptive system, as defined by the system's abilities to evolve, self-organize, and anticipate disruptions. These systems contain several subsystems including transportation infrastructure assets, suppliers, manufacturing facilities, customers, information, people, and services (Lummus & Vokurka, 1999). Effective supply chain operations require efficient and healthy transportation networks as well as available workforce sectors, resource inputs, technologies, cyber networks, and other functioning subsystems, among others. Because consequences of disasters can be severe, such as the $125 billion damage from the 2017 Hurricane Harvey (NOAA Office for Coastal Management, 2018) or the $90 billion annual impact of influenza in the United States (Molinari et al., 2007), it is imperative to enable these types of complex systems to maintain operations or to quickly recover operations following a disruptive event.

The term "complex system" is often used to characterize a system that contains many parts or interdependent subsystems (Bar-Yam, 2002). Furthermore, "complex adaptive systems" are systems

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that evolve by improving their ability to interact with surrounding subsystems; they synergize through the ability to perform through interactions of subsystems; and they anticipate through seeking to adapt to changes in circumstances (Holland, 1992). Once a complex adaptive system has been disrupted, regardless of the status of recovery efforts, the system would subsequently develop or morph into an adapted and reorganized system. Indeed, Rose and Krausmann (2013) emphasized that a system's inherent (or static) resilience should be supplemented with adaptive (or dynamic) resilience, which is the ability of the system to improvise and implement creative measures when subjected to stress. In fact, the aspects of transformability or reconfiguration are viewed as key dimensions in the evaluation of resilience for sociotechnical systems (Amir & Kant, 2018). More resilient systems may perform this type of adaptation more easily and more acutely than others, but the original complex system is not the same as prior to the disruption (Hughes, Bellwood, Folke, Steneck, & Wilson, 2005).

If a broadened measurement of resilience includes abilities to recover, adapt, and reorganize, various levels or attributes of system performance should be studied in relation to each other. Particular attributes may have varying levels of importance for a given purpose, stakeholder, disruptive event, or investment. A measurement approach that is only based on recovery time or single performance metrics, such as in singular resilience curves (Ayyub, 2014; Henry & Ramirez-Marquez, 2012), may undermine the future system needs. In other words, a slow and agile system recovery may allow for systems to adapt to postdisruption needs such as capacities, demographics, and functions, among others. Thus, a broadened measurement of resilience should contain measurements of performance that extend beyond single status quo metrics. They should also acknowledge stakeholder needs through both analytics and decision-support processes (Linkov et al., 2018; Thorisson et al., 2017). For example, Table I provides a sample of performance indicators that apply to stakeholders at some point within the infrastructure life cycle. The relevance of particular indicators may be influenced by system functions, the operating environment, interested stakeholders, and many other factors. A subset of these performance indicators will be used for the case study in subsequent sections of this article.

This article will address the challenges by presenting a methodology that contributes to the process of understanding and modeling resilience for complex systems, such as supply chain systems, with consideration of multiple and possibly competing valuations of performance. First, this approach will model resilience for complex systems using several competing attributes of performance, such as workforce, infrastructure capacities, and sustainability initiatives. Next, this approach will demonstrate decision making with the plural resilience measurements using models for multicriteria and multistakeholder prioritization of protective alternative investments.

This article is the first to capture the plurality of resilience measurements for increasingly complex systems such as supply chains, including issues of system recovery and reorganization, in a multistakeholder model. The methodology is applicable to a wider variety of system types, such as infrastructure systems and information systems. The methods and results will be of interest to managers of complex systems, such as supply chains and large-scale infrastructure networks.

This article is organized as follows. Section 2 will provide an overview of relevant literature for understanding the topic of resilience, risk, and performance management. Section 3 will provide the general mathematical approach of this article. Section 4 will demonstrate the approach on a hypothetical case study involving a distributed supply chain network. Section 5 will provide general conclusions and opportunities for future research.

2. BACKGROUND

2.1. Modeling Resilience

Research involving the protection of or risk to supply chain networks has traditionally involved the understanding of how a network responds to various specific disruptive scenarios (Klibi & Martel, 2012; Thekdi & Santos, 2016) and evaluating other event-specific risk mitigation options (Jüttner et al., 2003). However, there is new and renewed interest in the topic of resilience, which involves understanding how a system recovers and adapts after a disruptive event. The topic of resilience has been studied across a wide variety of disciplines. For example, ecosystems (Holling, 1973; Hughes et al., 2005), social systems (Adger, 2000; López-Cuevas, Ramírez-Márquez, Sanchez-Ante, & Barker, 2017), infrastructure (Bruneau et al., 2003; Zobel, 2011), economies (Rose, 2004), cyber systems (Gisladottir, Ganin, Keisler, Kepner, & Linkov, 2017), and many

Table I. Sample of Performance Indicators for Infrastructure Systems

System Characteristics	Performance Indicator	Relevant Metrics
Function	• Geography for service	Service coverage, capacities for regions
	• Schedules for service	Frequency of service, efficiency
	• Environmental conditions	Emissions, air quality
Capacity	• Redundancy in design	Network redundancy
	• Geographic growth	System utilization, system area, changes in capacity
Users	• Population shifts	System utilization, usage on segments
	• Demographic changes	Transportation modes
Stakeholders	• Ownership changes	Public owners, private owners, public-private partnerships
Social	• Social capital	Social trust
	• Social memory	Past deficiencies, public relations issues
Sustainability	• Eco-friendliness	Carbon footprint, environmental impact, neighboring ecosystems
	• Energy efficiency	Energy usage
Health and Safety	• Health conditions	Accident rates, employee sick days
Economy	• Availability of goods and services	Economic activity
Infrastructure	• Transportation	Road, rail, air, sea transport condition
	• Schools	School condition

others. Typical engineering system definitions rely on the understanding of robustness, rapidity, resourcefulness, and redundancy for the system following disruption (Bruneau et al., 2003). There has been significant work in developing a broad understanding of these metrics and formalizing decision-making concerns (Ayyub, 2014). These models often assume there is a single (or aggregated) measurement of performance, such as the percentage quality of infrastructure functionality or figure of merit (e.g., network efficiency, connectivity flow, throughput rate) (Henry & Ramirez-Marquez, 2012). In contrast, emerging research has studied resilience in the context of "success criteria," representing possibly competing stakeholder goals (Thorisson et al., 2017). The resulting analysis often supports organizations to invest in policies and practices that target a predecided status-quo level for operational performance.

In assessing and managing the operational performance of a system, it is necessary to evaluate how the system performs under "business as usual" scenarios and how it behaves when it is subjected to a disrupted event. The concept of "resilience triangle" is one of the widely used visualization models for describing the ability of a system to resist degradation relative to its status quo (robustness) and the speed with which it recovers to an acceptable level of operational performance (rapidity). Consider the notation used for a resilience triangle as depicted

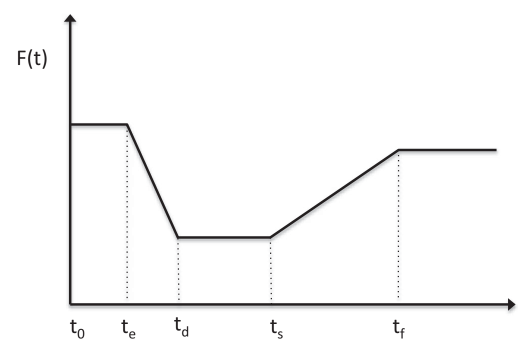

Fig. 1. Resilience triangle definition using notation from Henry and Ramirez-Marquez (2012).

in Fig. 1, using the assumptions and notation given in Henry and Ramirez-Marquez (2012). Let $F(t)$ represent the performance function for the system, t_0 represents time at the initial state, t_e is the time of the disruption, t_d is the time of the final disruptive state, t_s is the time of the resilience action, and t_f is the time of recovery. Now suppose $E = \{e_1, e_2, \ldots, e_m\}$ is the set of all disruptive events and resilience is computed at time t_r, where $t_r \in (t_d, t_f)$. Then, resilience $\mathcal{R}(t_r|e_j)$ is represented as the ratio of recovery and maximum loss, computed in Equation (1) as follows (Henry & Ramirez-Marquez, 2012):

$$\mathcal{R}(t_r|e_j) = \frac{F(t_r|e_j) - F(t_d|e_j)}{F(t_0) - F(t_d|e_j)}. \quad (1)$$

This definition can be broadened to apply to complex systems in several ways. First, this notation and definition should characterize the possibility that a system can adapt and be made stronger following a disruptive event. Hence, modeling methods are needed to understand resilience beyond the achievement of a status quo performance function. Second, this notation and definition should consider multiple and possibly conflicting measures of performance that may exist in a complex adaptive system. As discussed below, measures of performance may be noncompensatory, thereby not allowing these measures to be represented in a single function.

2.2. Pluralistic Considerations for Risk

Foundational principles of risk and resilience involve a nuanced understanding of time-dependent system states. The performance indicators or capabilities of a system are a function of the state vector. The resilience vector is a function of system inputs, system states, and time (Haimes, 2009b). These principles support the notion that risk and resilience management are multidimensional, with possibly noncommensurate objectives, or involve stakeholder disagreement.

Risk and resilience management of complex systems requires an understanding of numerous subsystems and related interdependencies. In addition, these complex systems often serve multiple functions, have multiple owners/operators, and involve a wide variety of stakeholders. For practical applications, the interdependencies within the system can be dynamic and partially understood. A commonly used tool to model risks and scenarios is hierarchical holographic modeling (HHM) (Haimes et al., 2002). This HHM model shows various perspectives on the system requirements using a hierarchical format. This structure can be used to generate risk scenarios, identify various stakeholder perspectives, and formalize understanding and management of risk sources.

Other methods have been used to understand the relationship between social and technical components of large-scale systems. For example, the functional resonance analysis method breaks down sociotechnical systems into three components: human, technical, and organizational (Hollnagel, 2012). Also, the driver-pressure-state-impact-resource approach combines socioeconomic modeling with spatial analysis (Pirrone et al., 2005). Furthermore, the PEOPLES model (Cimellaro et al., 2016) presents a multidisciplinary approach to account for the plural dimensions of resilience as follows: population and demographics; environmental and ecosystem; organized governmental services; physical infrastructures; lifestyle and community competence; economic development; and social-cultural capital.

2.3. Performance Measurement and Relationship to Risk

Principles of performance management are deeply integrated with concepts of risk. Lebas (1995) states that "[a] performing business is one that will achieve the objectives set by the managing coalition, not necessarily one that has achieved the objective." Similarly, the understanding of risk is formed on a future projection of events, albeit these are potential events that can cause losses to the studied system.

For practical management applications, no single measure of performance or risk is sufficient for investment decision making. Some applications prefer to include multiple measures of performance using monetized valuations for a wide variety of performance metrics. However, the translation from a nonmonetary performance metric into monetary terms can lack objectivity and be inconsistent with stakeholder valuations. The reader is invited to explore ethical concerns for monetizing environmental, safety, and health topics in Kelman (1981).

When multiple objectives are included in a decision-making problem, either a compensatory or noncompensatory approach can be used. A compensatory approach allows for low performance for a particular criterion to be offset by high performance for another criterion. Conversely, a noncompensatory approach involves an analysis of tradeoffs among relevant criteria (Goodwin & Wright, 2014). In the case of complex systems, it can be argued that a noncompensatory approach is critical for decision making. For example, decisionmakers may be unwilling to state that overperformance in sustainability criteria compensates for underperformance in safety criteria.

3. METHODS

3.1. Overview of Approach

Fig. 2 provides an overview of methods for this article. First, we identify relevant performance metrics and model parameters, acknowledging that a

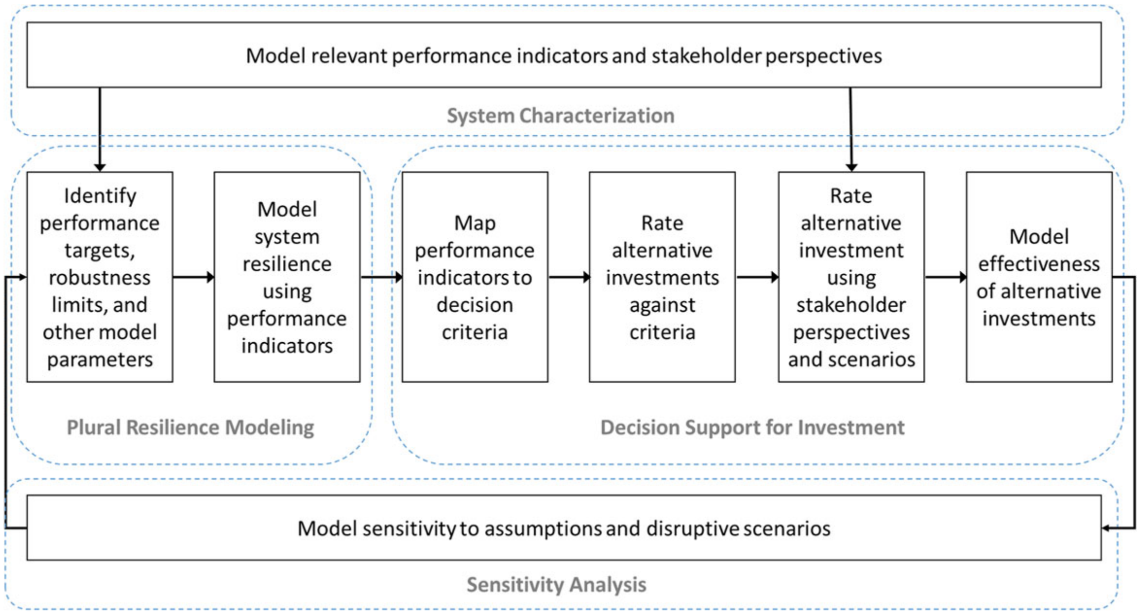

Fig. 2. Overview of methodology for decision-making analytics using plural resilience parameters.

complex system can be evaluated from several competing performance perspectives. Next, we model system resilience using the relevant performance indicators. Then, we develop a decision-support model for understanding the effectiveness of alternative investments using stakeholder perspectives and scenario analysis. Although the methods of this article are data focused and are designed to be objective, these performance values will be vital for understanding how to choose investments and policies that can enhance system resilience.

This section is organized as follows. Section 3.2 describes the approach for system characterization, allowing for decisionmakers to understand problem scope and model plural resilience characteristics. Section 3.3 provides the approach for multicriteria decision support, allowing for identifying relevant criteria, understanding relative importance of criteria, and ranking potential investments that can be used to enhance resilience. Section 3.4 provides sensitivity analysis to understand the appropriateness of decisions.

3.2. Formulation of Plural Resilience Measures

Table II provides a summary of the parameters used for the problem formulation. These parameters include plural performance and resilience characteristics, F and R, respectively. Also included are elements for multicriteria decision making, including potential alternative investments, relevant criteria, ratings for alternative investments against criteria, and relevant stakeholders.

Here, we introduce an alternative measurement of resilience that allows for flexible understanding of how recovery will meet the needs of a transformed or reorganized system, as shown in Equation (2):

$$R_i\left(t_r|e_j\right) = \begin{cases} \dfrac{F_i\left(t_r|e_j\right) - F_i\left(t_d|e_j\right)}{G_i\left(t\right) - F_i\left(t_d|e_j\right)}, & F_i\left(t_d|e_j\right) < G_i,\ F\left(t_r|e_j\right) > B_i\left(t\right) \\ 1, & F_i\left(t_d|e_j\right) \geq G_i,\ F\left(t_r|e_j\right) > B_i\left(t\right) \\ 0, & F\left(t_r\right) \leq B_i \end{cases} \quad (2)$$

Similar to the formulation by Henry and Ramirez-Marquez (2012), this resilience formulation compares system recovery to loss at time t_r. However, this differs from the established model in the following ways. First, instead of measuring loss as compared to the system's initial state, we compare with a specified performance target, G_i. This target may increase or decrease with time, contingent on system reorganization, during or following a disruption. This is an agreement with emerging principles of performance and risk management that call for reference to some target performance level, which may change over time (Thekdi & Aven,

Table II. Summary of Notation Used in the Problem Formulation

Parameter	Description
$F_i(t)$	Function for performance indicator i, such that $0 \leq F_i(t) \leq 100, i = 1, \ldots, p$
$G_i(t)$	Target for performance indicator i, such that $0 \leq G_i(t) \leq 100, i = 1, \ldots, p$
$B_i(t)$	Robustness limit (minimum performance) indicator i, such that $0 \leq B_i(t) \leq 100, i = 1, \ldots, p$
R_i	Resilience measured for performance indicator i, such that $R_i \geq 0$ $i = 1, \ldots, p$
C	Criteria used to evaluate alternative investments, $C = (c_1, \ldots, c_m)$
A	Alternative investments used to improve system resilience, $A = (a_1, \ldots, a_n)$
S	Stakeholders considered for evaluating alternative investments $S = (s_1, \ldots, s_q)$
W	Weights assigned to criteria, $0 \leq w_{ij} \leq 1, \sum_{j=1}^{m} w_{ij} = 1$ for all $i = 1, \ldots, q$
Z	Rating for each alternative investment against criteria, $0 \leq z_{jk} \leq 5$, for $j = 1, \ldots, m$ and $k = 1, \ldots, n$
V	Scenarios considered for evaluating alternative investments $V = (v_1, \ldots, v_b)$
t_o	Time of initial state
t_e	Time of disruption
t_d	Time of final disruptive state
t_s	Time of resilience action
t_f	Time of recovery
t_r	Time of resilience computation R_i

2016). It is also in agreement with broadly defined complex adaptive systems as they evolve and adapt to changes in circumstances (Holland, 1992). For example, following the 2005 Hurricane Katrina, there is evidence to suggest that the recovery and rebuilding efforts led to more strengthened levee systems and other features that improved the city's ability to withstand future storms (Kates, Colten, Laska, & Leatherman, 2006). Thereby, this model recognizes that target performance levels are a function of the system's current features, allowing decisionmakers to consider the option to model changes or uncertainties in target performance levels. The function in Equation (2) does not improve after the target is exceeded. Second, resilience is measured for each of the p performance measurements instead of using a single global measure. This is also in agreement with recent literature that supports resilience modeling using multiple operational perspectives (Thekdi & Chatterjee, 2018). Third, this function considers a robustness limit B_i representing the minimum possible level of performance such that recovery is still possible. If system performance falls below this robustness limit, resilience is assumed to be zero. Similar to the formulation of specified performance target, G_i described above, the robustness limit B_i is assumed to be time dependent, such that this term may change before and after a disruption. While decisionmakers can define how this robustness limit metric changes over time, they can only choose to do so when they believe the system has intrinsically changed.

3.3. Decision Support for Investment

This section will describe the multicriteria decision support method for identifying the most appropriate alternative investments that can be used to improve system resilience. The method includes the selection of model inputs, consisting of a set of alternative investments, performance measurements, criteria, stakeholders, and rating of alternative investments against the criteria. The model input selection methodology may differ by application and the needs of the various decisionmakers. However, common methodologies may include the use of expert elicitation (Clemen & Winkler, 1999). In cases where expert-elicited data are unavailable or unreliable, brainstorming sessions among relevant stakeholders (Lunenburg, 2011), and group decision-making processes (Hwang & Lin, 2012) can be used. However, care should be taken to ensure these values remain objective in order to avoid any intentional or unintentional bias (Kynn, 2008). Decisionmakers should also recognize that even expert opinions can have limited or varying accuracy (Camerer & Johnson, 1997), and involve uncertainties (Paté-Cornell, 1996).

Consider a set of n predefined alternative investments or policies, $A = \{a_1, a_2, \ldots a_n\}$. These policies are not specific to a particular event, and therefore can be applicable to system recovery from all studied scenarios. Potential alternative investments of policies could include investing in cyber-security experts, increasing monitoring (e.g., surveillance sensors and cameras), workforce awareness training, strengthening perimeter security, implementation of backup plans, and others.

Let F represent the set of p predefined performance measurements, such that $F = \{f_1, f_2, \ldots, f_p\}$. Relevant performance measurements include travel time, accident rates, efficiency, and other attributes, as given in Table I. We can visually represent the relationship between performance measurements and criteria as shown in Fig. 3. We recognize that the set of criteria and performance measurements may also influence each other.

To select among the alternative investments or policies, a set of m predefined criteria are introduced, $C = (c_1, c_2, \ldots, c_m)$. Although the importance of criteria may differ among stakeholders and may change as a result of system reorganization, this set represents key aspects of performance, F, determined in the previous step. Relevant criteria may include elements such as sustainability, economic competitiveness, security, and ease of implementation, among others.

Next, we define a set of q predefined stakeholders for the system, $S = (s_1, s_2, \ldots, s_q\}$. These stakeholders are carefully selected to avoid overlap in stakeholder values. If stakeholder groups contain overlapping values, the later decision-making models may overprioritize alternative investments that concurrently meet those stakeholder needs, thereby promoting bias in the methods. For each stakeholder, we elicit weights for all criteria, w_{ij}, for stakeholder i and criterion j, such that:

$$0 \leq w_{ij} \leq 1,$$

$$\sum_{j=1}^{m} w_{ij} = 1, \quad \text{for } i = 1 \ldots, q.$$

Next, we create a matrix Z, which allows us to rate n alternative investments (columns) against relevant m criteria (rows). This score represents how well each alternative investment or policy will improve system resilience compared to a target. While the case study of this article assumes the ratings are consistent across all studied disruptive event scenarios and stakeholder perspectives, some applications may require the rating to be a function of each disruptive scenario. For example, a simple scoring system may use a five-point scale, such that a value of -2 would suggest that the alternative investment would have a highly negative impact on resilience, a value of -1 suggests a slightly negative impact, a value 0 suggests no impact, a value of 1 suggests slightly positive impact, and a value of 2 suggests a highly positive impact. Such scale values and interpretations will be revisited in the actual survey conducted in the case study (see Section 4). Furthermore, such values can be populated using detailed engineering data, expert elicitation, voting among stakeholder groups, or decided by the relevant decisionmakers. More detailed discussion and study of refined data sourcing strategies is a future research opportunity.

$$Z = \begin{bmatrix} z_{11} & \cdots & z_{1n} \\ \vdots & \ddots & \vdots \\ z_{m1} & \cdots & z_{mn} \end{bmatrix}$$

Next, we define a relative scoring for each stakeholder $i = 1 \ldots q$ and each alternative investment $k = 1 \ldots n$ as follows:

$$Rating_{ik} = \sum_{j=1}^{m} w_{ij} z_{jk}.$$

Finally, we define a relative scoring for each of the k alternative investments by summarizing the $Rating_{ik}$ score across the studied stakeholders. A straightforward summarization method involves applying equal weight to each stakeholder, thereby computing the average rating across the q stakeholders as follows:

$$Rating_k = \frac{\sum_{i=1}^{q} \sum_{j=1}^{m} w_{ij} z_{jk}}{q}.$$

However, in some situations the average rating across stakeholders may be too sensitive to outlier stakeholder perspectives. Instead, the $Rating_k$ could be computed using the median $Rating_{ik}$ score across stakeholders. If there is reason to believe that some stakeholders are more influential than others, the $Rating_{ik}$ score can be weighted by the credibility and relevant experience of the stakeholders, as well as the quality of their provided information (Kaplan, 1992).

The ratings can then be used to compare the effectiveness of alternative investments in enhancing system resilience. Although this rating can be calibrated to a 100-point scale, a calibration would be unnecessary for ordinal prioritization purposes.

3.4. Modeling of Sensitivity to Assumptions and Disruptive Scenarios

This section will study model sensitivity to assumptions and disruptive scenarios. The resilience function presented earlier includes critical assumptions regarding the value of targets, which may be

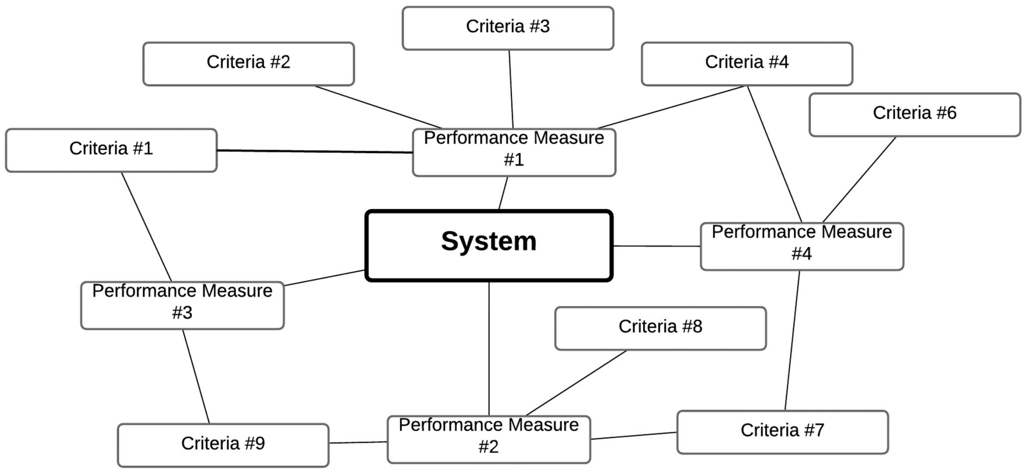

Fig. 3. Sample mapping of criteria to performance measurements for resilience modeling and investment.

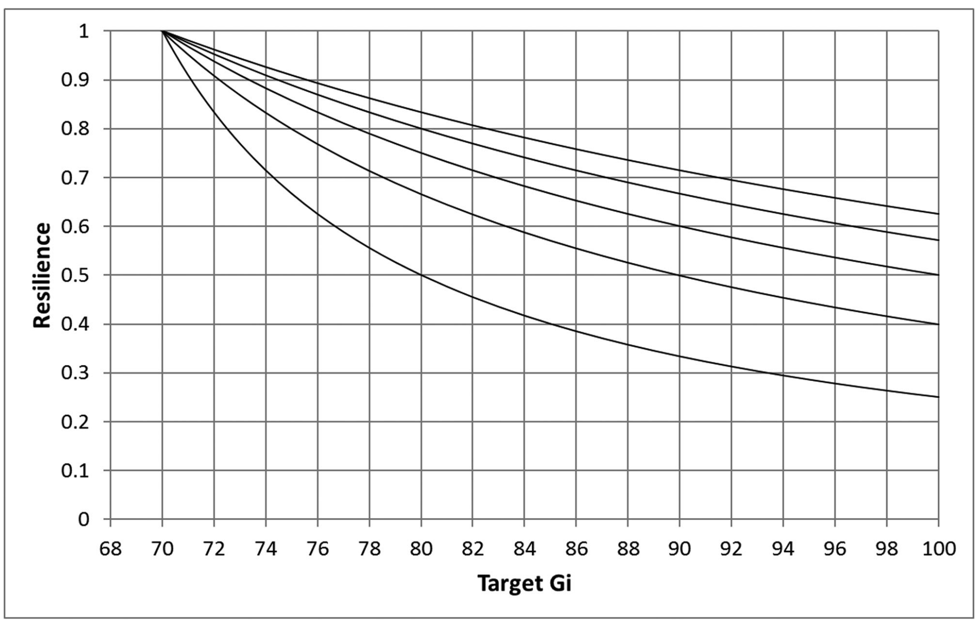

Fig. 4. Resilience to target (G_i) with each line holding $F(t_d)$ constant.

uncertain (see Section 3.2). Suppose for event e_j, the target resilience value will change according to some function. Fig. 4 shows a contour of resilience to target modeled for a test scenario holding $F(t_r)$ constant at a value of 70, signifying 70% relative to an ideal 100% performance level. Each curve on the chart assumes the performance at the final disruptive state $F(t_d)$ is constant, while the target G_i changes. The figure shows that as the target G_i increases, the resilience curve slopes downward. Conversely, resilience increases as the target decreases.

There is a need to understand sensitivity of the resilience model to various disruptive events. Following the tradition of risk and safety analysis, we can assume a worst-case scenario and assume that a system protected from a worst case is by definition also protected from less catastrophic events. Survey information presented in Section 4 will be used to measure how system recovery and system target performance will change under specific disruptive events.

There is also a need to understand sensitivity of the resilience model to various stakeholders.

Although established methods identify the most critical criterion and ratings within multicriteria models (Triantaphyllou & Sánchez, 1997), we aim to understand empirically how model assumptions are expected to change. Expert elicitation data presented in Section 4 will measure how criteria importance varies among studied stakeholder perspectives.

When the sensitivity analysis is complete, there is need for decisionmakers to consider an additional iteration of the methods. This additional iteration may involve the following changes. First, there is opportunity to discard infeasible or poorly rated alternative investments. Conversely, alternative investments that are more applicable to the criteria may be added to the model. Second, decisionmakers may choose to adjust model parameters, such as the relevant performance indicators, target performance levels, and criteria. Third, there may be need for a more detailed analysis that includes more granular rating scales, such as when evaluating the effectiveness of alternative investments. Additionally, this could involve eliciting scenario-dependent rating scales for populating model parameters.

4. CASE STUDY

4.1. Description of Case Study and Data

For the application of methods described above, consider a case study involving risk and resilience modeling for the movement of goods and services in an expansive region. As an example, consider the supply chain system of the U.S. Washington metropolitan area, including Washington, DC, parts of Maryland, Virginia, and West Virginia. With a population of over 6 million, this is the sixth largest metropolitan area in the country (U.S. Census Bureau, 2016). This network is notable as it contains several subsystems with unique valuations of performance. This region contains headquarters for several Fortune 500 companies, contains multiple major airports, is home to several public transportation systems, and is a hub for national political activities. The first challenge of this case study is to understand what attributes of performance most appropriately model the characteristics of this region, then translate those attributes into possibly competing measures of resilience. The second challenge is to identify the most appropriate protective investments while considering the variety of criteria and stakeholder values within the region. The third challenge is to understand how uncertainties, as modeled using scenarios, influence decisions for the most appropriate protective investments in the region.

Expert elicitation was conducted to understand the system response to disruptive events, including natural disasters and health emergencies. The elicitation was conducted using a survey that was created using the Qualtrics survey hosting service, and distributed via e-mail in October 2016. The distribution list was selected to include eight researchers and industry professionals with five or more years of experience related to transportation and supply chain systems. The elicitation process collected data for five performance indicators ($p = 5$), as shown in Table III, five ($m = 5$) criteria, shown in Table IV, five ($q = 5$) stakeholders, shown in Table V, four ($n = 4$) alternative investments, shown in Table VI, and four ($b = 4$) scenarios, shown in Table VII.

The studied scenarios have varying temporal characteristics. The scenario V_1 (Pandemic) time scale could range from months to years (Potter, 2001); scenario V_2 (Hurricane) may transpire over the course of days (Evans & Hart, 2003); scenario V_3 (Cyber Attack) may involve a timescale of hours or months (U.S. House of Representatives, 2017); while scenario V_4 (Climate Change) may transpire over the course of decades (Moss et al., 2010). While the set of scenarios encompass a collection of both rapid-onset and slow-onset events, there are some commonalities and differences in the potential investments for preparedness, mitigation, and response among those scenarios. The decision-support component of this article aims to exploit these differences in scenarios to understand the sensitivity of those investments among studied stakeholders and scenarios. Therefore, this variety in scenarios is intended to demonstrate the methods and contribution of this article.

The questions were designed to provide structured data inputs to the resilience models of this article. Respondents were primarily asked to characterize the relationship between disruptive scenarios and the supply chain infrastructure. For example, a respondent may view a hurricane as having a direct impact on all elements of the supply chain infrastructure, such as roads, production facilities, and consuming sectors, among others. In contrast, a respondent may view a disease pandemic as having a minimal impact on the supply chain infrastructure, resulting in the indirect impact to not be portrayed in the survey response. The expert elicitation questions are as follows.

Table III. Relevant Performance Indicators ($p = 5$) Used in the Case Example

	Performance Indicator	Description
F_1	Workforce availability/mobility	Absence of major obstacles that could impede workers to access their workplace and/or perform their duties
F_2	Commodity travel time efficiency	Minimal unexpected delay for the movement of goods and services
F_3	Transportation infrastructure capacity	Volume of people, goods, and services that can be transported at an acceptable quality level
F_4	Availability of production inputs	Availability of raw materials, supplies, and inventory used to support operations
F_5	Ideal level of consumption	Optimal level of goods and services purchased by consumers

Table IV. Relevant Criteria ($m = 5$) Used in the Case Example

	Criteria	Description
C_1	Safety of people and commodities	Safety of people, production inputs, and production outputs during transport
C_2	Environmental sustainability	Promotion of sustainability for land, air, and water
C_3	Supply chain "user" satisfaction	People, goods, and services that arrive at an acceptable time and quality level
C_4	Transportation network efficiency	Movement of people, goods, and services at an acceptable time and cost
C_5	Balanced supply and demand	Optimal level of goods and services available

Table V. Relevant Stakeholders ($q = 5$) Considered in the Case Example

	Stakeholder	Description
S_1	Economic development officials	Responsible for promoting community revenue growth
S_2	Suppliers	Responsible for supplying production inputs
S_3	Customers	Consumers of production outputs
S_4	Emergency managers	Responsible for ensuring community safety in the aftermath of a disruptive event
S_5	Community members	Citizens in the studied community

Table VI. Alternative Investments ($n = 4$) Considered in the Case Example

	Alternative Investments	Description
A_1	System monitoring	Tools for tracking the health and performance of the system (e.g., surveillance tools such as cameras or sensors)
A_2	Data mining	Identification, collection, and analysis of near real-time data sources (e.g., social media posts or tweets)
A_3	Transportation management	Strategies for improving mobility and efficiency in transportation networks (e.g., alternative routes or future capacity increase)
A_4	Human resource management	Strategies for enhancing availability of workers (e.g., telework)

Survey Question #1: Mapping of relevant performance metrics with relevant criteria. This question allows each expert to rate the importance of each criterion on each performance indicator. For each performance indicator given in Table III, experts rated the importance of safety of people and commodities; environmental sustainability; supply chain "user" satisfaction; transportation network efficiency; and balanced supply and demand. The rating scale contained the following options: *not important* (0), *somewhat important* (1), *important* (2), and *very important* (3). The task is done with understanding that particular criteria may be more relevant to some performance indicators versus others. The model assumed that criteria assigned to be not important (0) on average would have zero weight in the multicriteria decision-support model. Conversely, the quantitative results allow more relevant criteria to have a larger weight of importance in the multicriteria decision-support model. The survey provided a

Table VII. Scenarios ($b = 4$) Considered in the Case Example

	Scenario	Description
V_1	Pandemic impacting workforce	Pandemic such as a public health emergency, influenza (for example, H1N1), zika, ebola, malaria, etc.
V_2	Hurricane	Hurricane of various categories
V_3	Cyber attack on monitoring system	Cyber attacks such as identity theft, denial of service, unauthorized access, and malwares
V_4	Climate change	Increased frequencies and intensities of hurricanes, floods, ocean level rise, diseases, droughts, among others

description of each performance indicator and criteria to address the challenges of this survey process.

Survey Question #2: Understanding stakeholder weights. This question allows experts to suggest the importance of criteria (given in Survey Question #1) for preidentified stakeholders of the system. The considered stakeholders are economic development officials, suppliers, customers, emergency managers, and community members. For each stakeholder perspective, experts provide a rating (scale 0–100) to represent the relative importance of each criterion. For each stakeholder perspective, the sum of all criteria weights must be 100. The web-based survey included a function that allowed the experts to check if the weights indeed add up to 100%.

Survey Question #3: Understanding the expected impact of alternative investments on system resilience. This question allows experts to understand four alternative investments and rate the effectiveness of these investments for system resilience using a five-point scale. A rating of "−2" implies a highly negative impact; a rating of "−1" implies a slightly negative impact; a rating of "0" implies no impact, a rating of "1" implies a slightly positive impact; and a rating of "2" implies a highly positive impact. The four alternative investments are (1) system monitoring (e.g., surveillance tools such as cameras or sensors), (2) data mining (e.g., analysis of social media posts or tweets), (3) transportation management (e.g., alternative routes or future capacity increase), and (4) human resource management (e.g., telework). While this demonstration of methods assumed that each score was consistent across all studied scenarios, this assumption may not be practical in more detailed applications. For a more detailed analysis, the analyst may choose to collect data on the rating of each alternative investment on resilience for each studied disruptive scenario.

Survey Question #4: Understanding how targets are expected to change after a disruptive scenario. This question allows experts to use a sliding bar to indicate how the performance targets (given in Survey Question #1) increase or decrease after a disruptive scenario. For example, a survey taker may suggest that the importance of cyber-security performance increases following a disruptive event. A response of "−2" implies a major decrease (valued as a 20% decrease), a response of "−1" implies a minor decrease (valued as a 10% decrease), a response of "0" implies no change, a response of "1" implies a minor increase (valued as a 10% increase), and a response of "2" implies a major increase (valued as a 20% increase). Limited discrete survey response choices were offered for two reasons. First, limited choices may help survey respondents choose among the options, as too many choices may hinder decision-making abilities (Iyengar & Lepper, 2000). Second, providing a simplified structure aids in providing a clear and concise demonstration of methods. Providing too few choices may promote biases in the research conclusions, particularly in cases when a respondent does not have the appropriate knowledge to answer the question, or when his or her true beliefs differ drastically from the available choices. It is also worth noting that literature supports the use of a Likert scale with discrete and odd number of choices in survey questionnaires to explicitly identify a neutral value (i.e., the midpoint value of the scale) that the expert can use as an anchor to make more refined assessments (Garland, 1991). Nonetheless, if the methods of this article are conducted in practice, it may be necessary for the survey to include additional response choices, such that a respondent is not forced to choose among limited discrete choices.

This model assumes that performance measures are system specific, while criteria that are supplied by the stakeholders are generalizable. Performance evaluations are assumed to be measurable using available data, while criteria are represented using elicited ratings.

Table VIII. Summary of Baseline Assumptions Used to Model the Case Study for Resilience Measurement

Performance Indicator	*Recovery Rate*	$F(t_o)$	$F(t_d)$	$F(t_f)$	G_i	B_i
$F_1(t)$: Workforce availability/mobility	0.2	80	20% reduction	$1.05{*}F_1(t_o)$	$1.1{*}F_1(t_o)$	$0.1{*}F_1(t_0)$
$F_2(t)$: Commodity travel time efficiency	0.05	75	20% reduction	$F_2(t_o)$	$1.1{*}F_2(t_o)$	$0.1{*}F_2(t_0)$
$F_3(t)$: Transportation infrastructure capacity	0.01	90	20% reduction	$F_3(t_o)$	$1.1{*}F_3(t_o)$	$0.5{*}F_3(t_0)$
$F_4(t)$: Availability of production inputs	0.2	95	20% reduction	$F_4(t_o)$	$1.1{*}F_4(t_o)$	$0.1{*}F_4(t_0)$
$F_5(t)$: Ideal level of consumption	0.05	95	20% reduction	$0.9{*}F_5(t_o)$	$1.1{*}F_5(t_o)$	$0.1{*}F_5(t_0)$

4.2. Modeling for Resilience Measurement

To demonstrate the methods of this article, we consider assumed data for the parameters given in Table VIII. The recovery rate represents the recovery process for each performance indicator, measured as % per time step; $F(t_o)$ represents the performance function of the system at the initial state; $T(t_d)$ represents the performance function for the system at the time of the final disruptive state, measured as a reduction from $F(t_o)$; $F(t_f)$ represents the performance function at the time of recovery; G_i represents the target performance level; and B_i represents the robustness limit representing the minimum possible level of performance such that recovery is still possible. As the contribution of this article is founded in methodological study of resilience, data sourcing via expert elicitation is used to populate the model parameters. In other applications outside of this case study, engineering estimates, surveys, voting among stakeholder groups, and other elicitation methods would be necessary.

All performance metrics are measured on a scale from 0 to 100, such that a value of 100 represents the maximum or highest possible achievable performance level. A baseline scenario is created to identify a reference point for the decision support described in the next section. This baseline scenario is populated using a common or plausible set of assumptions for performance targets, robustness limits. While these quantitative parameters are founded on the experts' past experiences with disasters, there may be limitations associated with applying quantitative metrics to experiences that have not been thoroughly quantified. However, the broader contribution of this article is to address how the sensitivity of resilience metrics influences decision making, therefore deemphasizing the quantitative assumptions in this baseline scenario, and rather emphasizing how these metrics change with varying scenarios and stakeholder valuations.

We assume a common disruption that reduces all performance indicators by 20%. The performance targets are set to be 10% above the starting conditions. The robustness limit, B_i, is set at 90% below starting conditions for most performance indicators. However, for Transportation Infrastructure Capacity ($F_3(t)$), the robustness limit is set to 50% below starting conditions, as network connectivity of transportation infrastructure causes the system to quickly degrade when key nodes are damaged. We assume a relatively quick recovery rate (20% per time step) for Workforce Availability/Mobility and Availability of Production Inputs, as these historically are shown to quickly adapt to disruptions. We assume a relatively slow recovery rate (5% per time step) for Commodity Travel Time Efficiency and Ideal Level of Consumption as these have historically shown to be slow to recover. We assume a recovery rate of 1% per time step for Transportation Infrastructure Capacity as this can involve large projects, such as rebuilding bridges and repaving roadways.

Fig. 5 shows a plot of $F(t_r)$ with the five studied performance metrics for 30 time-steps. The disruption occurs as a sudden onset in time-step 3. The results show a relatively rapid recovery for $F_1(t)$: Workforce Availability/Mobility and $F_4(t)$: Availability of Production Inputs. In contrast, $F_3(t)$: Transportation Infrastructure Capacity is relatively slow to recover. While these studied performance indicators all recovered within a relatively similar timeframe, it is possible that the performance indicators could recover over vastly different time periods. In that case, the differences in recovery behavior would be reflected in the subsequent analysis.

4.3. Decision Support for Investment

The decision-support component of this analysis allows for understanding the relative importance of alternative investments using a multicriteria model. Table IX provides the mapping of criteria to performance indicators. Higher average ratings (closest to

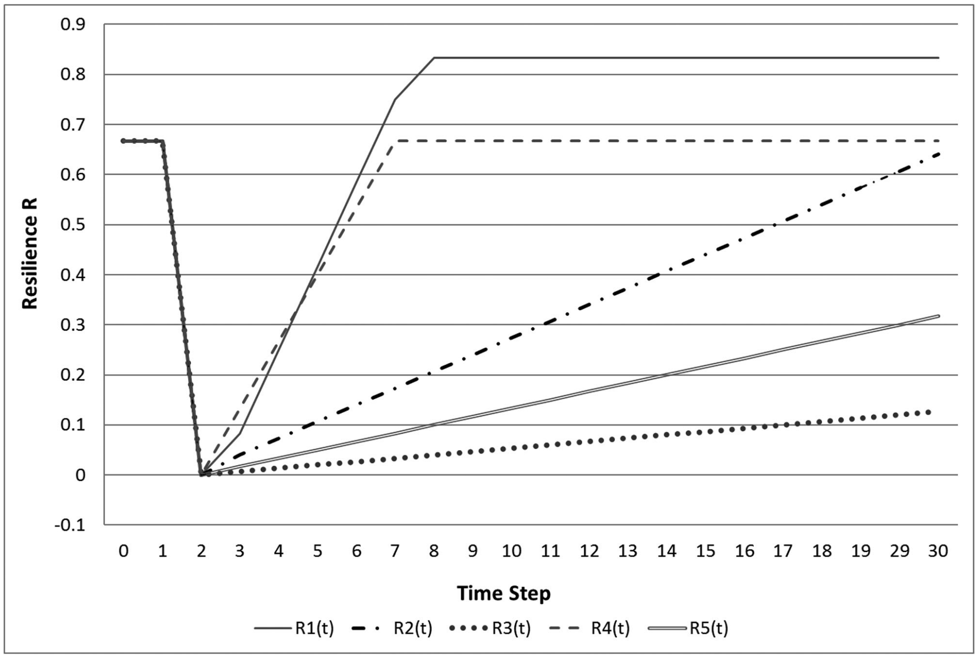

Fig. 5. Plot of resilience for each performance indicator in the case study.

Table IX. Average Importance of Criteria on a Scale from 0 (Not Important) to 3 (Very Important), Based on Survey Responses

		Criteria				
	Performance Indicator	Safety of People and Commodities	Environmental Sustainability	Supply Chain "User" Satisfaction	Transportation Network Efficiency	Balanced Supply and Demand
F_1	Workforce availability/mobility	2.8	1.0	1.6	2.2	1.8
F_2	Commodity travel time efficiency	1.8	1.0	1.8	2.8	2.2
F_3	Transportation infrastructure capacity	1.6	0.8	2.4	2.8	2.6
F_4	Availability of production inputs	1.0	1.4	1.8	2.0	2.8
F_5	Ideal level of consumption	1.2	1.2	2.4	2.2	2.6

"3") suggest that the criteria are of relatively high importance for assessing performance indicators. Conversely, lower average ratings (closest to "0") suggest that the criteria have little to no importance for assessing performance indicators. For example, the results show that aspects of safety were highly relevant to performance indicators related to mobility, but less relevant to economic performance indicators, such as F_4: Availability of Production Inputs.

Table X provides the criteria weights for each studied stakeholder, measured as the average across survey respondents. All criteria weights are given on a scale from 0 to 100, with higher criteria weights associated with greater importance to a given stakeholder. For a given stakeholder, the sum of all criteria weights is 100. For example, the results show the S_5: Community Members place high importance on aspects of safety and sustainability. Conversely, S_1: Economic Development Officials place high

Table X. Criteria Weights for Each Studied Stakeholder Based on Survey Responses

	Stakeholder	Criteria					
		Safety of People and Commodities	Environmental Sustainability	Supply Chain "User" Satisfaction	Transportation Network Efficiency	Balanced Supply and Demand	Total
S_1	Economic development officials	10	12	22	29	27	100
S_2	Suppliers	9	8	32	30	21	100
S_3	Customers	18	14	23	22	23	100
S_4	Emergency managers	58	4	4	22	12	100
S_5	Community members	34	30	12	16	8	100

Table XI. Average Effectiveness of Investments on Resilience Using a Scale from −2 to 2, Based on Survey Responses

	Alternative Investment	Effectiveness
A_1	System monitoring (e.g., surveillance tools such as cameras or sensors)	1.6
A_2	Data mining (e.g., analysis of social media posts or tweets)	1.2
A_3	Transportation management (e.g., alternative routes of future capacity increase)	1.8
A_4	Human resource management (e.g., telework)	1.2

importance on transportation network efficiency and other aspects that promote economic activity.

Table XI provides the average effectiveness of alternative investments measured on a scale from −2 to +2. Higher values (closer to +2) indicate that the alternative investment is relatively more effective toward improving system resilience. The results show that all studied alternative investments showed a positive impact on system resilience. However, the use of alternative investment A_3: Transportation Management was the most effective option based on survey results.

Table XII shows the relative scoring for each alternative investment for each stakeholder, with the average across all stakeholders shown in the bottom row of the table. These were computed using the $Rating_{ik}$ and $Rating_k$ formulations discussed in Section 3.3. To ease readability and facilitate a clear interpretation of this scoring system, this relative scoring is multiplied by 100. Fig. 6 shows a comparison of alternative investments in a graphical format. The results show that Alternative Investment 3: Transportation Management (e.g., alternative routes of future capacity increase) is highly rated across all stakeholders. Alternative Investment 4: Human Resource Management (e.g., telework) received low ratings, with high variability across stakeholders. This high variability may be explained by the wording used to define the alternative. Survey respondents may have interpreted this alternative as being directed toward disasters, while the other alternatives were applicable to a wider variety of system disruptions.

Decisionmakers can potentially use the decision support described above in several ways. First, they may need to perform an additional iteration of this approach to focus on a more refined list of alternative investments. For example, because the *transportation management* alternative investment was highly rated across stakeholders, decisionmakers may want to consider a more specific set of transportation alternative investments. Second, decisionmakers may need to consider eliminating some types of alternative investments from further study. For example, alternative investments that received relatively low ratings, such as *human resource management*, could be given less priority or removed from a list of potential options. Third, decisionmakers may supplement the alternative investment scores from Fig. 5 and

Table XII. Rating of Alternative Investments for Each Stakeholder for the Case Study Example

	Alternative Investment			
Stakeholder	A_1: System Monitoring	A_2: Data Mining	A_3: Transportation Management	A_4: Human Resource Management
S_1: Economic development officials	100	130	170	50
S_2: Suppliers	110	130	180	60
S_3: Customers	100	120	180	70
S_4: Emergency managers	160	120	190	120
S_5: Community members	110	120	190	110
Average across stakeholders	120	120	180	80

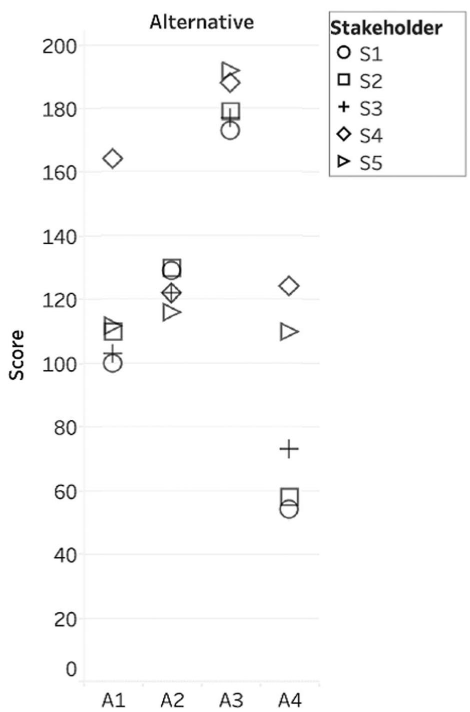

Fig. 6. Rating of alternative investments across stakeholders for the case study example. Note that the ratings have been multiplied by 100.

Table XII with scores that are weighted toward the most influential stakeholders. However, care should be taken when interpreting scores that are weighted by stakeholder influence because the variability among stakeholder scores may be an important decision-making factor.

4.4. Modeling of Sensitivity to Assumptions and Disruptive Scenarios

This section describes the sensitivity to model assumptions and disruptive scenarios. Table XIII describes sensitivity of system recovery following a disruptive event or scenario. In particular, this shows the quantitative change in recovery time, as compared to the baseline scenario recovery rate given in Table VIII. Table XIV describes sensitivity of system target performance level, G_i, following each disruptive event, as compared to the baseline target system performance (G_i column) given in Table VIII. Table XV describes sensitivity of the minimum allowable performance level, B_i, also known as the robustness limit, representing the lowest performance level such that recovery is possible following each disruptive event. This robustness limit sensitivity is compared to the baseline scenario robustness limit (B_i column) given in Table VIII. For each of Tables XIII–XV, the data in each column signify the percentage of survey respondents who chose the specified percentage change in the studied metric, as specified in the column title.

The sensitivity analysis is populated using the expert elicitation described earlier in this article. The system sensitivity for each scenario is described by five categories: *decrease by* 20% (20% value), *decrease by* 10% (10% value), *no change* (0 value), *increase by* 10% (10% value), *increase by* 20% (20% value). To summarize each type of sensitivity, we compute a *factor of effectiveness*. For each scenario i ($i = 1 \ldots, b$) *and category* j ($j = 1 \ldots, 5$), the *factor of effectiveness* is computed as follows:

$$\textit{Factor of effectiveness}_i = \sum_{j=1}^{5} \textit{Percent response}_{ij} * \textit{Category value}_{ij}.$$

For example, for the *Pandemic impacting workforce* scenario, the expected change in recovery time *factor of effectiveness* for each scenario is:

Table XIII. Percentage of Survey Respondents Who Selected Each Specified Change in Recovery Time Following Each Disruptive Event Scenario

Scenario	Decrease by 20%	Decrease by 10%	No Change	Increase by 10%	Increase by 20%	Factor of Effectiveness
Pandemic impacting workforce	20%	20%	20%	20%	20%	0%
Hurricane	40%	20%	0%	20%	20%	−4%
Cyber attack on monitoring systems	0%	60%	0%	40%	0%	−2%
Climate change	20%	20%	20%	40%	0%	−2%

Table XIV. Percentage of Survey Respondents Who Selected Each Specified Change in System Target Performance Level Following Each Disruptive Event Scenario

Scenario	Decrease by 20%	Decrease by 10%	No Change	Increase by 10%	Increase by 20%	Factor of Effectiveness
Pandemic impacting workforce	40%	0%	20%	40%	0%	−4%
Hurricane	60%	20%	0%	20%	0%	−12%
Cyber attack on monitoring systems	0%	60%	20%	0%	20%	−2%
Climate change	20%	40%	20%	20%	0%	−6%

Table XV. Percentage of Survey Respondents Who Selected Each Specified Change in Minimum Allowable Performance Level, Representing the Lowest Level Such that Recovery Is Possible, Following Each Disruptive Event Scenario

Scenario	Decrease by 20%	Decrease by 10%	No Change	Increase by 10%	Increase by 20%	Factor of Effectiveness
Pandemic impacting workforce	20%	20%	60%	0%	0%	−6%
Hurricane	20%	60%	20%	0%	0%	−10%
Cyber attack on monitoring systems	0%	60%	40%	0%	0%	−6%
Climate change	20%	40%	40%	0%	0%	−8%

$-20\%*20\% - 10\%*20\% + 0\%*20\% + 10\%*20\% + 20\%*20\% = 0\%$.

Because the survey responses were given without reference to any particular system intervention, the *factor of effectiveness* calculations are also interpreted to be without reference to any given intervention. Therefore, the assumptions on the *factor of effectiveness* are applied across all alternative investments.

The results show that the expected recovery *factor of effectiveness* for the *Pandemic impacting workforce* scenario is 0%. This can be explained by the fact that stakeholders have not witnessed a mass pandemic in recent times. The closest comparison is the 2009 H1N1 outbreak, which is considered by public health officials as a relatively mild pandemic (Santos et al., 2013). In contrast, the expected recovery time *factor of effectiveness* for the *Hurricane* scenario is −4%. Recent memory of Hurricane Katrina may impact these findings.

The results show that the expected change in system target performance level *factor of effectiveness* for the *cyber attack on monitoring systems* scenario is −2%. This can be explained by historical evidence of cyber attacks not directly impacting physical structures. However, as technologies advance in "Internet of things" networking, there is potential for this sensitivity estimation to change. Furthermore, there have been recent indications of the rising trends in "state-sponsored" hacks and data leaks that could put cyber security at the forefront of the national security agenda. In contrast, the expected change in target performance level *factor of effectiveness* for a hurricane is −12%, reflecting recent history of Hurricane Katrina, Hurricane Sandy, and Hurricane Florence causing significant damage to transportation infrastructure.

The results show that the expected change in minimum allowable performance level *factor of effectiveness* for a *pandemic impacting workforce* scenario is −6%. Similar to the sensitivity in recovery shown in Table XIII, the relatively small expected change in minimum allowable performance level may be due to no relatable pandemics in recent history. In contrast, the expected change in minimum allowable performance level *factor of effectiveness* for climate change is −8%. This can be explained by experts considering a variety of indirect impacts of climate change, such as propensity for natural disasters and disease.

5. CONCLUSIONS

This article presented a data-driven risk-analytic approach to managing infrastructure resilience. This approach allows for system managers to measure a system's ability to recover, adapt, and reorganize after a system disruption. The approach consisted of: (1) modeling resilience for complex systems with several competing measures of performance, such as workforce, infrastructure capacities, sustainability initiatives, and others, and (2) including plural resilience measures for multicriteria and multistakeholder decisions for protection of the system.

The approach was demonstrated on a hypothetical case study populated by baseline data and expert-elicited information gathered via a web-based survey questionnaire. Assumptions were based on a large metropolitan supply chain network of the United States containing several subsystems with unique valuations of performance. The case study parameters associated with the plural dimension of resilience were quantified using a series of survey questions that were used to characterize the relationship between disruptive scenarios and the supply chain infrastructure. The results demonstrate that a wide variety of relevant system perspectives, as characterized by the diverse set of performance indicators, translate into widely varying resilience behavior. For example, the case study showed a rapid recovery for $F_1(t)$: Workforce Availability/Mobility and a slower-paced recovery for $F_3(t)$: Transportation Infrastructure Capacity. The results also showed how diversity of stakeholder perspectives can highly influence the relevance of potential alternative investments. For example, Fig. 5 showed that some alternative investments were highly rated across all stakeholders, while others exhibited high variability across stakeholders.

The case study demonstration contributed to the study of risk for complex systems in several ways. First, this case study characterized the scope of the system by recognizing the broad array of included subsystems. In addition to the movement and availability of commodities, the case study also included the movement and availability of workforce; the related transportation infrastructure; and both producing (origins) and consuming (destinations) sectors. Second, this case study improved risk modeling for a complex system through a systematic and tractable series of steps. Although related literature typically models risk using a single (or aggregated) measure of performance, this case study considered the wider variety of system functions that are the result of diversified ownership, broadened definitions of system stakeholders, or evolving legislative ramifications of system decisions. Third, the case study addressed system adaptability, such that the goal of future system performance may not necessarily match predisruption status quo operations. Fourth, this case study complemented scenario-specific risk studies with initiatives for building system resilience. Fifth, the proposed framework and the associated case study explicitly included sensitivity analysis to determine the extent to which variations in model parameter values could impact decision making.

This work has contributed to the subject of risk and resilience literature in several ways. To our knowledge, the approach presented in this article is the first to model plural competing performance metrics into resilience measurement, such as workforce availability, health, capacities, efficiency, and safety. This work is also the first to include resilience in multicriteria multistakeholder decision models for identifying the most appropriate protective strategies and policies. Although the application of this article was directed towards supply chain infrastructure, the generalized approach is applicable to any complex system. For example, this can be applied to the study of cyber systems, transportation systems, electric power grids, and others.

Future work will expand on the findings as follows. First, there is opportunity to use expert elicitation to understand how decisionmakers value multiple measures of performance for complex systems. For example, there is need to study whether linear/additive models for weighting multiple criteria are appropriate in this setting. Second, there is need to understand which system performance indicators are most important for large-scale decision models, which are highly relevant to a variety of applications such as infrastructure management and supply chain management. When performing the expert elicitation survey discussed in the case study, survey respondents may have been challenged by the process of commenting on the predefined set of performance indicators and criteria. Additional surveys may be necessary to further refine and understand the relationships among these model inputs. Third, future work will study how to include plural resilience metrics into decision models for spatially distributed networks. Fourth, opportunities also exist to analyze the extent to which heuristics and biases inherent in expert elicitation methods could impact the evaluation of disaster consequences and efficacy of resilience enhancement strategies. Finally, there is opportunity to apply the strategic principles of this article to tactical and operational resilience modeling. For example, this could involve integrating the methods with simulation analysis, data-driven learning, and other artificial intelligence models that are able to adapt to new information and technologies.

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REFERENCES

Adger, W. (2000). Social and ecological resilience: Are they related? *Progress in Human Geography*, *24*(3), 347–364.

Amir, S., & Kant, V. (2018). Sociotechnical resilience: A preliminary concept. *Risk Analysis*, *38*(1), 8–16.

Aven, T. (2011). On some recent definitions and analysis frameworks for risk, vulnerability, and resilience. *Risk Analysis*, *31*(4), 515–522.

Aven, T. (2015). Implications of black swans to the foundations and practice of risk assessment and management. *Reliability Engineering & System Safety*, *134*, 83–91.

Ayyub, B. M. (2014). Systems resilience for multihazard environments: Definition, metrics, and valuation for decision making. *Risk Analysis*, *34*(2), 340–355.

Bar-Yam, Y. (2002). General features of complex systems. In *Encyclopedia of life support systems (EOLSS)*. Oxford, UK: UNESCO, EOLSS Publishers.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., … Von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, *19*(4), 733–752.

Camerer, C. F., & Johnson, E. J. (1997). The process-performance paradox in expert judgment: How can experts know so much and predict so badly. *Research on Judgment and Decision Making: Currents, Connections, and Controversies*, 342.

Cimellaro, G. P., Renschler, C., Reinhorn, A. M., & Arendt, L. (2016). PEOPLES: A framework for evaluating resilience. *Journal of Structural Engineering*, *142*(10), 04016063.

Clemen, R. T., & Winkler, R. L. (1999). Combining probability distributions from experts in risk analysis. *Risk Analysis*, *19*(2), 187–203.

Evans, J. L., & Hart, R. E. (2003). Objective indicators of the life cycle evolution of extratropical transition for Atlantic tropical cyclones. *Monthly Weather Review*, *131*(5), 909–925.

Garland, R. (1991). The mid-point on a rating scale: Is it desirable. *Market Bull*, *2*(1), 66–70.

Gisladottir, V., Ganin, A. A., Keisler, J. M., Kepner, J., & Linkov, I. (2017). Resilience of cyber systems with over-and underregulation. *Risk Analysis*, *37*(9), 1644–1651.

Goodwin, P., & Wright, G. (2014). *Decision analysis for management judgment* (5th ed.). Hoboken, NJ: John Wiley and Sons.

Haimes, Y. Y. (2009a). On the complex definition of risk: A systems-based approach. *Risk Analysis*, *29*(12), 1647–1654.

Haimes, Y. Y. (2009b). On the definition of resilience in systems. *Risk Analysis*, *29*(4), 498–501.

Haimes, Y. Y., Kaplan, S., & Lambert, J. H. (2002). Risk filtering, ranking, and management framework using hierarchical holographic modeling. *Risk Analysis*, *22*(2), 383–397.

Henry, D., & Ramirez-Marquez, J.E. (2012). Generic metrics and quantitative approaches for system resilience as a function of time. *Reliability Engineering & System Safety*, *99*, 114–122.

Holland, J. (1992). Complex adaptive systems. *Daedalus*, *121*(1), 17–30.

Holling, C. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, *4*, 1–23.

Hollnagel, E. (2012). *FRAM, the functional resonance analysis method: Modelling complex socio-technical systems*. Boca Raton, FL: CRC Press.

Hughes, T., Bellwood, D., Folke, C., Steneck, R., & Wilson, J. (2005). New paradigms for supporting the resilience of marine ecosystems. *Trends in Ecology & Evolution*, *20*(7), 380–386.

Hwang, C. L., & Lin, M. J. (2012). *Group decision making under multiple criteria: Methods and applications* (Vol. 281). New York, NY: Springer Science & Business Media.

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology*, *79*(6), 995.

Jüttner, U., Peck, H., & Christopher, M. (2003). Supply chain risk management: Outlining an agenda for future research. *International Journal of Logistics: Research and Applications*, *6*(4), 197–210.

Kaplan, S. (1992). "Expert information" versus "expert opinions": Another approach to the problem of eliciting/combining/using expert knowledge in PRA. *Reliability Engineering & System Safety*, *35*(1), 61–72.

Kates, R. W., Colten, C. E., Laska, S., & Leatherman, S. P. (2006). Reconstruction of New Orleans after Hurricane Katrina: A research perspective. *Proceedings of the National Academy of Sciences*, *103*(40), 14653–14660.

Kelman, S. (1981). Cost-benefit analysis: An ethical critique. *Regulation*, *5*, 33.

Klibi, W., & Martel, A. (2012). Scenario-based supply chain network risk modeling. *European Journal of Operational Research*, *223*(3), 644–658.

Kynn, M. (2008). The "heuristics and biases" bias in expert elicitation. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *171*(1), 239–264.

Lebas, M. J. (1995). Performance measurement and performance management. *International Journal of Production Economics*, *41*(1–3), 23–35.

Linkov, I., Bridges, T., Creutzig, F., Decker, J., Fox-Lent, C., Kröger, W., … Nyer, R. (2014). Changing the resilience paradigm. *Nature Climate Change*, *4*(6), 407.

Linkov, I., Fox-Lent, C., Read, L., Allen, C. R., Arnott, J. C., Bellini, E., … Hynes, W. (2018). Tiered approach to resilience assessment. *Risk Analysis*, *38*(9), 1772–1780.

López-Cuevas, A., Ramírez-Márquez, J., Sanchez-Ante, G., & Barker, K. (2017). A community perspective on resilience analytics: A visual analysis of community mood. *Risk Analysis*, *37*(8), 1566–1579.

Lummus, R., & Vokurka, R. (1999). Defining supply chain management: A historical perspective and practical guidelines. *Industrial Management & Data Systems*, *99*(1), 11–17.

Lunenburg, F. C. (2011). Decision making in organizations. *International Journal of Management, Business, and Administration*, *15*(1), 1–9.

Molinari, N., Ortega-Sanchez, I., Messonnier, M., Thompson, W., Wortley, P., Weintraub, E., & Bridges, C. B. (2007). The annual impact of seasonal influenza in the US: Measuring disease burden and costs. *Vaccine*, *25*(27), 5086–5096.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., Van Vuuren, D. P., … Meehl, G. A. (2010). The next generation of scenarios for climate change research and assessment. *Nature*, *463*(7282), 747.

NOAA Office for Coastal Management. (2018). Retrieved from https://coast.noaa.gov/states/fast-facts/hurricane-costs.html.

Paté-Cornell, M. E. (1996). Uncertainties in risk analysis: Six levels of treatment. *Reliability Engineering & System Safety*, *54*(2–3), 95–111.

Pirrone, N., Trombino, G., Cinnirella, S., Algieri, A., Bendoricchio, G., & Palmeri, L. (2005). The driver-pressure-state-impact-response (DPSIR) approach for integrated catchment-coastal zone management: Preliminary application to the Po catchment-Adriatic Sea coastal zone system. *Regional Environmental Change*, *5*(2–3), 111–137.

Potter, C. W. (2001). A history of influenza. *Journal of Applied Microbiology*, *91*(4), 572–579.

Rose, A. (2004). Defining and measuring economic resilience to disasters. *Disaster Prevention and Management: An International Journal*, *13*(4), 307–314.

Rose, A., & Krausmann, E. (2013). An economic framework for the development of a resilience index for business recovery. *International Journal of Disaster Risk Reduction*, *5*, 73–83.

Santos, J. R., May, L., & El Haimar, A. (2013). Risk-based input-output analysis of influenza epidemic consequences on interdependent workforce sectors. *Risk Analysis*, *33*(9), 1620–1635.

Thekdi, S., & Aven, T. (2016). An enhanced data-analytic framework for integrating risk management and performance management. *Reliability Engineering & System Safety*, *156*, 277–287.

Thekdi, S. A., & Chatterjee, S. (2018). Toward adaptive decision support for assessing infrastructure system resilience using hidden performance measures. *Journal of Risk Research*, 1–24.

Thekdi, S. A., & Santos, J. R. (2016). Supply chain vulnerability analysis using scenario-based input-output modeling: Application to port operations. *Risk Analysis*, *36*(5), 1025–1039.

Thorisson, H., Lambert, J. H., Cardenas, J. J., & Linkov, I. (2017). Resilience analytics with application to power grid of a developing region. *Risk Analysis*, *37*, 1268–1286.

Triantaphyllou, E., & Sánchez, A. (1997). A sensitivity analysis approach for some deterministic multi-criteria decision-making methods. *Decision Sciences*, *28*(1), 151–194.

U.S. Census Bureau. (2016). *Four Texas metro areas add more than 400,000 people in the last year*. Retrieved from https://www.census.gov/newsroom/press-releases/2016/cb16-43.html.

U.S. House of Representatives. (2017). *Testimony of Richard F. Smith before the U.S. House Committee on Energy and Commerce Subcommittee on Digital Commerce and Consumer Protection*. Retrieved from https://docs.house.gov/meetings/IF/IF17/20171003/106455/HHRG-115-IF17-Wstate-SmithR-2017-1003.pdf.

Zobel, C. W. (2011). Representing perceived tradeoffs in defining disaster resilience. *Decision Support Systems*, *50*(2), 394–403.