

# Uncertainty modeling of hurricane-based disruptions to interdependent economic and infrastructure systems

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**Abstract** Extreme risks associated with natural and man-made disasters involve disruptions to the production of goods or provision of services in interdependent systems. The reduced supply of goods and services will degrade “as-planned” production and create ripple effects. Hence, maintaining above-minimum levels of inventory is a resilience strategy that could effectively reduce the onset of disruption. This research integrates the uncertainty in inventory levels to assess the economic impacts of moderate and extreme disastrous events on interdependent systems. The unique contribution of this research is the formulation of a stochastic inventory-based risk assessment model using a multi-objective optimization framework for minimizing (1) extreme economic losses and (2) sector inoperability. Empirical distributions are derived from inventory-to-sales ratio (ISR) of the manufacturing and trade sectors from the Bureau of Economic Analysis database. Simulations of inventory enable the initialization of inoperability functions of a dynamic inoperability input–output model (DIIM). The stochastic inventory-based DIIM-computed values of economic loss and inoperability are simultaneously minimized to identify inventory-enhancement opportunities for critically disrupted systems. A lean production case for a moderate-intensity hurricane in Virginia reveals an overestimation of regional economic loss relative to the expected inventory levels from the ISR data. The conditional expected value of regional economic loss for an extreme event is found to be \$12 M higher than a moderate-intensity case. Identification of resilience-enhancement opportunities using the proposed multi-objective optimization framework could reduce expected economic loss by \$24 M for an extreme-event and \$17 M for a moderate-intensity case.

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## 1 Introduction

Natural disasters, such as hurricanes, evidently bring varying degrees of disruption to the functions of economic and infrastructure systems that provide essential goods and services to a society. A disrupted sector becomes incapable of fulfilling the production output demanded by the other sectors of an economic region. A cascading effect of disruption results from the reduction in the flow of expected output from one disrupted sector to another. Hence, the inherent physical, economic, and logical interdependencies in most large and complex infrastructure and economic systems can accelerate the propagation of disaster consequences across the various sectors of the society (Perrow 1999; Barker and Santos 2010). To wit, supply chain disruptions and lean production schedules have been found to have adverse effects on both regional profitability and sector recovery from extreme events (Heal et al. 2006; Hendricks and Singhal 2005; Little 2005). As a result, the entire region is brought to a higher level of disruption with greater associated economic losses. From a survey of Webb, Tierney and Dahlhamer, such economic losses incurred by directly and indirectly disrupted sectors were found to be as significant as the equivalent monetary worth of property damages from disastrous events (Webb et al. 2000). La Porte associates the failure to prepare for such disruptions with “widespread uncertainty in service restoration, lack of viable economic and social networks, serious loss of public confidence, and even social collapse (La Porte 2006).”

To suppress the propagation of disaster consequences, the formulation of disaster preparedness plans must address the need for a holistic and immediate recovery management for disrupted critical economic and infrastructure systems. Recent paradigm shifts of risk management and decision-making for disastrous events have refocused on prevention and protection to recovery and response (Barker and Santos 2010). Loss estimation that previously accounted only for immediate damages has evolved into a time-dependent analysis of the impact on the flow of goods and services among intricately disrupted interdependent systems (Rose and Liao 2005). These have been influenced by the growing concern on the relationship between preparedness and resilience (Haines 2006; Haines and Jiang 2001). Resilience is defined as the ability to “mute the potential losses” (Rose and Liao 2005). Preparedness activities and proper positioning of limited resources were observed to promote higher sector resilience and inhibit the impact of disastrous events. These allow for shorter recovery times and minimal economic losses between critical infrastructure and economic systems (Resurreccion and Santos 2011, 2012a). Specifically, resilience adjustment measures such as inventories, input substitution, conservation, and production rescheduling can temporarily satisfy a sector’s input production requirement and can serve as strategies to mitigate the disaster consequences (Rose and Liao 2005). Hence, planning for above-minimum levels of inventory is a risk management strategy to delay the onset of inoperability brought about by disasters (Barker and Santos 2010; Resurreccion and Santos 2012a).

This research is motivated by an emerging concept that maintaining flexibility in achieving higher levels of inventory could strengthen a region’s resilience. The authors recognize the additional costs associated with holding inventory. Nevertheless, flexible inventory readjustments particularly in times of disasters can lead to significant economic

savings that markedly outweigh the costs associated with inventory (Barker and Santos 2010). In particular, this paper explores the extent to which inventory strategies could impact the way sectors transition from their disrupted states toward recovery from a disastrous event. Utilizing input–output (I–O) accounting information published by the Bureau of Economic Analysis (BEA), the paper implements a dynamic inoperability input–output model (DIIM) to monitor the propagation of direct and indirect impacts of disruption over time with respect to a macroeconomic perspective of the US economy. Previous applications of the DIIM have incorporated uncertainty inventory modeling (Barker and Santos 2010; Resurreccion and Santos 2012a). However, these applications only used discrete-point estimates for the individual inventory-level parameter. Hence, the research develops an integration of a stochastic model of inventory with the DIIM to relax the limitations of the deterministic inventory model. There are multiple sources of uncertainty for modeling disrupted interdependent systems, but the focus of this research is to characterize the associated economic risks from a hurricane-based disruption with respect to inventory uncertainty. Probability density functions are derived from monthly inventory-to-sales ratio data from BEA (US Economic Accounts 2009) for each of the 21 manufacturing and retail and trade sectors classified in the North American Industry Classification System (NAICS). The proposed stochastic inventory-based DIIM (SIDIIM) will provide more reliable estimates for risk analysis metrics, namely *economic losses* and sector *inoperability* (a measure of the sector's degree of disruption). Using Monte Carlo simulations, the SIDIIM generates effective and sector-based distributions of these metrics. Effective distributions of regional economic loss and individual sector inoperability distributions allow for the computation of statistics such as the expected value (or mean) and conditional expected value for analyzing average and extreme events (Santos 2008a). The research adapts the dynamic cross-prioritization plot (DCPP) technique developed by Resurreccion and Santos (2012a) to prioritize critical sectors for resilience-enhancement planning. The proposed SIDIIM is capable of evaluating these resilience-enhancement plans with respect to average and conditional expected values of the risk. Thereby, the application of SIDIIM develops an extension of the application and analysis of the DCPP for investigating extreme-event scenarios. In particular, the contributions of the current paper are as follows:

- Incorporating inventory-level probabilistic distributions that define the initial sector inoperability parameter relaxes the current limitations of the DIIM. In previous applications, inventory models that were integrated to the DIIM utilized discrete user-defined inventory-level inputs (Barker and Santos 2010; Resurreccion and Santos 2012a). The extension of the DIIM using probability distributions obtains more generalizable estimates of the associated impacts of various disaster risk scenarios. Its predecessor model, the inoperability input–output model (IIM), has been integrated with probability distributions derived from expert-elicited values (Santos 2008b). However, the probability distribution analysis was previously applied only to the demand perturbation using a static version of the input–output model. In addition, the IIM is not yet capable of analyzing the temporal evolution of disruption levels to represent sector recovery behavior.
- The proposed SIDIIM builds on the large database of monthly sector-specific inventory values that are regularly updated on the BEA Web site. This will be the first-ever application of the comprehensive inventory-to-sales (ISR) database for economic risk modeling of disasters. Further analysis on these data could provide more reliable projections of the performance metrics of future specific resilience-enhancement plans.

- The dynamic cross-prioritization plot (DCPP) is a multi-objective decision support tool that was developed to prioritize critical sectors and identify areas for broader preparedness applications including opportunities for resilience enhancement (Resurreccion and Santos 2012a). The framework for treating expected and conditional expected values has been introduced in recent input–output applications (Lian et al. 2007; Santos 2008a). With the framework built into the SIDIIM, the integration of expected and extreme-event scenario analysis significantly supports the resilience-enhancement opportunities as identified by the DCPP in reducing the risks associated with disasters.

The remainder of the paper is organized as follows. Section 2 presents a methodological background that includes an overview for modeling interdependent systems using risk analysis (2.1) and discussions on input–output modeling (2.2), deterministic inventory DIIM (2.3), and multi-objective decisionmaking (2.4). Section 3 presents the development of the SIDIIM components, namely data sources, inventory cumulative distribution functions, Monte Carlo simulation code and integration of stochastic inventory and DIIM models, the DCPP generated list of the risk and inventory-enhancement scenarios for the Commonwealth of Virginia as an *ex post* case study of Hurricane Isabel, and the implementation of expected and conditional expectations for extreme-event analysis. Section 4 includes the results and discussion of the case study. Finally, Sect. 5 presents the summary of findings of the research as well as areas for further study.

## 2 Methodological background

### 2.1 Risk analysis and modeling of disrupted interdependent systems

Due to their adverse consequences, disasters such as hurricanes are well documented in the literature (Blake 2005). Hurricane Katrina in 2005 brought \$96 billion worth of damages to the Gulf Coast region (Garber 2006). Hurricane Isabel of 2003 brought massive flooding and destruction to the Hampton Roads region with \$625 million worth of damages and a death toll of 36 people to the Commonwealth of Virginia (Virginia Department of Emergency Management 2007; Smith and Graffeo 2005). More recently, hurricane Irene that was classified as a category 1 hurricane was still considered to be one of the 10 disasters of 2011 with an order of magnitude of losses amounting to billions of dollars (National Oceanic and Atmospheric Administration 2011). Recognizing the risks involved in such high-impact, low-probability disasters, the US Department of Homeland Security (DHS) policy makers have explicitly included hurricane events in its fifteen planning scenarios (Homeland Security Council 2004). The DHS further emphasized the importance of risk management strategies through the implementation of preparedness and resilience plans for the nation's critical infrastructure and key resources in times of extreme events.

Risk is associated with an unwanted deviation from a predefined normal state as it exposes a system to adverse consequences. Risk measures the likelihood of such deviation and the corresponding severity of the consequences (Lowrance 1976). Risk assessment and risk management have been applied to minimize the risks identified with natural and man-caused disasters. Risk assessment is a process of answering the questions (Kaplan and Garrick, 1981): (1) What can go wrong? (2) What is the likelihood? and (3) What are the consequences? In addition, risk management aims to answer the following set of questions (Haimes, 2009): (1) What can be done and what options are available? (2) What are the

tradeoffs in terms of all costs, benefits, and risks? and (3) What are the impacts of current decision on future options?

Recent research for infrastructure renewal has highlighted the impact of system interdependency in risk analysis (Chandana and Leung 2010; Arboleda et al. 2009; Chang et al. 2007; Bagheri and Ghorbani 2007; Brown et al. 2004). Furthermore, econometric models (Ellson et al. 1984) and extensions of Leontief's economic input–output (I–O) model (Miller and Blair 1985; Isard 1960) offer a more holistic and quantitative framework for analyzing the economic impacts of disasters and system interdependencies (MacKenzie et al. 2012; Resurreccion and Santos 2011). I–O models are capable of evaluating the propagation of disaster consequences in terms of the flow of goods and services for multi-sectoral economic regions. Hence, inventory models that can reflect the minimum level of goods upon the impact of a disastrous event integrate well with I–O analysis (Barker and Santos 2010). The I–O model and proposed extensions focusing on inventory enhancements are pursued in subsequent sections.

## 2.2 Input–output (I–O) modeling

A depiction of the American economic structure, the I–O model was awarded a Nobel Prize in 1973 (Leontief 1936; MacKenzie et al. 2012). Wassily Leontief presented the I–O model for an economic system as a set of interrelated sectors assuming producer and consumer roles in the production process (Leontief 1936). The original input–output model is a representation of the interindustry flow of goods and services through economic transactions (Santos and Haines 2004). The total production output (supply) of a sector is distributed for intermediate consumption among interdependent sectors and for satisfying the demand of final consumers.

The availability of high-resolution economic data and social accounting matrices collected by many countries worldwide (Dietzenbacher and Lahr 2004) has motivated many recent publications on I–O modeling. Literature on I–O foundations and extensions can be found in Miller and Blair (1985) and Dietzenbacher and Lahr (2004). I–O data along with social accounting matrices have also been used in disaster-related applications that implement computable general equilibrium (Rose and Liao 2005). In recent years, an extension of the I–O model incorporated the concept of inoperability or the proportional extent to which a system is unable to satisfy its as-planned level of output. The resulting model—the inoperability input–output model (IIM)—has been deployed in applications ranging from infrastructure interdependencies and risks of terrorism (Santos 2006, 2008), regional electric power blackouts (Anderson et al. 2007), inventory management (Barker and Santos 2010), sequential decisions with multiple objectives (Santos et al. 2008), multi-regional disaster preparedness policies (Crowther et al. 2007), and agent-based simulation (Santos et al. 2007).

The IIM investigated losses resulting from the cascading effects of disruptive events among interdependent sectors by introducing the now widely used risk analysis metrics, namely economic loss and inoperability (Haines and Jiang 2001; Santos and Haines 2004). With the technical requirements assumed invariant to changes in output and consumption levels in the event of a disaster, the IIM defines economic loss as the unfulfilled proportion of the required production output in terms of its associated monetary value (in thousands of dollars). Intuitively, the total economic risk is the sum of economic losses of all the  $n$  sectors of a region directly and indirectly affected by the disaster. The sectors experiencing the highest economic losses are critical to the region's economic recovery following the disastrous event. On the other hand, inoperability,  $q$ , is defined as a sector's

failure to function at its “as-planned” performance level due to internal or external disruptions (Resurreccion and Santos 2011, 2012b). It is the normalized economic loss with respect to its required total output. A completely disrupted sector has an inoperability of 1, while a totally unaffected sector has an inoperability of zero.

To model how the inoperability metric evolves within the recovery period, Lian and Haimes incorporated a time-varying component of inoperability to the IIM (Lian and Haimes 2006) that expands the IIM into the dynamic IIM (DIIM) in Eq. (1). Further extensions of the DIIM to analyze extreme events are presented in Lian et al. (2007) and Santos (2008b) including an uncertainty index developed by Barker and Haimes (2009) to perform sensitivity analysis on the interdependency parameters. Shortcomings raised by Kujawski (2006) with respect to the use of I–O data have been addressed with recent DIIM extensions (Santos et al. 2007; Barker and Haimes 2009; Santos et al. 2009). For the derivations of the inoperability in Eq. (1), the reader is referred to the works of Santos and Haimes (2004) and Lian and Haimes (2006). The DIIM formulation of the variability of  $\mathbf{q}$  over time is

$$\mathbf{q}(t + 1) = \mathbf{q}(t) + \mathbf{K}[\mathbf{A}^* \mathbf{q}(t) + \mathbf{c}^*(t) - \mathbf{q}(t)] \tag{1}$$

where  $\mathbf{q}(t + 1)$  and  $\mathbf{q}(t)$  = inoperability vectors at discrete points in time,  $\mathbf{K}$  = resilience matrix,  $\mathbf{A}$  = interdependency matrix,  $\mathbf{c}^*(t)$  = demand perturbation vector at time  $t$ .

Note that each element,  $a^*_{ij}$ , of the interdependency matrix  $\mathbf{A}^*$  in (1) represents the contribution of sector  $i$  to the inoperability of sector  $j$ . The resilience matrix,  $\mathbf{K}$ , is a diagonal matrix that reflects the collection of resilience coefficients,  $k_i$ , which represent the recovery capability of a sector  $i$  from a disruptive event.

### 2.3 Deterministic inventory DIIM

An adaptive response discussed by Rose and Liao (2005) along with Chopra and Sodhi (2004) and Barker and Santos (2010) to reduce system losses is the improvement of individual sector resilience through the use of inventory. Such strategy has recently gained recognition in inventory management to improve disaster preparedness of interdependent systems (Barker and Santos 2010; Okuyama et al. 2004). A balance has to be made between allocating some resources to keep a level of inventory against the possible costs of disruption. Hence, a paradigm shift of steering away from implementing the just-in-time (JIT) inventory minimization strategy is more practical in the context of disaster management (Resurreccion and Santos 2012a).

Barker and Santos (2010) measured the efficacy of inventory policies in absorbing the negative impacts of disruption by extending the DIIM into an inventory DIIM. It presented an updating of inoperability in (1) to model the depletion of as-planned inventory as it is utilized to compensate for production inoperability (Resurreccion and Santos 2012a). Initial sector inoperability in (2) was classified into different cases (Barker and Santos 2010):

$$q_i(0) = \begin{cases} 0 & \text{if } X_i(0) \geq p_i(0)x_i(0) \\ 1 - \frac{X_i(0)}{p_i(0)x_i(0)} & \text{if } 0 \leq X_i(0) \leq p_i(0)x_i(0) \\ p_i(0) & \text{if } X_i(0) = 0 \end{cases} \tag{2}$$

Initial inoperability is zero when the finished goods inventory,  $X_i(0)$ , available to cushion physical inoperability is greater than the production demand  $p_i(0)x_i(0)$  that cannot be produced. When there is no available inventory ( $X_i(0) = 0$ ), the initial inoperability is

equivalent to the production inoperability. When inventory is less than the production demand  $p_i(0)x_i(0)$ , initial inoperability becomes the remaining fraction of production demand that cannot be covered by  $X_i(0)$ . As formulated by Barker and Santos (2010), the levels of inventory for a succeeding period,  $t + 1$ , are obtained by reducing inventory levels at  $t$  by the amount of inventory consumed for the production demand until time  $t$  as given in (3).

$$X_i(t + 1) = \max \{X_i(t) - p_i(t)x_i(t), 0\} \quad (3)$$

The relationship in (2) is adapted and repeated over other time periods,  $t$ , with Eq. (3) updated before implementing Eq. (1) for every  $t$ . Barker and Santos (2010) provide the detailed discussion of the deterministic inventory DIIM.

#### 2.4 Multi-objective decisionmaking: the dynamic cross-prioritization plot (DCPP) framework

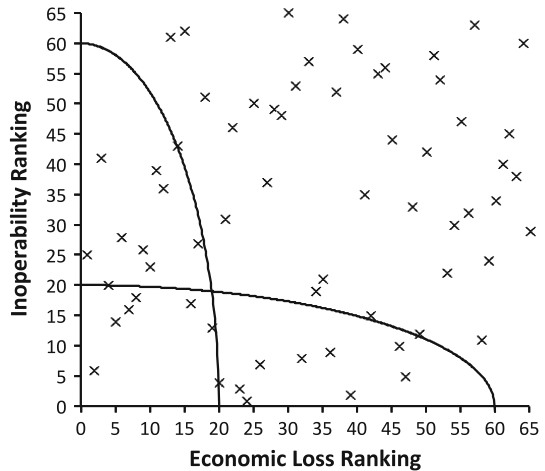
Disaster preparedness policy-making involves multiple objectives that are often noncommensurate and in competition. Visualization tools have proven effective in addressing the inherent multi-objective nature of decisionmaking. A case in point, to aid decision-makers from the Virginia Department of Transportation, Gokey et al. (2009) developed a visualization technique for selecting different portfolios of critical bridges for maintenance. The technique comprised of three primary objectives: (1) bridge structural reliability, (2) rehabilitation cost, and (3) maintenance budget. A bridge is evaluated on its relative criticality based on objectives (1) and (2)—representing the coordinates of a two-dimensional graph. On the other hand, objective (3) is represented as circular arcs that can vary in radius depending on budget-level assumptions. The circular arc assumption limits the capability of this visualization technique because it inherently assumes equal preference assignments with respect to two objectives (see Fig. 1). Hence, Resurreccion and Santos (2011, 2012b) developed the analytical formulations of the dynamic cross-prioritization plot (DCPP), allowing the flexibility of using generalizable curves to accommodate user-specified preferences on the objective functions. User-specified preferences may arise from having various stakeholders, experts, and policy makers and may consequently influence the decision-making process. Packaged as a decision support system, the DCPP features a front-end graphical user interface (GUI) capable of identifying different portfolios of critical sectors for inventory enhancement, given various combinations of preference levels across inoperability and economic loss minimization objectives, and various levels of resources.

Resurreccion and Santos (2012b) adapted and extended the visualization technique in the context of prioritizing critical economic and infrastructure sectors for disaster preparedness plans. As depicted in Fig. 1, the first two objectives representing the  $x$  and  $y$  coordinates are now based on the *economic loss* and *inoperability* ranks associated with a specific sector, respectively, as utilized within the DIIM. Depending on whether higher preference is given to economic loss or inoperability, the elliptical regions capture more critical sectors that are closer to the resulting major axis as defined by the user inputs.

### 3 Methodology

Recent catastrophic disasters have underscored the urgency of coordinated strategic disaster preparedness across interdependent systems. Earlier applications of

**Fig. 1** Prioritization arcs for different preferences to inoperability and economic loss objectives



interdependency analysis using input–output models utilized point estimates representing discrete input such as calculating the reduction in demand due to sector disruption (Barker and Santos 2010; Santos 2008a). This use of single-point estimates as risk assessment parameters can significantly alter and misrepresent the risk assessment outcomes for certainty (Hattis and Burnmaster 1994; Rose 2004; Santos 2008a). Risk is the measure of the degree of impact as well as the probability of occurrence with respect to such events (Lowrance 1976). Lian and Haines discussed how understanding uncertainty influences the analysis of the impact of disastrous events (Lian and Haines 2006). To address the shortcomings of implementing discrete technical coefficients for analyzing risk, Gerking (1976) developed an estimation technique for dealing with temporal and statistical variations. Most of these developments concentrated on the vector  $\mathbf{c}^*$  of Eqs. (3) and (4) that represent demand changes or perturbations. The proposed SIDIIM focuses on the initial inoperability component,  $q_i(0)$  from Eqs. (1) and (2).

### 3.1 Data sources

The data requirements to perform an economic interindustry or I–O analysis must reflect the assumed mutual relationships existing among the various elements comprising an economic region (Miller and Blair 1985). These relationships are encapsulated in the economic transactions that transpire among the various manufacturing and service sectors forming the economic region (Leontief 1936). In 1947, the Bureau of Labor Statistics started the aggregation of these transactions based on industry consumption and presented them as a collection of industry consumer tables in terms of the billions of dollars' worth of goods and services exchanged within the U.S. economy (Leontief 1936; Miller and Blair 1985). To date, the Bureau of Economic Analysis (BEA) Web site publishes data on the industry-by-industry total requirements between 65 infrastructure and economic sectors for the United States. I–O model extensions have since heavily relied on these data to populate the input–output matrices of supply and demand (i.e., interdependency matrix,  $\mathbf{A}$ ).

The subsequent sections of this paper discuss hurricane scenarios that necessitate regionally specific data sources. The Commonwealth of Virginia, where the case study will be implemented, is home to the largest naval base and one of the largest maritime ports in the United States. However, its location has also brought an increased susceptibility of the



region to disastrous events. The region belongs to one of the ten states with the highest number of hurricane landfalls in the country, with 8 being within the last decade (Blake et al. 2005). Therefore, the research implements the SIDIIM through a case study on the Commonwealth of Virginia to investigate further the susceptibility of the economic and service sectors of this region against the impacts of disruption. State data from the Regional Economic Information System are combined with the industry-by-industry total requirements of the United States for 2009 to obtain Virginia's interdependency matrix (Bureau of Economic Analysis, 2009). The 65 sectors are as identified by the North American Industry Classification System (NAICS) and coded in an alphanumeric format to facilitate in the analysis of this research (Resurreccion and Santos 2011, 2012b). The set of sector names and codes have been provided as an "Appendix" (e.g., S1 pertains to Sector 1, which encompasses the "Farms" sector). The BEA also provides the gross domestic product by state. This represents the consumption of the end users in the SIDIIM (i.e., consumption vector  $\mathbf{c}$  in Eq. 1). The SIDIIM also utilizes the large database of monthly sector-specific ISR values that can be found in the BEA Web site. The inventory model to be integrated with the DIIM constitutes of a time series of 168 data points spanning 14 years of monthly documented ISR information for each of the 21 manufacturing and retail and trade sectors.

### 3.2 Cumulative inventory distribution functions

The sector-specific empirical cumulative distribution functions (CDF) representing inventory uncertainty have been generated from the ISR data for Virginia. The ISR CDFs of six out of 21 sectors are shown in Fig. 2. The ISR value of a sector is the level of inventory of the finished goods as a proportion of expected sales (i.e., consumption) within a time period. Though expected sales are defined for a given month, the actual consumption level or sales may vary with respect to the day of month. Hence, the investigated perturbations are assumed to occur either at the beginning or at the end of a month when consumption levels (and ISR values) are known. For consistency, the simulation has been designed for initial direct disaster perturbations to occur at the beginning of a month. This corresponds to a period of sector disruption starting at the beginning of that month. Correspondingly, the level of inventory available for the purpose of augmenting the production demand of the disrupted sector is based on what remains from the inventory of the previous month. The simulation algorithm is discussed in Sect. 3.3.

### 3.3 Monte Carlo simulation: stochastic inventory and DIIM integration

Instead of predetermined or discrete inventory levels, this research derives  $X_i(0)$  for Eq. (3) through a simulation in Matlab of inventory values from the generated empirical cumulative distribution functions (CDFs) of ISR of each of the 21 manufacturing and retail and trade sectors as coded according to the North American Industry Classification System (NAICS). The ISR values forming the CDFs assume inventory levels that are capable of satisfying the demands of a sector at the beginning of a current period. The quantity  $ISR\_1$  reflects the portion of inventory of sector  $i$  that is capable of satisfying the demand should a disaster occurs at the beginning of the succeeding period. The initial inoperability in Eq. (3) in terms of ISR value is modified by the relationship in Eq. (4). Further, Eq. (5) illustrates how the ISR value for a sector  $i$ ,  $ISR_i$ , is simulated from its corresponding CDF.

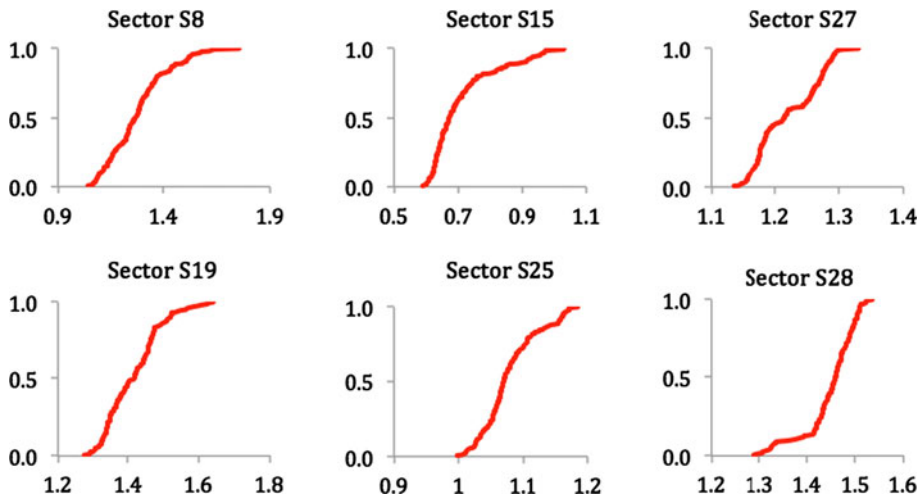


Fig. 2 Cumulative distribution functions of ISR per sector

$$ISR_i - 1 = \frac{X_i(0)}{p_i(0)x_i(0)} \tag{4}$$

$$ISR_i = \frac{(rand_i - F(Y_{i,j})) * Y_{i,j+1} + (F(Y_{i,j+1}) - rand_i) * Y_{i,j}}{F(Y_{i,j+1}) - F(Y_{i,j})} \tag{5}$$

where  $i$  = sector code,  $ISR_i$  = inventory-to-sales ratio for sector  $i$ ,  $Y_{i,j}$ ,  $Y_{i,j+1}$  = actual ISR values,  $F(Y_{i,j}) = \Pr(Y \leq Y_{i,j})$ ,  $F(Y_{i,j}) \leq rand_i \leq F(Y_{i,j+1})$ , ( $1 \leq i \leq 65$ ),  $n = 168$  observations ( $1 \leq j \leq n$ ).

The SIDIIM computer code was ran in Matlab and adapted built-in random number generator for the simulation of inventory levels. A simulation run is a 20-level, 10 replications per level design to specifically store the maximum economic loss incurred for every replication. This is to capture upper 10 percentile for an extreme-event analysis. The program was run to account for 5,000 replications for every defined stochastic inventory scenario.

### 3.4 Generating risk and inventory-enhancement scenarios: the consequence distribution functions for the SIDIIM

#### 3.4.1 Expected and conditional expectations for extreme-event analysis

Extreme events are associated with periods of abrupt change, ambiguous likelihood, and large and unpredictable losses where usual assumptions for existing systems are violated (Lantsman et al. 2010; Basili 2006). Such is the case when disruption is intense and widespread among the economic and infrastructure systems forming an economic region. In the context of disasters, recent natural and man-caused extreme events include hurricanes Katrina (category 4 at landfall) and Irene (category 1), the earthquakes in Haiti on 2010 (magnitude  $M = 7.0$  on the Richter scale) and Japan on 2011 ( $M = 9.0$ ), and the 9–11 terrorist attacks. These extreme events are considered rare, but not improbable (Haimes 2009; Ismail-Zadeh and Takeuchi 2007). Santos (2008a) and Santos et al. (2008) have provided analysis on the impact of these extreme events on disrupted interdependent systems.

Analysis of extreme events involves capturing the tail (often the upper tail) of the resulting probability density function of consequences that represent the low likelihood of high-impact events (Asbeck and Haimes 1984; Santos et al. 2008). Each sector has a random variable corresponding to each realization of a consequence. In the case of the SIDIIM, two types of consequences are being generated for each sector, economic loss and inoperability. The total economic loss of the region is the sum of the realizations drawn from the economic loss distribution of each the  $n$  sectors. Due to the convolution, the analytical form for the resulting distribution for total economic loss is difficult to derive (Santos et al. 2008). Alternatively, using Monte Carlo simulation with initial disruption values for the SIDIIM results into the distributions of economic loss and inoperability per sector.

The expected value (or mean, typically denoted by  $\mu$ ) is perhaps the most commonly used metric to describe a random variable. Denoting the probability density function of a random variable  $X$  by  $f(x)$ , the expected value is defined as follows:

$$\mu = E[X] = \int_{-\infty}^{+\infty} xf(x)dx \tag{6}$$

In discrete form, Eq. (6) can be alternatively written by replacing the integral with a summation operator as shown in Eq. (7). Further, the probability of the observation  $x_i$  is denoted by  $p(x_i)$ .

$$\mu = E[X] = \sum_i x_i p(x_i) \tag{7}$$

When each of  $n$  given observations is equally likely to occur, the probability for each observation becomes  $1/n$ ; hence, Eq. (7) simplifies to a simple arithmetic average shown in Eq. (8).

$$\mu = E[X] = \frac{1}{n} \sum_i x_i \tag{8}$$

The expected value of economic loss can be calculated by taking the sum of all observations and dividing this sum by  $n$  (i.e.,  $n$  is the number of Monte Carlo simulation iterations performed in the case study).

Although the expected value is a common metric for representing risk, it is not complete. Since it is a measure of the central tendency of a distribution, it commensurates high likelihood, low consequence realizations (business-as-usual scenarios) with low likelihood, high consequence realizations (i.e., extreme-case scenarios). A nation’s infrastructure and economic systems are normally designed to cope only with the average living necessities of its population and may view disaster consequences with respect to averages as well. Hence, a region may fall into the fallacy of treating “business-as-usual” events and extreme events in the same category of risk. While some events may have relatively low frequency of occurrence, the consequences can be dire and irreversible. To remedy the limitations of the expected value, the analysis can be supplemented with other risk metrics. In particular, the partitioned multi-objective risk method (PMRM) has the capability to provide extreme-risk metrics in addition to the traditional expected value of risk through the use of various conditional expectations (Asbeck and Haimes 1984; Haimes 2004). Placing more importance on the tail of the distribution of consequences will provide a stronger justification for risk management and prevent the mischaracterization of extreme events for computed expected values (Haimes 2009; Santos 2008b).

Conditional expectations are widely used in conducting reliability and survival analysis. Specifically, the construction of hazard functions makes use of conditional expectations at the upper tail region of a distribution. In their analysis of extreme events, Asbeck and Haimes (1984), Santos et al. (2008), and Frohwein et al. (1999) have included the conditional expected value as a measure of risk. In general, a conditional expectation is defined as the expected value of a random variable  $x$  within a prespecified interval  $x \in [\beta_L, \beta_U]$ . Equation (9) shows the location of a conditional expectation for a given partition of a hypothetical probability distribution function. The subscript  $k$  in the notation  $f_k(\cdot)$  distinguishes one type of conditional expectation from another. A specific type of conditional expectation, which this paper denotes as  $f_4(\cdot)$  (or  $f_4$  for simplicity), is a partition corresponding to a high consequence/low-probability region of a distribution. For a continuous random variable, the conditional expectation can be calculated using Eq. (9).

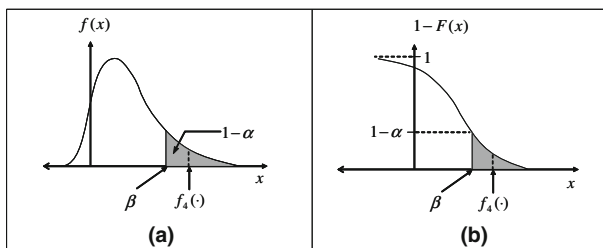
$$f_k(\cdot) = E[X|\beta_L < x < \beta_U] = \frac{\int_{\beta_L}^{\beta_U} xf(x)dx}{\int_{\beta_L}^{\beta_U} f(x)dx} \tag{9}$$

When the interval covers all the feasible values of  $x$ ,  $f_k(\cdot)$  becomes the expected value of  $x$  expressed as  $\mu$  in Eqs. 6–8. This expected value will later be denoted by  $f_5(\cdot)$  (or  $f_5$  for simplicity) in the case study to make it harmonious with the notation for conditional expectations.

In the analysis of hazard functions and as presented by Asbeck and Haimes (1984) in their discussion of the PMRM, the conditional expectation,  $f_4$ , corresponding to high consequence/low-probability scenarios is typically associated with either a lower or an upper tail of a distribution. For the analysis of extreme economic risks in this research, the desired measures of interest are that of a higher value of economic loss and worse (i.e., high value of) inoperability. Hence, an upper-tail partitioning is appropriate to use in these cases where the higher the values of the conditional expected value of risk correspond to the more dire consequences.

Figure 3 shows a distribution of a random variable  $x$  with the upper tail region defined by  $x > \beta$  such that  $\Pr(x > \beta) = 1 - \alpha$ . The conditional expected value,  $f_4$ , is shown in Eq. (10).

$$f_4 = E[X|\beta < x < +\infty] = \frac{\int_{\beta}^{+\infty} xf(x)dx}{\int_{\beta}^{+\infty} f(x)dx} \tag{10}$$



Upper-tail region of:  
 (a) probability distribution function  $f(x)$ ; and  
 (b) exceedance function  $1-F(x)$

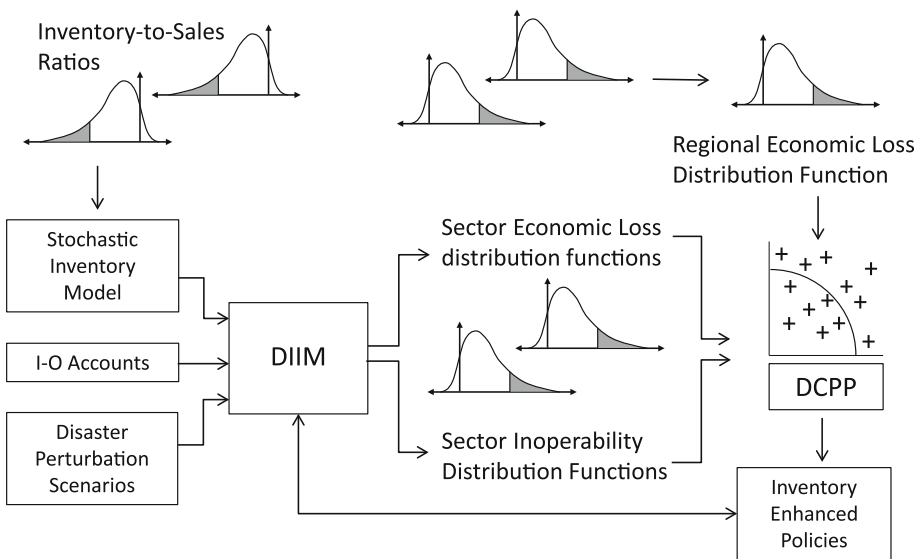
**Fig. 3** Conditional expected value for upper-tail partitioning

### 3.4.2 Distribution functions of simulated disaster consequences

I–O models including the SIDIIM quantify disaster consequences on an individual sector level typically over a predetermined recovery period. As a result of the stochastic nature of inventory, let the random variables  $x_i$  and  $y_i$  represent the economic loss and inoperability of each sector  $i$ , respectively. The DIIM provides realizations of the economic loss variable as an accumulated value over the predetermined recovery period. Therefore,  $x_i$  represents the total of daily economic losses incurred by sector  $i$  over the research simulation period (i.e., referred to as the economic loss of sector  $i$ ). Further, the 65 economic and service sectors will each have its  $x_i$  variable and distribution function of economic loss (see Fig. 4). The expected value of economic loss for each  $x_i$  is given by Eq. (8) based on 5000 replications. In the same manner, the expected value of inoperability for each sector  $i$  can also be obtained. The DCPD utilizes the expected values of the variables  $x_i$  and  $y_i$  to rank the relative performance of the sectors with respect to the economic loss and inoperability metrics.

To analyze the impact of inherent system interdependency and different inventory-enhanced scenarios, the holistic approach involves determining the disaster consequence to the entire economic region. This entails finding the total regional economic loss (i.e., referred to as the total economic loss,  $z$ ) which is equal to the sum of all of the sector variables,  $x_i$ . The sum,  $z$ , of  $n$  individual random variables,  $x_i$ , is shown in Eq. (11), and the expected value of  $z$  expressed in terms of the expected values of  $x_i$  is presented in Eq. (12).

$$z = a_1x_1 + a_2x_2 + \dots + a_nx_n = \sum_{i=1}^n a_ix_i \tag{11}$$



**Fig. 4** Relationship of distributional inventory input, initial sector inoperability, and resulting sector distributional economic loss and inoperability

$$E[z] = \sum_{i=1}^n a_i E[x_i] \quad (12)$$

The expected value of regional economic loss can be interpreted as the economic impact after factoring all categories of risk. To focus the analysis for the direct consequences, conditional expectations of  $z$  must be obtained. In particular, the upper tail of the distribution of  $z$  will be appropriate in representing higher-risk categories. The calculations required for the conditional expected value is analogous to the traditional expected value (or mean). To demonstrate how the  $f_4$  can be calculated for  $z$ , first identify a desired significant value ( $\alpha$ ) corresponding to the upper-tail partition. Suppose that the  $\alpha$  value of 0.1 (or 10 %) is chosen, this would translate to the highest 500 out of the original 5,000 observations conducted in the simulation experiment of this paper. After extracting the highest 500 values, take the “arithmetic average” of this reduced set to obtain the conditional expected value pertaining to the highest 10 % of the distribution. Figure 4 shows the  $f_4$  and  $f_5$  values for the resulting regional economic loss distribution as well as for the individual sector consequences. The conditional expected value of extreme risk (which, in this case, pertains to the realization of the 10 % worst possible values of regional economic loss,  $z$ ) complements the expected value. The use of conditional expected value is analogous to the analyses of “worst-case scenarios” or “pessimistic states of nature” that are used in tools such as decision trees and payoff matrices. Combined with *business-as-usual* analysis (as represented by the expected value), the conditional expected value of extreme risk provides additional insights into how an organization can increase its preparedness and resilience to manage the possibility of extreme events.

### 3.4.3 Inventory-enhanced scenarios

To compare any inventory-enhanced scenario or strategy proposed for the critical sectors captured by the DCP, a baseline case scenario 1 assumes that the region functions with stochastic inventory levels as derived from the ISR database when a simulated disaster occurs. A scenario 0 is also provided to compare the case of applying the DCP to a deterministic inventory model. Generated inventory-enhanced scenarios 2–4 are anchored on scenario 1 and not on scenario 0 to be able to reflect the uncertainty in inventory modeling. Scenario 1 has been calibrated for the set of disruptions that match the resulting regional economic loss incurred by the Commonwealth of Virginia from hurricane Isabel in 2003. Moreover, the composition of critical sectors may vary depending on the decision-maker’s objective preferences (Resurreccion and Santos 2012a). Table 1 provides a summary of the investigated preference levels for scenarios 2–4. An *ELPreference* of 0.5 represents an equal preference between the minimization of economic loss and the minimization of inoperability. An *ELPreference* lower than 0.5 (i.e., 0.2 for scenario 2) corresponds to a higher importance in achieving the minimization of inoperability over economic loss. Consequently, an *ELPreference* above 0.5 provides higher preference in minimizing economic loss over inoperability.

## 4 Results and discussion

### 4.1 Stochastic inventory model: baseline

Results depicted in Fig. 5 show that scenarios 0 and 1 differ in the sets of the 10 most critical sectors for each objective. There is evidence that shows the significance of incorporating uncertainty in inventory as it affects economic losses and sector

**Table 1** SIDIIM disruption scenarios

Scenario no.	Scenario description	<i>ELPreference</i>
0	Deterministic inventory	N/A
1	Current stochastic inventory	N/A
2	Inoperability reduction preference	0.2
3	Equal preference	0.5
4	Economic loss reduction preference	0.8

inoperability. Consistent with the findings of Resurreccion and Santos (2012a), more manufacturing sectors experience the highest inoperability values than service and infrastructure systems. However, by incorporating the stochastic behavior of inventory, even at the current level data, the capacity of inventories to increase disaster preparedness is supported by the drastic reduction in the number of critical manufacturing sector from scenario 0 (e.g., 90 % in the top ten are from manufacturing sectors) into only 3 after considering current inventory levels. Also, there is a significant reduction from \$760 M to \$623 M in total regional economic loss between the two scenarios. The cushioning effect of inventory is evident from the inoperability curve for S8 for scenario 1 (Fig. 5). It had the second highest initial inoperability of almost 13 % in scenario 0 but was not inoperable at the time that the simulated disaster struck from scenario 1. Sector S8 experienced an inoperability level of no more than 8 % throughout the recovery period. Finally, the expected regional economic loss,  $f_5$ , increases from \$623 M to an  $f_4$  of \$635 M for an extreme-event case under the current levels of inventory.

#### 4.2 Enhanced inventory scenarios

Applying the DCPD to the rankings resulting from scenario 1, Table 2 summarizes the critical manufacturing and retail and trade sectors identified for the chosen enhanced inventory scenarios.

##### 4.2.1 Scenario 2: enhanced inventory at $ELPreference = 0.2$

Among the enhanced inventory scenarios considered, scenario 2 exhibited the least reduction in expected economic losses ( $f_5$ ) as well as having the highest extreme-event expectations of  $f_4$  for economic loss. A probable cause would be the lower *ELPreference* specification set for this scenario compared to scenarios 3 and 4. However, no similar pattern follows with respect to sector inoperability. This implies that there is evident improvement in the individual inoperability behavior of the critical manufacturing sectors and an average improvement of 2 % functionality (e.g., a drop of 0.02 inoperability to the individual sectors as a result of interdependence as shown in Fig. 6).

##### 4.2.2 Scenario 3: enhanced inventory at $ELPreference = 0.5$

Similar to scenario 2, there were also three critical manufacturing sectors found for scenario 3, but enhancing the inventory level of sector S19 instead of S23 has reduced expected economic losses by at least \$16 M more than the result of scenario 2 (Figs. 6, 7). The variability of individual sector inoperability,  $y_i$ , has been reduced, but, in general, the scenario did not have the same effect on its mean.

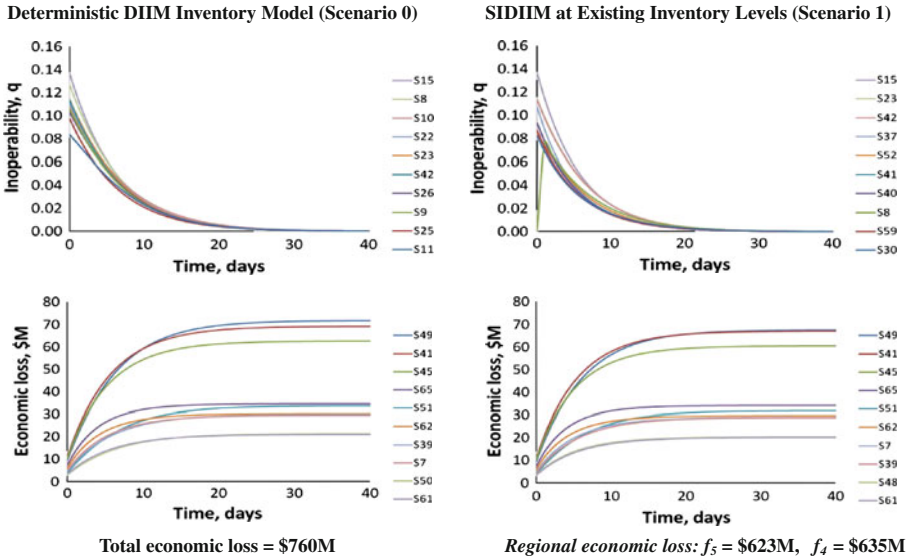


Fig. 5 Inoperability and economic loss behavior without and with stochastic inventory model

Table 2 Inventory-enhanced scenario description

	<i>ELPreference</i> value	Critical manufacturing sectors
Scenario 2	0.2	S8, S15, S23
Scenario 3	0.5	S8, S15, S19
Scenario 4	0.8	S19, S25, S27, S28

4.2.3 Scenario 4: enhanced inventory at *ELPreference* = 0.8

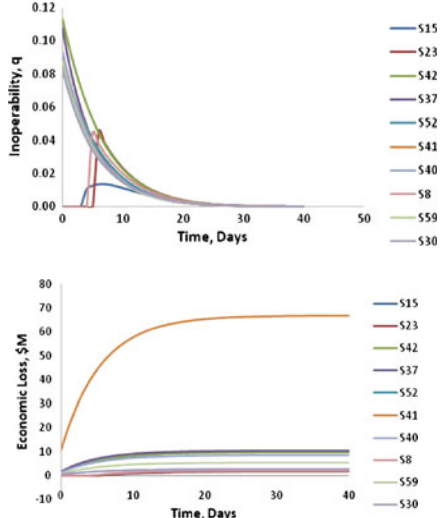
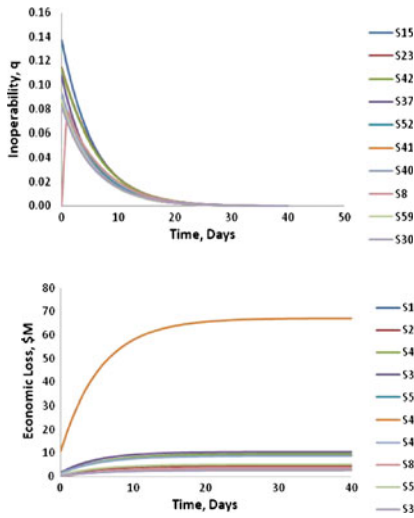
The proposed enhanced inventory for sectors S27 and S28 did not result into drastic reduction in sector inoperability (Fig. 8). On the other hand, enhanced inventory for sectors S19 and S25 has kept these sectors undisrupted within the first few days of the disruption period for the region. This is evidently reflected in the lower inoperability curves from Fig. 8. Despite the varying performance in bringing down sector inoperability, interdependency has managed to propagate the benefits of the enhancement scenario by reducing the expected regional economic loss by \$14 M and the expected cost of extreme risk by \$24 M.

Table 3 integrates and summarizes the results across the different scenarios. Scenario 1 is used as the reference strategy (i.e., baseline) for the computations of savings in various inventory-enhancement scenarios (i.e., scenarios 2, 3, and 4). We can clearly see from the table that inventory reduces the baseline economic losses in both moderate ( $f_5$ ) and extreme-event ( $f_4$ ) cases. Several important observations can be made about preference allocations between economic loss and inoperability objectives. Ignoring the inoperability objective, or equivalently, putting a larger weight to economic loss minimization (i.e., higher *ELPreference* value) does not necessarily lead to optimal savings. In the moderate case ( $f_5$ ), the savings from scenario 4 (larger weight for economic loss) are inferior to both scenario 2 (larger weight for inoperability) and scenario 3 (equal weights). In the extreme-



**Scenario 1: Stochastic Inventory DIIM at Existing Inventory Levels**

**Scenario 2: ELPreference=0.2 w/ Inventory Enhancement**



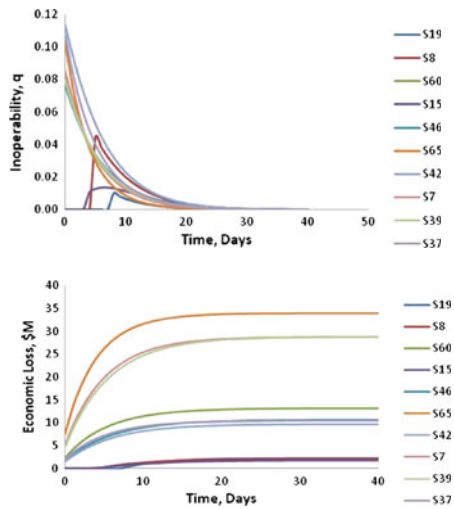
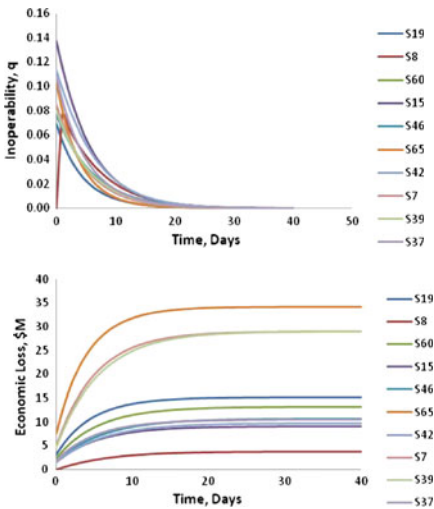
Regional economic loss:  $f_5 = \$623M$ ,  $f_4 = \$635M$

Regional economic loss:  $f_5 = \$607M$ ,  $f_4 = \$618M$

**Fig. 6** Inoperability and economic loss behavior with stochastic inventory model (ELPreference = 0.2)

**ELPreference=0.5 w/out Inventory Enhancement**

**ELPreference=0.5 w/ Inventory Enhancement**

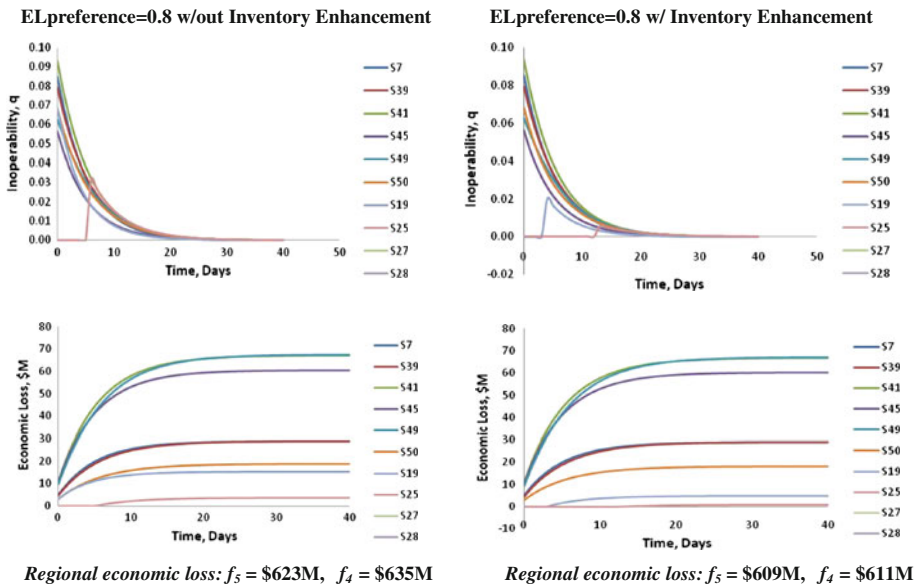


Regional economic loss:  $f_5 = \$623M$ ,  $f_4 = \$635M$

Regional economic loss:  $f_5 = \$602M$ ,  $f_4 = \$605M$

**Fig. 7** Inoperability and economic loss behavior with stochastic inventory model (ELPreference = 0.5)

event case, scenario 4 is found to be inferior to scenario 3. In the moderate case, the equal preference scenario (scenario 3) led to the largest savings of \$21 M or 3.4 % savings relative to the baseline. In the extreme-event case, scenario 3 also produced the largest



**Fig. 8** Inoperability and economic loss behavior with stochastic inventory model (ELPreference = 0.8)

savings of \$30 M or 4.7 % savings relative to the baseline. These results indicate that sector prioritization and inventory management in times of disasters must go beyond the myopic strategy of only minimizing economic losses. In this case study, we have shown that economic loss when coupled with inoperability minimization could further improve the rate of recovery, leading to larger savings.

### 5 Conclusions and areas for future research

In this research, we integrated a stochastic inventory model to interdependency analysis and critical sector prioritization. In particular, we derived empirical cumulative distribution functions to model the inventory levels of manufacturing and retail and trade sectors. We investigated how inventory serves as resiliency adjustment medium that can delay the propagation of disaster consequences while certain sectors of an economic region remain inoperable. We generated and evaluated inventory-enhancement policies by revisiting the

**Table 3** Comparisons of economic losses across various inventory scenarios

Scenario	Scenario description	Economic loss		Savings	
		$f_5$	$f_4$	$f_5$	$f_4$
1	Current stochastic inventory (Baseline)	\$623 M	\$635 M	–	–
2	Inoperability reduction preference	\$607 M	\$618 M	\$16 M	\$17 M
3	Equal preference	\$602 M	\$605 M	\$21 M	\$30 M
4	Economic loss reduction preference	\$609 M	\$611 M	\$14 M	\$24 M

Relative to scenario 1 (baseline case)

DIIM and the DCP. With the inclusion of published inventory levels for estimating disaster scenario parameters and user-elicited preference structure pertaining to the DIIM objectives (i.e., inoperability and economic loss), we obtained a closer replica of actual regional sector relationships.

In anticipation of disasters, such as hurricanes, results from the scenarios reveal that maintaining enhanced levels of inventories can significantly reduce associated losses and expedite recovery. Although inventory minimization in the context of JIT has proven to be cost-effective for “as-planned” scenarios, prudence in its implementation must be exercised particularly in times of disasters (despite their seemingly low likelihoods). More so, caution must be taken as extreme-event conditions prove to be more costly even with enhanced levels of inventory.

The hurricane-based scenarios performed in this research have exposed a host of other potential contributions in the area of disaster preparedness and recovery. Although the focus of the current application is on enhancing inventory levels in Virginia’s manufacturing sectors, a complementary analysis is needed to manage the resilience of workforce sectors—particularly those involved in the provision of essential services to further expedite recovery. Sensitivity analysis of inoperability and loss reduction objectives with respect to recovery assumptions can be performed to generate robust resource allocation policies. Finally, the flexibility and scalability of the current methodology and resulting decision support system can also be extended to accommodate analysis of other regions and other disaster scenarios.

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## Appendix

See Table 4.

**Table 4** Sector classification codes used in the case studies

Sector	Description	Sector	Description
S1	Farms	S34	Pipeline transportation
S2	Forestry, fishing, and related activities	S35	Other transportation and support activities
S3	Oil and gas extraction	S36	Warehousing and storage
S4	Mining, except oil and gas	S37	Publishing industries (includes software)
S5	Support activities for mining	S38	Motion picture and sound recording industries
S6	Utilities	S39	Broadcasting and telecommunications
S7	Construction	S40	Information and data processing services
S8	Food and beverage and tobacco products	S41	Federal Reserve banks and credit intermediation
S9	Textile mills and textile product mills	S42	Securities, commodity contracts, and investments
S10	Apparel and leather and allied products	S43	Insurance carriers and related activities

**Table 4** continued

Sector	Description	Sector	Description
S11	Wood products	S44	Funds, trusts, and other financial vehicles
S12	Paper products	S45	Real estate
S13	Printing and related support activities	S46	Rental and leasing services
S14	Petroleum and coal products	S47	Legal services
S15	Chemical products	S48	Miscellaneous professional and scientific services
S16	Plastics and rubber products	S49	Computer systems design and related services
S17	Nonmetallic mineral products	S50	Management of companies and enterprises
S18	Primary metals	S51	Administrative and support services
S19	Fabricated metal products	S52	Waste management and remediation services
S20	Machinery	S53	Educational services
S21	Computer and electronic products	S54	Ambulatory health care services
S22	Electrical equipment, appliances, and components	S55	Hospitals and nursing and residential care facilities
S23	Motor vehicles, bodies and trailers, and parts	S56	Social assistance
S24	Other transportation equipment	S57	Performing arts, spectator sports, and museums
S25	Furniture and related products	S58	Amusements, gambling, and recreation industries
S26	Miscellaneous manufacturing	S59	Accommodation
S27	Wholesale trade	S60	Food services and drinking places
S28	Retail trade	S61	Other services, except government
S29	Air transportation	S62	Federal government enterprises
S30	Rail transportation	S63	Federal general government
S31	Water transportation	S64	State and local government enterprises
S32	Truck transportation	S65	State and local general government
S33	Transit and ground passenger transportation		

Source: Bureau of Economic Analysis ([www.bea.gov](http://www.bea.gov))

## References

- Anderson C, Santos JR, Haimes YY (2007) A risk-based input–output methodology for measuring the effects of the August 2003 northeast blackout. *Econ Syst Res* 19(2):183–204
- Arboleda CA (2009) Vulnerability assessment of health care facilities during disaster events. *J Infrastruct Syst* 15(3):149–161
- Asbeck E, Haimes YY (1984) The partitioned multiobjective risk method. *Large Scale Syst*, pp 13–38
- Bagheri E, Ghorbani AA (2007) Conceptualizing critical infrastructures as service oriented complex interdependent systems. *Proc. of the Int. Conf. on Inf. Technol. and Manag*
- Barker KA, Haimes YY (2009) Uncertainty analysis of interdependencies in dynamic infrastructure recovery: applications in risk-based decision making. *J Infrastruct Syst* 15(4):394–405
- Barker KA, Santos JR (2010) Measuring the efficacy of inventory with a dynamic input-output model. *Int J Prod Econ* 126(1):130–143
- Basili M (2006) A rational decision rule with extreme events. *Risk Anal* 26(6):1721–1728

- Blake ES (2005) The deadliest, costliest, and most intense US tropical cyclones from 1851 to 2004 (and Other Frequently Requested Hurricane Facts). National Hurricane Center, Miami
- Brown T, Beyeler W, Barton D (2004) Assessing infrastructure interdependencies: the challenge of risk analysis for complex adaptive system. *Int J Crit Infrastruct* 1(1):108–117
- Bureau of Economic Analysis. US Economic Accounts (2009). Available at: [www.bea.gov](http://www.bea.gov)
- Chandana S, Leung H (2010) System of systems approach to disaster management. *IEEE Commun Mag* 48:138–145
- Chang SE (2007) Infrastructure failure interdependencies in extreme events: power outage consequences in the 1998 ice storm. *Nat Hazard* 41(2):337–358
- Chopra S, Sodhi M (2004) Managing risk to avoid supply-chain breakdown. *MIT Sloan Manag Rev* 46(1):53–61
- Crowther KG, Haimes YY, Taub G (2007) Systemic valuation of strategic preparedness with illustrations from hurricane Katrina. *Risk Anal* 27(5):1345–1364
- Dietzenbacher E, Lahr ML (2004) *Leontief and input-output economics*. Cambridge University Press, Cambridge
- Ellson RW, Milliman JW, Roberts RB (1984) Measuring the regional economic effects of earthquakes and earthquake predictions. *J Reg Sci* 24(4):559–579
- Federal Emergency Management Agency (2010) HAZUS-MH: FEMA's Methodology for estimating potential losses from disasters. <http://www.fema.gov/plan/prevent/hausuz/>
- Frohwein HI, Lambert JH, Haimes YY (1999) Alternative measures of risk of extreme events in decision trees. *Reliab Eng Syst Saf* 66(1):69–84
- Garber M (2006) Hurricane Katrina's effects on industry employment and wages. *Mon Labor Rev* 129(8):22–39
- Gerking SD (1976) Estimation of input-output models: Some statistical problems. Martinus Nijhoff Social Sciences Division, Leiden
- Gokey J (2009) Development of a prioritization methodology for maintaining Virginia's bridge infrastructure systems. *Proc. of the 2009 IEEE Syst. and Inf. Eng. Des. Symp* pp 252–257
- Haimes YY (2006) On the definition of vulnerabilities in measuring risks to infrastructures. *Risk Anal* 26(2):293–296
- Haimes YY (2009) *Risk modeling, assessment, and management*, 3rd edn. John Wiley and Sons, New York
- Haimes YY, Jiang P (2001) Leontief-based model of risk in complex interconnected infrastructures. *J Infrastruct Syst* 7(1):1–12
- Hattis D, Burmaster DE (1994) Assessment of variability and uncertainty distributions for practical risk analyses. *Risk Anal* 14(5):713–730
- Heal G, Kearns M, Kleindorfer P, Kunreuther H (2006) Interdependent security in interconnected networks. In: Auerswald PE, Branscomb LM, La Porte TM, Michel-Kerjan EO (eds) *Seeds of disaster, roots of response: how private action can reduce public vulnerability*. Cambridge University Press, New York
- Hendricks KB, Singhal VR (2005) An empirical analysis of the effect of supply chain disruptions on long-run stock price and equity risk of the firm. *Prod Oper Manag* 14(1):35–52
- Homeland Security Council: Planning Scenarios, 2004. Available at: <http://www.globalsecurity.org/security/library/report/2004/hsc-planningscenarios-jul04.htm>
- Isard W (1960) *Methods of regional analysis: an introduction to regional science*. MIT Press, Cambridge
- Ismael-Zadeh A, Takeuchi K (2007) Preventive disaster management of extreme natural events. *Nat Hazard* 42:459–467
- Kaplan S, Garrick BJ (1981) On the quantitative definition of risk. *Risk Anal* 1(1):11–27
- Kormos M, Bowe T (2006) Coordinated and uncoordinated crises responses by the electric industry. In: Auerswald PE, Branscomb LM, La Porte TM, Michel-Kerjan EO (eds) *Seeds of disaster, roots of response: how private action can reduce public vulnerability*. Cambridge University Press, New York
- Kujawski E (2006) Multi-period model for disruptive events in interdependent systems. *Syst Eng* 9(4):281–295
- La Porte TM (2006) Managing for the unexpected: reliability and organizational resilience. In: Auerswald PE, Branscomb LM, La Porte TM, Michel-Kerjan EO (eds) *Seeds of disaster, roots of response: how private action can reduce public vulnerability*. Cambridge University Press, New York
- Lantsman Y, Russo P (2010) Expect extreme events. *RMA J* 92(6):32–37
- Leontief WW (1936) Quantitative input and output relations in the economic system of the United States. *Rev Econ Stat* 18(3):105–125
- Lian C, Haimes YY (2006) Managing the risk of terrorism to interdependent infrastructure systems through the dynamic inoperability input-output model. *Syst Eng* 9(3):241–258
- Lian C, Santos JR, Haimes YY (2007) Extreme risk analysis of interdependent economic and infrastructure sectors. *Risk Anal* 27(4):1053–1064

- Little RG (2005) Organizational culture and the performance of critical infrastructure: modeling and simulation in socio-technological systems. Proceedings of the 38th Hawaii International Conference on System Sciences
- Lowrance WW (1976) Of acceptable risk. William Kaufmann, Los Altos
- MacKenzie C, Santos JR, Barker K (2012) Measuring changes in international production from a disruption: case study of the Japanese earthquake and tsunami. *Int J Prod Econ* 138(2):293–302
- Miller RE, Blair PD (1985) Input-output analysis: foundations and extensions. Englewood Cliffs, Prentice-Hall
- National Oceanic and Atmospheric Administration, United States Department of Commerce Report, August 31, 2011. <http://www.ncdc.noaa.gov/oa/reports/billionz.html>
- Okuyama Y, Hewings GJD, Sonis M (2004) Measuring economic impacts of disasters: interregional input-output analysis using sequential interindustry model. In: Okuyama Y, Chang S (eds) Modeling the spatial economic impacts of natural hazards. Springer, Heidelberg, pp 77–102
- Perrow C (1999) Normal accidents: living with high-risk technologies. Princeton University Press, Princeton
- Resurreccion JZ, Santos JR (2011) Developing an inventory-based prioritization methodology for assessing inoperability and economic loss in interdependent sectors. *IEEE Proc Syst Inf Eng Des Symp* vol 2011, pp 176–181
- Resurreccion JZ, Santos JR (2012a) Multiobjective prioritization methodology and decision support system for evaluating inventory enhancement strategies for disrupted interdependent sectors. *Risk Anal* 32(10):1673–1692
- Resurreccion JZ, Santos JR (2012b) Stochastic modeling of manufacturing-based interdependent inventory for formulating sector prioritization strategies in reinforcing disaster preparedness. *IEEE Proc of Syst and Inf Eng Des Symp*
- Rose A, Liao S (2005) Modeling regional economic resilience to disasters: a computable general equilibrium analysis of water service disruptions. *J Reg Sci* 45:75–112
- Santos JR (2006) Inoperability input-output modeling of disruptions to interdependent economic systems. *Syst Eng* 9(1):20–34
- Santos JR (2008a) Inoperability input-output model (iim) with multiple probabilistic sector inputs. *J Ind Manag Optim* 4(3):489–510
- Santos J (2008b) Interdependency analysis with multiple probabilistic sector inputs. *J Ind Manag Optim* 4(3):489–510
- Santos JR, Haimes YY (2004) Modeling the demand reduction input-output (I-O) inoperability due to terrorism of interconnected infrastructures. *Risk Anal* 24(6):1437–1451
- Santos JR, Haimes YY, Lian C (2007) A framework for linking cybersecurity metrics to the modeling of macroeconomic interdependencies. *Risk Anal* 27(5):1283–1297
- Santos JR, Barker KA, Zelinke PJ (2008) Sequential decision-making in interdependent sectors with multiobjective inoperability decision trees. *Economic Syst Res* 20(1):29–56
- Santos JR, Bond EJ, Orsi MJ (2009) Pandemic recovery analysis using the dynamic inoperability input-output model. *Risk Anal* 29(12):1743–1758
- Virginia Department of Emergency Management: Virginia hurricane history, 2007. Available at: <http://www.vaemergency.com/newsroom/history/hurricane.cfm>
- Webb G, Tierney K, Dahlhamer J (2000) Business and disasters: empirical patterns and unanswered questions. *Nat Hazard Rev* 1:83–90