An Input-Output Framework for Assessing Disaster Impacts on Nashville Metropolitan Region

Author: Joost R. Santos
Assistant Professor, Engineering Management and Systems Engineering
The George Washington University
Phone: 1-434-604-0490
E-mail: joost@gwu.edu

Abstract

Disasters damage physical infrastructure systems, disrupt movement of people and commodities, and give rise to significant economic losses. This paper develops an input-output model extension to explicitly identify regional perturbations pursuant to disaster scenarios. Historical data pertaining to the impacts of disasters on various economic sectors are utilized as input scenarios to a dynamic input-output model. The resulting model is specifically implemented for the Nashville region, which is a major metropolitan area in the United States known for its vibrant music and tourism industry sectors. The region is regularly visited by natural disasters like tornadoes and floods. The model developed in this paper is capable of estimating and visualizing the distribution of ripple effects across different economic sectors. Results of the study will help identify the critical sectors and can ultimately provide insights to formulating preparedness decisions to expedite disaster recovery.

1. Overview

The immense physical, economic, and social consequences caused by recent disasters have prompted federal, state, and local agencies to develop policies for preparedness and recovery. The extensive focus of the United States on protecting critical infrastructure has grown since the establishment of the President's Commission on Critical Infrastructure Protection (PCCIP) as stipulated in Executive Order 13010 [The White House 1996]. Several federal directives have been issued to underscore the need for disaster planning and management. Such directives [see, for examples, Department of Homeland Security (DHS) 2003a, 2003b] call for the development of risk analysis tools to prepare the nation against disruptive events, prevent the occurrence of dire consequences, and ensure efficient response and recovery in the aftermath of such events. The National Response Framework [DHS 2008] and National Infrastructure Protection Plan [DHS 2009], among others have been formulated to support the realization of such goals. In particular, man-made and natural disasters have been explicitly identified within the planning scenarios developed in conjunction with the DHS [see Howe 2005].

Natural or man-made disasters bring damage to properties and critical infrastructure systems, disrupt economic productivity, and cause mortalities in extreme situations. In addition to the disruptions to infrastructure systems, these disasters can trigger a variety of economic effects including the inability of many employees to commute to work, as well as the disruptions to shipments of commodities. Destruction of critical infrastructure assets, such as electric power substations, can create cascading adverse effects across interdependent economic systems. Workforce absence translates to production losses. Delayed commodity shipments also adversely impact production because local businesses are unable to operate at full capacity without the necessary resources.

This paper uses regional input-output modeling to estimate the total economic risk and resilience – including all direct losses and "ripple effects." The model is an extension of classical input-output modeling that explicitly identifies regional perturbations pursuant to disaster scenarios. Historical data pertaining to the impacts of disasters on various economic sectors are utilized as input scenarios to a dynamic input-output model, with an example based specifically on Tennessee's Nashville metropolitan area. The result is a new computer-based decision support system capable of estimating the distribution of losses across the economic sectors in the region and provides a visualization capability to identify the economic sectors most heavily impacted. These results of the study will help identify the critical sectors and can ultimately provide insights to formulating preparedness decisions to expedite disaster recovery.

2. Model Description

2.1 Background and Previous Uses

At the core of the disaster risk model developed in this paper is the concept of input-output (I-O) modeling. The I-O model views the economy as a set of interconnected sectors, which both produce goods as well as consume goods in the process of production. When the intermediate consumption is combined with the final consumer demand for products, the result is a model useful for understanding the interdependent nature of an economy [Leontief 1936]. Leontief's model has been extended and applied to myriad problems, including the effect of new technologies or taxes on the energy industry, and pollution creation and elimination [Miller and Blair 2009]. Understanding the interdependencies and resulting cascading impacts from an emergency event is essential in developing an effective security plan [TISP 2006]. The I-O model is a method for modeling interdependencies across multiple sectors of a given regional economy [Leontief 1951a and 1951b, Isard 1960, Miller and Blair 2009]. The National Cooperative Highway Research Program [2001] recognizes the I-O method in its guidebook for assessing the social and economic factors in infrastructure management domain. Extensions and current frontiers on I-O analysis can be found in Dietzenbacher and Lahr [2004].

Geographic modeling and decomposition enable a more focused and hence a more accurate analysis of regional characteristics as well as the associated regional interactions. Interdependencies across regions are becoming more and more prevalent due to the increasing trend in interregional transportation and trading activities. Significant segments of the working population commute across regions, as evidenced from the Journey to Work and Place of Work data [US Census Bureau 2007]. The increasing number of commodity shipments across regions bolsters the activities of the freight and trade sectors based on the Commodity Flow Survey [Bureau of Transportation Statistics 2008]. Several Lowry/Echenique input-output model derivatives are available for analysis of disruptions and their adverse effects on workforce and supply chains [e.g., Ruiz-Juri and Kockelman 2006]. The benefits of input-output-based models are many, particularly with respect to modeling the effect of disruptive events on interdependent regional sectors. There exists a wealth of data that describe the relationships among the many different sectors of the economy, namely provided by the Bureau of Economic Analysis (BEA) and the US Census. Furthermore, input-output data are essential components within the larger social accounting matrices used in computable general equilibrium modeling [see, for example, Minnesota IMPLAN Group, 2008].

The Leontief I-O model is formulated as follows:

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{c} \qquad \text{(Eq. 1)}$$

Where:

- $\mathbf{x}$ is the production output vector (i.e., the element, x_i, denotes the output of sector i)
- $\mathbf{A}$ is the Leontief technical coefficient matrix (i.e., the element a_{ij} denotes the input requirement of sector j from sector i, normalized with respect to the total input requirements of sector j)
- $\mathbf{c}$ is the final demand vector (i.e., the element, c_i, denotes the final demand for sector i)

One of the strengths of the Leontief model is that it is supported by detailed data collected and compiled by national census and statistical agencies. In the United States, for example, extensive I-O data are published by the Bureau of Economic Analysis (BEA) to generate the technical coefficient matrix [Miller and Blair 2009]. This methodology is coupled with the BEA's Regional Input-Output Multiplier System (RIMS II) to provide a useful framework for evaluating economic interdependencies [U.S. Department of Commerce 1997]. These data are available from BEA for the nation as a whole, each state, metropolitan regions (using the U.S. Census definitions), and counties. The availability of high-resolution economic data and social accounting matrices enables the application of I-O model and its hybrids for analysis of relatively small regions (e.g., analysis of infrastructure disruptions in Portland [Rose and Liao 2005]). Other I-O based models can be found in USDOT [2009] and Zhao and Kockelman [2004].

Haimes and Jiang [2001] revisited the Leontief model and expanded it to account for *inoperability*, or the inability for sectors to meet demand for their output. This model, the Inoperability Input-Output Model (IIM), has been featured in several applications. Examples include modeling of infrastructure interdependencies and risks of terrorism [Santos 2006, 2008], multi-state regional electric power blackouts [Anderson et al. 2007], inventory management [Barker and Santos 2010], and hurricane scenarios [Haggerty et al. 2008, Crowther et al. 2007]. The IIM was also applied to problems with sequential decisions and multiple objectives, such as the biofuel subsidy analysis explored by Santos et al. [2008]. Santos et al. [2007] have also formulated a conceptual framework for bridging I-O analysis with agent-based simulation for interdependent infrastructure systems.

2.2 Inoperability Input-Output Model (IIM)

The IIM is structurally similar to the Leontief I-O model in Eq. (1). The mathematical formulation is as follows:

$$\mathbf{q} = \mathbf{A}^{*}\mathbf{q} + \mathbf{c}^{*} \qquad \text{(Eq. 2)}$$

- $\mathbf{q}$ is the inoperability vector (i.e., the element, q_i, denotes the inoperability of sector i)
- $\mathbf{A}^{*}$ is the interdependency matrix (i.e., the element a^{*}_{ij} describes the inoperability contribution of sector j to sector i, see further discussions below)
- $\mathbf{c}^{*}$ is the demand perturbation vector (i.e., the element, c^{*}_{i}, denotes the demand perturbation to sector i)

The parameters descriptions of the IIM, as well as additional discussions on the dynamic model extensions are found below. Details of model derivation and an extensive discussion of model components are found in Santos and Haimes [2004] and also in Santos et al. [2008].

Sector Inoperability

Inoperability is conceptually related to the term unreliability, which expresses the ratio with which a sector's production is degraded relative to some ideal or 'as-planned' production level. Sector inoperability (**q**) in this paper is an array comprised of 65 elements. Each element represents the resulting inoperability value for each of the 65 interdependent economic sectors. Table 1 summarizes the sector classifications used in the regional model and examples. The inoperability of each sector represents the ratio of unrealized production (i.e., ideal production minus degraded production) relative to the ideal production level of the industry sectors. To understand the concept of inoperability, suppose that a given sector's ideal production output is worth \$100. Suppose also that a natural disaster causes this sector's output to reduce to \$90. The production loss is \$10, which is 10% of the ideal production output. Hence, the inoperability of the sector is 0.10. Since a region is comprised of interacting sectors, the value of inoperability will further increase due to the subsequent ripple effects caused by sector interdependencies.

Interdependency Matrix

The interdependency matrix ($\mathbf{A}^*$) is a transformation of the Leontief technical coefficient matrix (**A**), which is published by the BEA and is publicly available. It is a square matrix with 65 rows and 65 columns. The elements in a particular row of the interdependency matrix can tell how much additional inoperability is contributed by a column industry sector to the row industry sector. When the interdependency matrix ($\mathbf{A}^*$) is multiplied with the sector inoperability (**q**), this will generate the intermediate inoperability due to endogenous sector transactions. Endogenous transactions in the context of this paper pertain to the flow of intermediate commodities and services within the 65 sectors. These endogenous commodities and services are further processed by the intermediate sectors (i.e., commodities and services that are not further transformed or those used immediately for final consumption are excluded from endogenous transactions). BEA's detailed input-output matrices can be customized for desired geographic resolutions using regional multipliers, or location quotients based on sector-specific economic data. This process of regionalization is performed to generate region-specific interdependency matrices like the ones used in the case studies for the Nashville metropolitan statistical area.

Demand Perturbation

The demand perturbation ($\mathbf{c}^*$) is a vector comprising of final demand disruptions to each sector in the region. The demand perturbation, just like the inoperability variable in the basic IIM shown in Eq. (2), is normalized between 0 and 1. In this basic IIM formulation, supply disruptions are modeled as "forced" demand reductions. Consider a hypothetical disruption where the supply for a commodity or service decreases but demand remains virtually unaffected. In this case, the consumers will have to temporarily sacrifice their need for that commodity or service until it bounces back to its as planned supply level. The limitation of the basic model in Eq. (2) is that it uses "forced" demand reduction as a surrogate to supply reduction. To address this shortcoming, the dynamic extension to the

IIM was developed to enable a more explicit definition of perturbation parameters, in addition to the formulation of a sector-specific economic resilience matrix.

Table 1: Sector Classification

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
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 scientificservices
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

Economic Resilience

A key motivation that led to the development of the dynamic IIM is the need for linking the concept of economic resilience with time varying sector inoperability for a given recovery horizon. In general, resilience is defined as the ability or capability of a sector to absorb or cushion against damage or loss [Holling 1973, Perrings 2001]. Rose and Liao [2005] suggest that resilience can be enhanced through: (i) expedited restoration of the damaged capability, (ii) using an existing back-up capability, (iii) conservation of inputs to compensate for supply shortfalls, (iv) substitution of inputs, or (v) shifting of production locations, among others. Rose [2009] provides comprehensive definitions and categories of economic resilience including static, dynamic, inherent, and adaptive.

The dynamic formulation of the IIM takes into account the economic resilience of each sector, which influences the pace of recovery of the interdependent sectors in the aftermath of a disaster. The formulation is as follows:

$$\mathbf{q}(t+1) = \mathbf{q}(t) + \mathbf{K}[\mathbf{A}^{*}\mathbf{q}(t) + \mathbf{c}^{*}(t) - \mathbf{q}(t)] \qquad \text{(Eq. 3)}$$

The term, **K**, is a sector resilience coefficient matrix that represents the rates in which sectors recover to their nominal levels of production following a disruption [Lian and

Haimes 2006]. The model dictates that the inoperability level at the following time step, $\mathbf{q}(t+1)$, is equal to the inoperability at the previous stage, $\mathbf{q}(t)$, plus the effects of the resilience of the sector. The values of $\mathbf{K}$ tend to be negative or zero, thereby detracting from the overall level of inoperability. As seen in Eq. (3), $\mathbf{K}$ is multiplied with the indirect inoperability resulting from other sectors, $\mathbf{A}^*\mathbf{q}(t)$, plus the degraded final demand, $\mathbf{c}^*(t)$, minus the current level of inoperability, $\mathbf{q}(t)$. The resilience coefficient, $\mathbf{K}$, is assumed to be an inherent characteristic of a particular sector, but multiplying it with the inoperability product term, $\mathbf{A}^*\mathbf{q}(t)$, will result in coupled resilience across directly related sectors. This is particularly relevant when analyzing a sector that heavily depends on another sector for achieving its as-planned productivity levels. Regardless of how inherently resilient a sector is, its productivity will be significantly compromised when another sector it heavily depends on becomes largely inoperable in the aftermath of a disaster.

The dynamic extension Eq. (3) answers one of the fundamental limitations of the basic IIM in Eq. (2), which is the ability to capture time varying recovery that adapts to some *a priori* and current levels of inoperability within the perturbation and recovery period. For the dynamic extension to the IIM, Lian and Haimes [2006] provide the formulation to estimate the sector resilience coefficient of each sector. This resilience coefficient is a function of: (i) sector inoperability, (ii) sector interdependencies, (iii) recovery period, and (iv) the desired level of inoperability reduction for the target recovery period. In this formulation, economic resilience is inversely proportional to the recovery period. This is because resilience is a desired attribute of any system and, hence, a higher level of resilience is preferred. On the other hand, recovery period (i.e., the time it takes to reach full recovery) is desired to be at minimum to the extent possible. The higher the value of the sector resilience metric, the better equipped it is to protect and recover itself from external perturbations. Hence, increasing the economic resilience metric of a sector reduces its recovery period as well as the associated economic losses. The dynamic version of the IIM is capable of analyzing the extent to which sector resilience can decrease the magnitude of sector inoperabilities and economic losses, as well as shorten the recovery period. This formulation would create a time-dependent value to better account for the impact of different intensities and durations of a disaster, as longer ones would tend to further stress the sectors impacting their ability to recover. Lian et al. [2007], Santos [2006], Lian and Haimes [2006], and Haimes et al. [2005] applied the model to various regional disaster scenarios to analyze the recovery behaviors of critical economic sectors and infrastructure systems.

Economic Loss

Similar to sector inoperability, economic loss is an array comprised of 65 interdependent economic sectors. Each element in this array indicates the magnitude of economic loss of each sector, in monetary units (or particularly in US dollars for the scenarios explored in the case studies). The economic loss of each sector is simply the product of the sector inoperability and the ideal production output. For example, an inoperability of 0.1 for a sector whose production output is $100 will result in an economic (or production) loss of $10. Economic loss is treated as a separate disaster metric since it complements and supplements the inoperability metric. Both the inoperability and economic loss metrics are desired to be kept at minimum. It is also worth noting that when the 65 sectors are ranked according to the magnitude of their inoperability and economic loss metrics, two distinct rankings will be generated. Suppose that a second sector has an inoperability of 0.2 and a production output of \$40. The resulting economic loss will be $0.2 \times \$40 = \$8$. Although the inoperability of the second sector (0.2) has a higher rank compared to the first sector (0.1), the direction of priority will reverse when economic loss is considered as the sole basis for ranking. To wit, the second sector has an economic loss of \$8, which has a lower rank in contrast to the first sector's \$10 economic loss.

2.3 Databases for the Nashville Metropolitan Region

Disasters can cause severe damage to existing infrastructure—consequently affecting economic productivity. Temporary closure of factories and stores, loss of mobility due to flooding and debris cleanup, repair of damaged infrastructure systems (among others) can drastically affect workforce and commodity flows for prolonged periods of time. Reduction in worker flow decreases productivity, reduction in commodity flow results in cascading demand and supply impacts, and social flows will impact business accessibility. Using detailed journey-to-work data, commodity flow surveys, and social accounting matrices permits modeling of disruptions to regional productivity. Modeling efforts include the potential for cascading failure, accounting for spatial dependencies and various economic and social travel patterns.

A region expects substantial disruptions to infrastructure capacity, as well as workforce availability and mobility in the aftermath of a disaster. These disruptions in turn can trigger sector productivity degradations. In order to quantify the impact of reduced sector productivity levels on the economy of Nashville, economic data (such as input requirements, commodity outputs, and income statistics, among others) for each sector of the region are collected and assembled from different sources.

Sector Classifications

This paper configures the data collection methodology using the North American Industry Classification System (NAICS). RIMS II adopts an aggregated version of the detailed sector classification—comprising of 65 sectors (see Table 1) [U.S. Department of Commerce 1997].

Input-Output Matrices

In a simplified I-O model formulation, each industry is assumed to produce a distinct commodity. The term "commodity" in this report refers to the output of an industry, which can take the form of goods or services. Realistically however, it is possible that a given industry produces more than one commodity. In addition, a given commodity may not be a unique output of an industry. The BEA makes distinction between an industry and a commodity in its published I-O data via the "industry-by-commodity" and "commodity-by-industry" matrices. Figure 2, adapted from Miller and Blair [2009], shows a summary of the types of national I-O accounts maintained by the BEA.

	Commodity	*Industry*		
Commodity		Use Matrix (**U**)	Exogenous Demand (**e**)	Total Commodity Output (**y**)
Industry	Make Matrix (**V**)			Total Industry Output (**x**)
		Value Added ($\mathbf{z}^T$)		
	Total Commodity Input ($\mathbf{y}^T$)	Total Industry Input ($\mathbf{x}^T$)		

Figure 1. Summary of economic I-O accounts

The *make* matrix, denoted by **V**, would show the monetary values of the different column commodities *produced* by the different row industries. The *use* matrix on the other hand, denoted by **U**, would show the monetary values of the different row commodities *consumed* by the different column industries. These matrices are typically associated with the following vectors: (i) **e** refers to the commodity-based exogenous (or final) demand; (ii) **y** refers to the commodity-based output; (iii) **x** refers to the industry-based output; and (iv) **z** refers to the value added. Note that Figure 1 does not directly specify the I-O matrix representing an industry-by-industry matrix. Hence, the make and use matrices are normalized first with respect to their column totals, and are then multiplied with each other. The resulting product matrix is typically known as the industry-by-industry technical coefficient matrix in I-O parlance. A column of this matrix shows the input contribution of the row industries to the column sector, expressed as a proportion of the total input requirements of that column sector. The technical coefficient matrix is used for computing the elements of the interdependency matrix of the IIM (i.e., the notation $\mathbf{A}^*$ in Eq. 1).

Gross Domestic Product

Gross Domestic Product (GDP) consists of final consumption, other than those used as intermediate production inputs to the 65 endogenous sectors. As such, GDP is also interpreted as the value of final uses (or consumptions), which includes personal consumption expenditure, gross private domestic investment, government purchases, and net foreign exports (i.e., difference in exports and imports) [Miller and Blair 2009].

Since the value of GDP is theoretically equal to the gross domestic income, it is also defined by BEA as "the market value of goods and services produced by labor and property in the United States, regardless of nationality; GDP replaced gross national product (GNP) as the primary measure of U.S. production in 1991."[1] GDP data is also available for all states and metropolitan areas within the United States.

Local Area Personal Income

Local Area Personal Income (LAPI) refers primarily to the wages paid to the workers in a given region. Other components of LAPI include "supplements to wages and salaries, proprietors' income with inventory valuation adjustment (IVA) and capital consumption adjustment (CCAdj), rental income of persons with CCAdj, personal dividend income, personal interest income, and personal current transfer receipts, less contributions for government social insurance."[2] LAPI data are available for each of the 65 sectors. To convert the output of disaster impact into a measure of workforce sector inoperability, there needs to be a way to translate a percentage decrease in workforce availability into a measure of sector inoperability. Arnold et al. [2006] accomplished this through estimates of worker productivity. To generate worker impact for the RIMS II sectors, the ratio of Local Area Personal Income (LAPI) to industry output is computed [BEA 2008]. The LAPI provides the value of workforce to the industry (the market value of the laborers' work) and dividing this by the industry output gives the proportion of output that is dependent on the workforce. This calculation of inoperability for a given sector is shown in Eq. (4). This LAPI-based approach is compatible with the commonly used metrics for assessing workforce input, which include number of hours, number of jobs, and number of employed people [OECD 2001].

$$\text{Sector Inoperability} = \frac{\text{Unavailable Workforce}}{\text{Size of Workforce}} \times \frac{\text{LAPI}}{\text{Sector Output}} \qquad \text{(Eq. 4)}$$

The impact on workers is then multiplied with the number of workers in that sector that are unavailable divided by the number of workers in that sector (giving percentage of workers missing) to determine overall sector inoperability. A case in point, Burrus et al. [2002] developed a comprehensive survey describing the impact of various disaster intensities on workforce availability. The sectors included in their survey are similar to the RIMS II classification employed in the study. Such historical workforce recovery data can be used to formulate the time-varying recovery functions.

Employment Numbers by Industry

Employment data are available for different states and metropolitan areas. For example, BEA publishes annual estimates of the total full-time and part-time employment by NAICS industry. These employment numbers are available only for a subset of the 65 sectors in the IIM. Hence, the regional *per capita income* can serve as a basis for

[1] BEA Glossary: http://www.bea.gov/glossary/glossary_g.htm
[2] BEA Glossary. http://www.bea.gov/glossary/glossary_l.htm

estimating the number of workers in sectors with missing data. These sector-specific employment numbers are used in determining the equivalent number of jobs lost within the disaster horizon.

3. Decision Support Tool

The decision support tool developed in this paper comprises a front-end graphical user interface (GUI) developed in Microsoft Excel™. The spreadsheet tool comprises of five modules: (i) scenario generation, (ii) computation, (iii) visualization, (iv) prioritization and sensitivity analysis, and (v) data analysis. These modules are described as follows:

3.1 Scenario Generation Module

The scenario generation module enables the user to provide the model scenario inputs. The user is asked to enter the initial inoperability for each of the 65 sectors, as well as the time it takes to achieve full recovery. Initial inoperability (denoted by q_0) is a number between 0 and 1, which describes the extent to which a given sector's production capacity is affected initially (i.e., 0.1 means that 10% of the production capacity is rendered inoperable by a disaster). On the other hand, the time to recovery (denoted by T) is the time that it is expected to take a sector to recover to its pre-disaster production level. In the model, the time to recovery is measured in days. In the absence of recovery period data for some sectors, a similar value for a sector with known recovery period can be used. The reasoning behind this is that a given sector—even if it is not directly affected by a disaster—will match (or even exceed) the recovery period of a sector that it is coupled with. By the same token, a sector whose dependence on other sectors is minimal will virtually remain unaffected regardless of the assumed recovery period. Figure 2 shows a partial screenshot of the scenario generation component with arbitrary parameter inputs.

ID	Sector	qo	T
S1	Farms	0.05	30
S2	Forestry, fishing, and related activities	0.18	30
S3	Oil and gas extraction	0.11	30
S4	Mining, except oil and gas	0.09	30
S5	Support activities for mining	0.50	30
S6	Utilities	0.06	30
S7	Construction	0.40	30
S8	Food and beverage and tobacco products	0.14	30
S9	Textile mills and textile product mills	0.16	30
S10	Apparel and leather and allied products	0.05	30

Figure 2. Screenshot of scenario definition GUI component

In addition, an advanced feature of the model allows the user to enter not only the initial inoperability values (q_0), but also to insert subsequent inoperability values across the recovery period (e.g., q_1, q_2, q_3, etc.). This is particularly useful for cases with known inoperability and recovery trends, such the disaster scenarios further explored in Section

4. This advanced feature also allows users to perform inoperability adjustments whenever risk management actions are introduced within the recovery period. The annotated diagram in Figure 3 explains this advanced feature for a sector with a recovery trend similar to a step function.

ID	Description	q0	q1	q2	q3	q4	q5	q6	q7	q8	q9	q10	q11
S1	Farms	0	0	0	0	0	0	0	0	0	0	0	0
S2	Forestry, fishing, and related activities	0	0	0	0	0	0	0	0	0	0	0	0
S3	Oil and gas extraction	0	0	0	0	0	0	0	0	0	0	0	0
S4	Mining, except oil and gas	0	0	0	0	0	0	0	0	0	0	0	0
S5	Support activities for mining	0	0	0	0	0	0	0	0	0	0	0	0
S6	Utilities	0.80	0.80	0.8	0.5	0.5	0.5	0.25	0.25	0.25	0.25	0.25	0.01

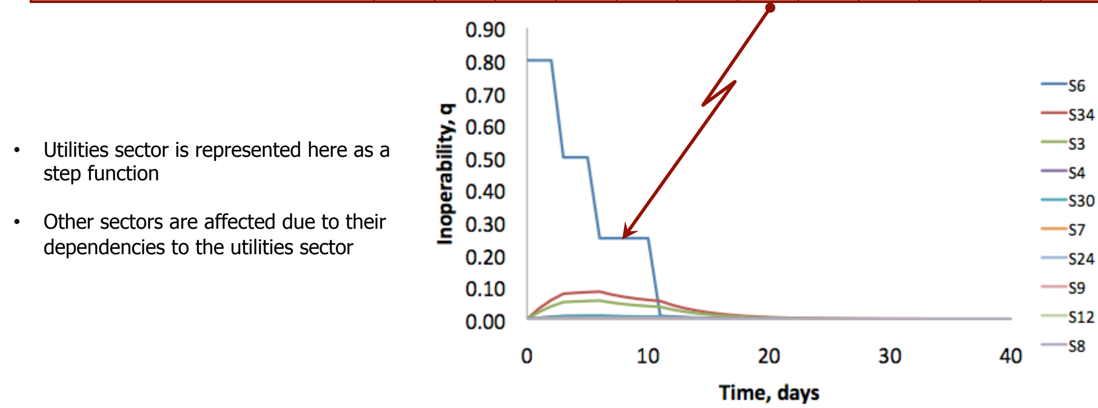

Figure 3. Screenshot of Scenario Definition GUI Component

3.2 Computation Module

This is the computing engine of the program containing the codes for the IIM. This module stores the simulation rules and algorithms needed for executing the IIM and its dynamic recovery model extensions. This module also includes the algorithms for visualizing the model results, namely the inoperability and economic loss for each sector and for each day within the recovery period.

In the computer tool, sector recovery is modeled as a time varying function instead of static or predetermined value as formulated previously. The resilience coefficient (discussed in Section 2.2) for each sector represents the ability of a sector to recover from some level of inoperability to a final level of inoperability in a given period of time. As a regional economy and its associated sectors recover from a large-scale disruption, the nominal resilience coefficients are expected to fluctuate. The reasoning behind this is that as sectors utilize inventories and capital resources to recover and mitigate the impacts of a disaster, they deplete these resources and thus are less able to recover. The pace of recovery is further compounded by sector interdependencies—creating indirect effects that continue to disrupt regional productivity. The new formulation of the resilience coefficient includes a variety of factors, including the current inoperability value, previous inoperability values (giving measures of trends and duration) and nominal sector recovery rates to determine a baseline scenario.

3.4. Visualization Module

The visualization module enables the user to view the recovery behaviors of the critical sectors given the parameter values entered in the scenario definition stage. The critical sectors are selected as the top-10 sectors (out of 65) with respect to the two primary metrics of the IIM, which are *inoperability* and *economic loss*. The rankings based on these two metrics are generally different, as explained in Section 2.2.

The following figures give sample visualizations of how inoperability and economic loss evolve across the recovery period. Although not directly included in the visualization, other important disaster consequence metrics are extrapolated from the economic loss estimates. These include tax loss, income loss, and equivalent number of jobs lost for the applicable recovery period. These loss estimates are provided in each of the scenarios explored in Section 4.

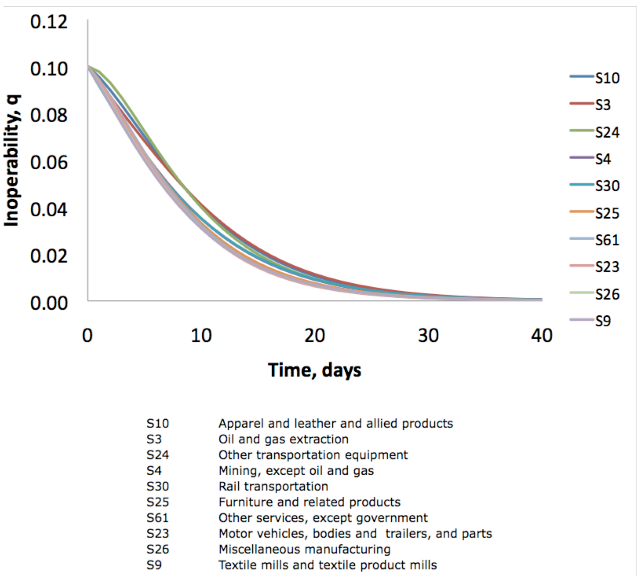

Figure 4. Top-10 sectors with largest inoperability

Figure 4 provides a sample depiction of the top-10 sectors with largest inoperability values. Inoperability rankings are based on magnitude of sector disruptions, normalized relative to sector total output. A uniform sector disruption scenario is applied to all 65 sectors to show the key sectors based on the inoperability metric. Inoperability metric highlights sectors that are tightly coupled with other sectors regardless of their economic values, such as: Manufacturing (S10, S25, S23, S26, S9); Oil and gas, Mining (S3, S4); Transportation (S24, S30).

On the other hand, Figure 5 depicts the associated top-10 sectors with largest economic losses. Economic loss rankings are based on cumulative economic losses incurred prior to full recovery. The same uniform initial disruption is applied to all 65 sectors to show the key sectors based on the economic loss metric. Economic loss metric highlights sectors that have higher production values, measured in monetary unit, such as: Banks, Insurance (S41, S43); Computer systems (S49); Administrative services (S51); Real Estate (S45); Trade (S 27, S28).

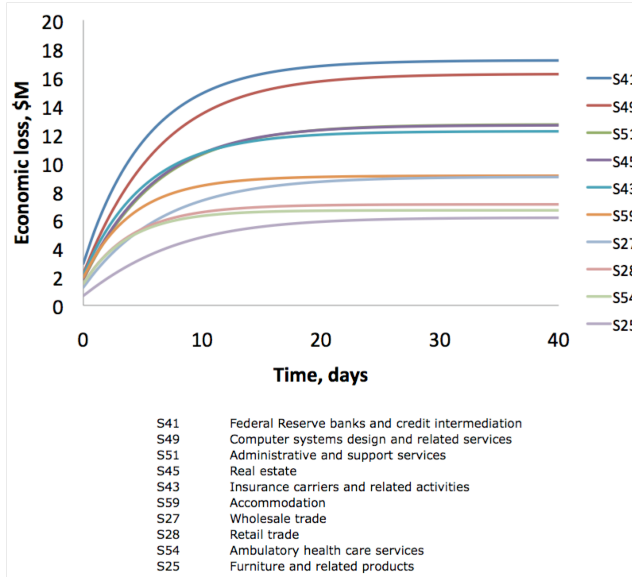

Figure 5. Top-10 sectors with largest inoperability

3.4 Prioritization Sensitivity Analysis Module

The tool is capable of visually searching for critical economic sectors that support two minimization objectives, which are economic loss and inoperability. We utilize the dynamic cross prioritization plot (DCPP) that uses more flexible threshold regions to capture critical sectors with varying preferences for the economic loss and inoperability objectives [Resurreccion and Santos 2011]. That is, the use of an arc orientation that captures more points closer to the x-axis (y-axis) to highlight the higher preference for the inoperability (economic loss) objective than the economic loss (inoperability) objective. Hence, the DCPP module can provide additional information on identifying and prioritizing the economic sectors that are expected to suffer the greatest consequences from a disaster scenario. These inoperability and economic loss consequences, as well as the extrapolated fiscal losses (i.e., tax loss, income loss, and equivalent number of jobs lost) can provide insights in planning for enhancements of regional resilience (e.g., backup capabilities, additional inventories, and production input substitutions, among others).

The prioritization sensitivity analysis module requires two categories of user inputs: (i) preference structure for economic loss and inoperability objectives, and (ii) prioritization scope to determine the size of the prioritization filter. The process and descriptions of these inputs are described as follows. First, the user is asked for the economic loss weight, or the relative importance of the economic loss objective with respect to inoperability. A scale of 0 to 1 is used, with the following interpretations:

- A value of 1 means economic loss is the only objective that matters (see Figure 6)

- A value of 0.5 means economic loss is equally preferred to inoperability (see Figure 7)
- A value of 0 means inoperability is the only objective that matters (see Figure 8)

In addition, the tool requires the user to enter a prioritization scope—a positive integer that can be adjusted to set the size of the prioritization area. This integer is increased when more sectors are to be prioritized, and decreased when fewer sectors can be prioritized (e.g., a budget constraint).

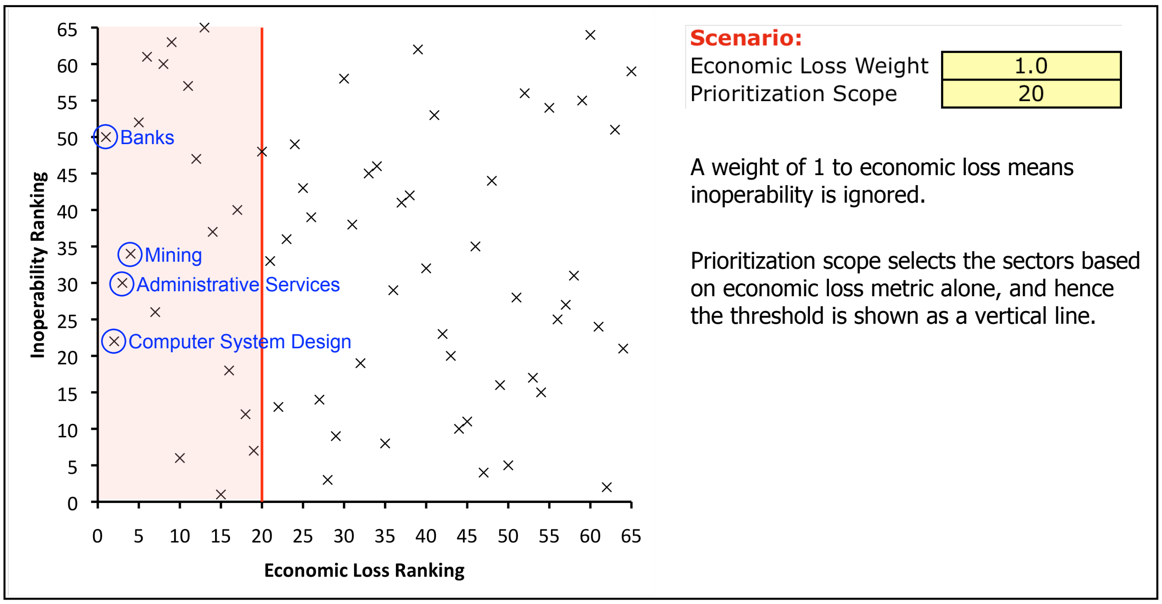

Figure 6. Prioritization using economic loss objective only

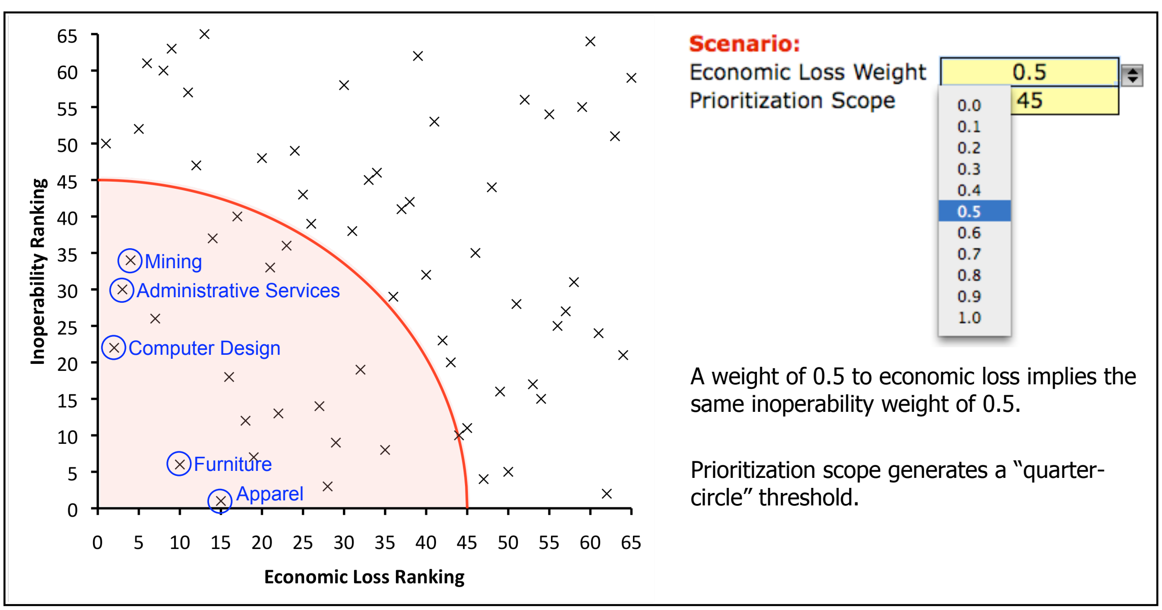

Figure 7. Prioritization with equal weights for economic loss and inoperability objectives

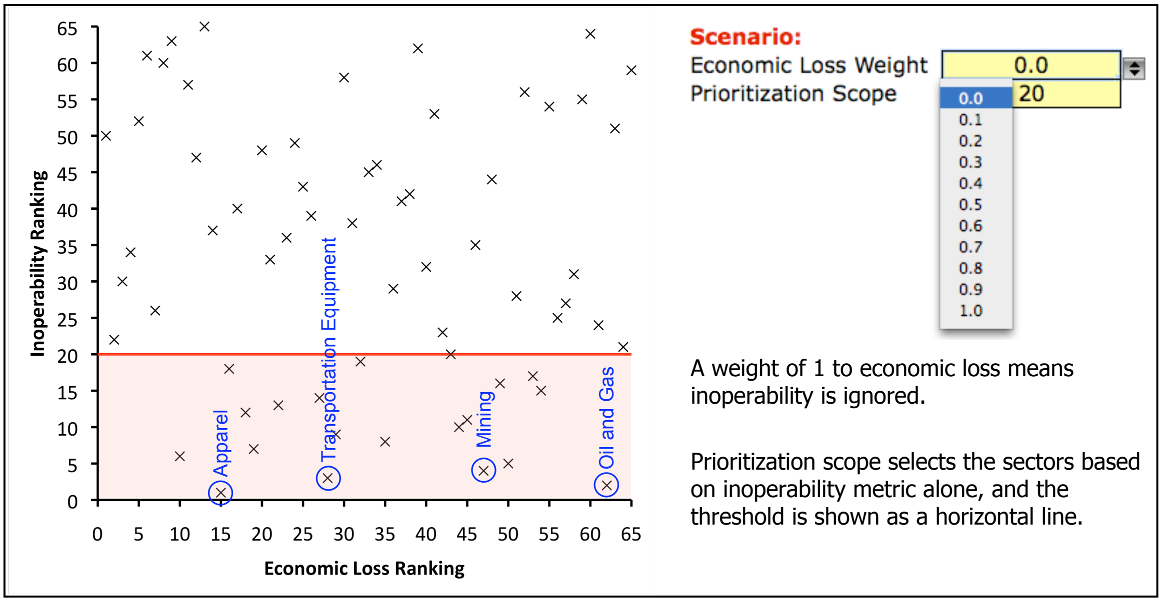

Figure 8. Prioritization using inoperability objective only

3.5 Data Module

The data module contains the relevant regional economic data. Examples of economic data that have been already described in Section Section 2.3 are input-output matrices, Gross Domestic Product (GDP), Local Area Personal Income (LAPI), employment statistics. These data are specific to the Nashville metropolitan region. In addition to the foregoing data sets, the spreadsheet tool also houses data extrapolated from other sources. These extrapolated data sets are used for estimating regional fiscal losses such as tax opportunity losses, personal income losses, and employment losses.

Tax Loss Estimation

Here, we assume that significant portions of the tax revenues collected at the county and state levels are pegged to the level of economic activity of the region. Examples of such tax categories include sales and use taxes, which are typically taken as percentages of the commodities and services sold locally. For the state of Tennessee (which encompasses Nashville), the sales tax rate for food is 5.5% and 7% for other merchandises[3]. Rates for use taxes are the same as sale taxes[4].

The following equation provides an estimate of sales and use tax losses for each sector *i*. Note that there are 65 sectors.

$$\text{Tax Loss}_i = (\text{PCE}_i \div x_i) \times (\Delta x_i) \times (\text{tax rate}_i) \qquad \text{(Eq. 5)}$$

[3] http://www.tn.gov/revenue/tntaxes/salesanduse.htm

[4] "It [use tax] is applied when merchandise (tangible personal property) is purchased from outside the state of Tennessee and imported into the state for use or consumption." Ibid.

Where:

- PCE_i is the Personal Consumption Expenditure for sector *i*
- x_i is the total output of sector *i* in the region
- Δx_i is the economic loss of sector *i* for a given disaster scenario, as computed by the model
- tax $rate_i$ is the applicable sales tax rate for sector *i* in the region

Because of the current capability of the I-O model to estimate production output losses, sales and uses tax losses will be estimated based on the percentage of the PCE relative to regional output. Other tax categories include property, excise, licenses and fees, and income, among others. Due to the current data module limitations on tax analysis, the computer tool is only capable of estimating losses from sales and use taxes.

Income Loss Estimation

Here, we focus our analysis on extrapolated data based on the Local Area Personal Income (LAPI). As discussed previously, LAPI is available for each of the 65 sectors. For each sector *i*, we first compute the proportion of LAPI with respect to the total regional output. When this proportion is multiplied with the production output loss of a particular sector *i* (due to a disaster), this will provide an estimate the income loss for sector *i*, and is formulated as follows:

$$\text{Income Loss}_i = (\ \text{LAPI}_i \div x_i\ ) \times (\Delta x_i\ ) \qquad \text{(Eq. 6)}$$

Where:

- $LAPI_i$ is the Local Area Personal Income for sector *i*
- x_i is the total output of sector *i* in the region
- Δx_i is the economic loss of sector *i* for a given disaster scenario, as computed by the model

Note that the loss estimated in the above formulation pertains to the aggregated income losses suffered by the workforce in sector *i*. Computation of the corresponding income tax loss by the local government can be complex (i.e., considering the different income tax brackets, federal vs. state distribution, disaster tax reliefs, etc.). Hence, extracting the associated income tax loss from the computed income loss is beyond the current scope of the current study.

Employment Losses

Traditional I-O employment multipliers analysis enables the computation of additional jobs created due to an increase in demand (and subsequently, production) of commodities and services for particular sectors. A similar concept is implemented here for estimating job losses that can stem disaster-induced income losses. The formulation for job losses[5] in each sector i is as follows:

$$\text{Job Loss}_i = (\text{ Income Loss}_i \div \text{LAPI}_i\text{ }) \times (\text{ Workers}_i\text{ }) \qquad \text{(Eq. 7)}$$

Where:

- Job Loss_i is the number of jobs lost in sector i
- Income_i is the workforce income loss in sector i
- LAPI_i is the local area personal income sector i
- Workers_i is the number of workers in sector i

4. Worked Examples with Screenshots

Disaster consequences encompass reductions in workforce productivity, loss of lives, and social disequilibrium. Workforce productivity losses can significantly decrease a sector's output regardless of the efficiency of other production factors. Regional economies, like Nashville, have limited resources to manage disaster consequences. The objective of the case studies is to manage impacts of various disaster scenarios in Nashville using available economic and survey data. This section demonstrates the use of the IIM and its dynamic extensions to assess the impacts of disaster scenarios on the Nashville's economic sectors. Data sets assembled from various economic and census agencies include input-output matrices, gross domestic product data, local area personal income data, and employment numbers, among others.

The following sections demonstrate the application of the IIM using different cases. Each case is introduced with scenario descriptions, as well as a summary of the different loss categories that could be of interest to regional policymakers. Recall that the two primary consequence categories provided by the IIM are *inoperability* and *economic loss*. The economic loss variable is denoted by Δx_i (see Eqs. 5 and 6) and is computed by the IIM for each of the 65 sectors. These economic loss values serve as the basis for estimating different categories of regional losses, including: (i) tax loss, (ii) income loss, and (iii) equivalent number of jobs lost.

In addition, the rankings of the critical sectors according to the inoperability and economic loss metrics are shown, along with the associated visualization outputs of the IIM. The DCPP tool also provides sample prioritization of key sectors based on priority assignments to the inoperability and economic loss objectives. As discussed in Section 3.4, the DCPP results can identify the economic sectors that are expected to suffer the greatest consequences from a disaster scenario and can help in formulating policies for enhancing regional resilience.

[5] Available data does not distinguish counts of full-time and part-time workers.

4.1 Case 1: Modeling Workforce Disruption

Consider a disaster hits the Nashville region that causes an initial inoperability of 50% to all its workforce sectors. For this scenario, it assumed that inoperability decreases exponentially and recovery is achieved over a 30-day horizon. The parameters that describe the initial effects of the disaster scenario are entered into the dynamic IIM and generated the economic loss and inoperability charts in Figure 9. The total economic loss for the simulated scenario is $800 million. From this economic loss, the following losses can be estimated based on the approaches discussed in Section 3.5. Note that the following losses are incurred only within the assumed recovery period of 30 days (or approximately 1 month):

- Tax loss: $7,221,193
- Income loss: $108,013,667
- Equivalent number of jobs lost: 2,465 jobs

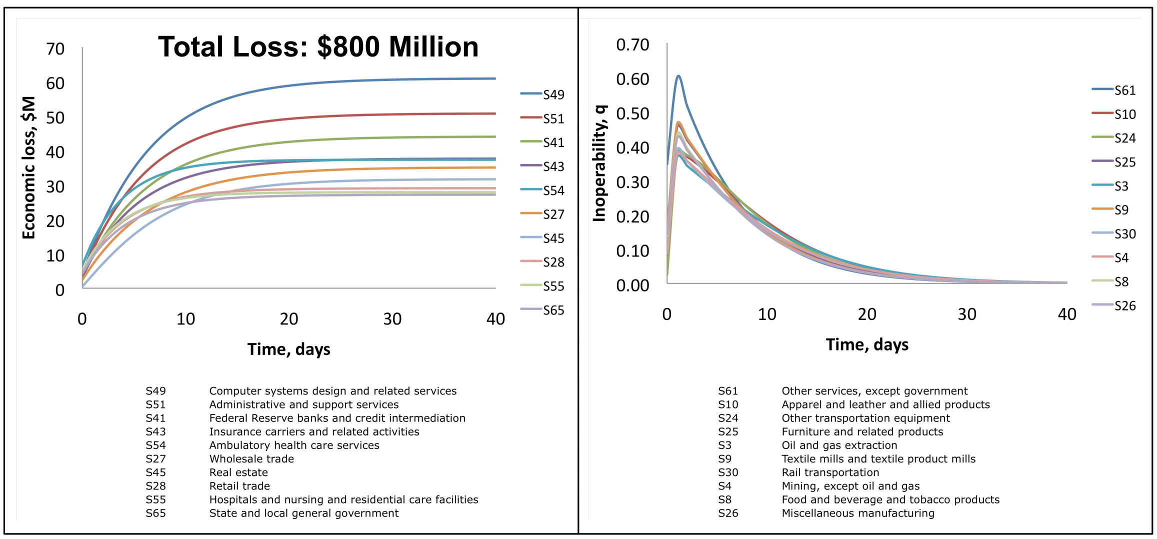

Figure 9. Top-10 critical sectors for Case 1 ranked according to: Economic loss (left) and Inoperability right

The top 10 sectors that suffer the highest economic losses (Figure 9, left panel) are: Computer systems design and related services (S49), Administrative and support services (S51), Federal Reserve banks and credit intermediation (S41), Insurance carriers and related activities (S43), Ambulatory health care services (S54), Wholesale trade (S27), Real estate (S45), Retail trade (S28), Hospitals and nursing and residential care facilities (S55), and State and local general government (S65). The top-10 sectors account for 48% of the total regional economic loss. It can also be observed that the economic losses increase sharply in the first 10 days, and start to “flatten out” after approximately 20 days. The inoperability charts indicate that recovery is almost completely achieved in 30 days.

For the same scenario, the top 10 sectors with highest inoperability values (Figure 9, right panel) are: Other services, except government (S61), Apparel and leather and allied products (S10), Other transportation equipment (S24), Furniture and related products (S25), Oil and gas extraction (S3), Textile mills and textile product mills (S9), Rail transportation (S30), Mining, except oil and gas (S4), Food and beverage and tobacco products (S8), and Miscellaneous manufacturing (S26).

The inoperability and economic loss rankings are different because the production outputs of the sectors could vary by orders of magnitude. As such, a sector that suffers a relatively low economic loss value can have a critical ranking in inoperability if its total production output is also lower relative to other sectors. By the same token, a sector with a relatively low inoperability value can have a critical ranking in economic loss if its total production output is significantly higher compared to the other sectors.

The dynamic cross prioritization plot (DCPP) tool enables the users to perform sensitivity analysis with respect to how they structure their preference between the economic loss and inoperability objectives. Two sample scenarios are presented in Figure 10. The vertical region corresponds to a preference strategy that gives importance to economic loss only, while the quarter-circle region corresponds to assigning equal weights to inoperability and economic loss objectives. For a purely economic loss minimizing strategy, there is a risk to exclude sectors that have critical ranking with respect to inoperability (e.g., transportation equipment). For the equal weighting strategy, equal priority is allocated between economic loss and inoperability. Nevertheless, there is also a risk of excluding sectors with critical economic loss rankings in this equal weighting strategy (e.g., banking and insurance). Hence, prioritizing sectors for recovery need careful consideration of the balance between economic loss and inoperability.

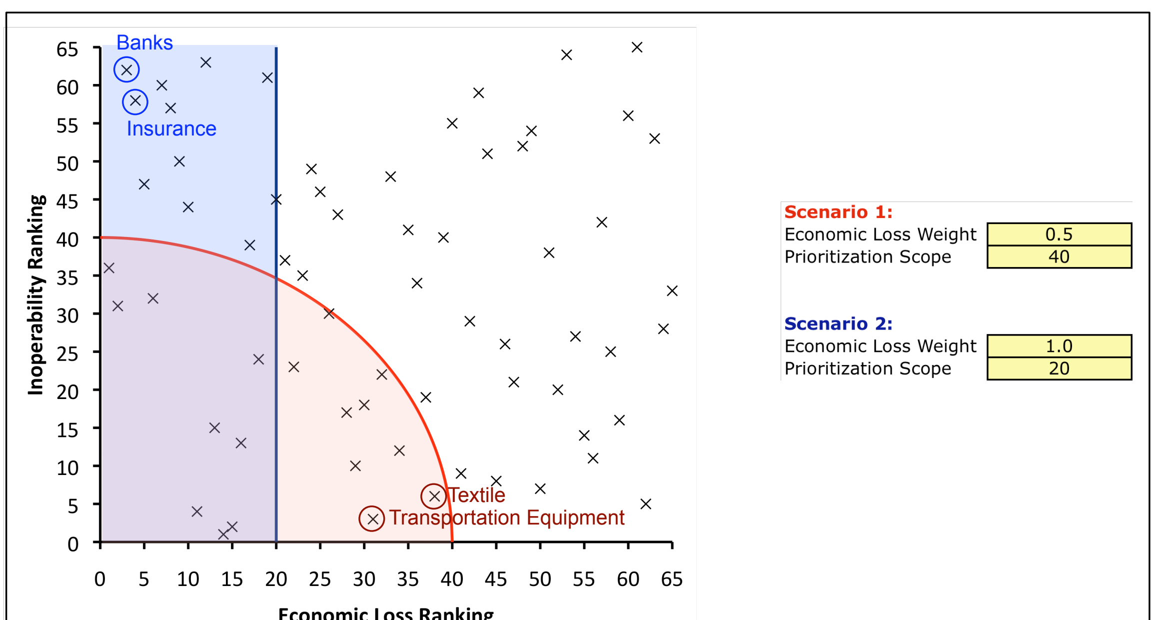

Figure 10. DCPP for Case 1

4.2 Case 2: Infrastructure Disruption with "Flat" Recovery Function

Suppose that Case 1 is expanded such that in addition to the 50% initial workforce inoperability, there is a constant 80% electric power outage[6] that persists for 10 days. These combined disruption scenarios comprise Case 2, which is explored in this section. The scenario parameters that describe Case 2 are entered into the dynamic IIM and generated the economic loss and inoperability charts in Figure 12. The total economic loss for the simulated scenario is $816 million. From this economic loss, the following losses can be estimated based on the approaches discussed in Section 3.5. Note that the following losses are incurred only within the assumed recovery period of 30 days (or approximately 1 month):

- Tax loss: $7,346,801
- Income loss: $108,831,472
- Equivalent number of jobs lost: 2,483

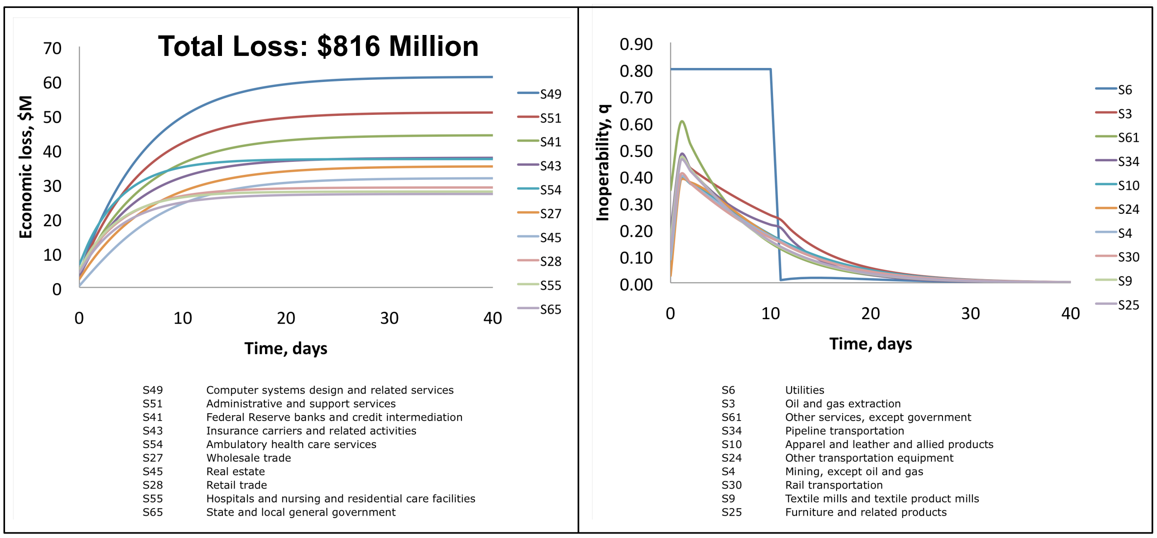

Figure 11. Top-10 critical sectors for Case 2 ranked according to: Economic loss (left) and Inoperability right

The top 10 sectors that suffer the highest economic losses (Figure 11, left panel) are: Computer systems design and related services (S49), Administrative and support services (S51), Federal Reserve banks and credit intermediation (S41), Insurance carriers and related activities (S43), Ambulatory health care services (S54), Wholesale trade (S27), Real estate (S45), Retail trade (S28), Hospitals and nursing and residential care facilities (S55), and State and local general government (S65). The top-10 sectors account for 47% of the total economic loss.

---

[6] Since regional I-O data typically lump electric power sector with the general "utility" sector, an approach to perform sector disaggregation is to pre-multiply the assumed "% outage" with the ratio of electric power output relative to the total utility sector output.

In contrast, the top 10 sectors with highest inoperability values (Figure 11, right panel) are: Utilities (S6), Oil and gas extraction (S3), Other services, except government (S61), Pipeline transportation (S34), Apparel and leather and allied products (S10), Other transportation equipment (S24), Mining, except oil and gas (S4), Rail transportation (S30), Textile mills and textile product mills (S9), and Furniture and related products (S25). In the inoperability charts for Case 2, we can directly observe that the electric power disruption is modeled as a "Utilities" sector disruption, which is flat for the first 10 days and completely restored thereafter.

The inoperability and economic loss rankings vary for the same reasons given earlier. The DCPP tool enables the user to perform sensitivity analysis with respect to how they structure their preference between the economic loss and inoperability objectives. The vertical region in Figure 11 corresponds to a preference strategy that gives importance to economic loss only, while the quarter-circle region corresponds to assigning equal weights to inoperability and economic loss objectives. For a purely economic loss minimizing strategy, there is a risk to exclude sectors that have critical ranking with respect to inoperability (e.g., Utilities, Pipeline Transportation). Nevertheless, there is also a risk of excluding sectors with critical economic loss rankings (e.g., Computer Design, Banking), when equal weights are allocated between economic loss and inoperability. Hence, prioritizing sectors for recovery need careful consideration of the balance between economic loss and inoperability.

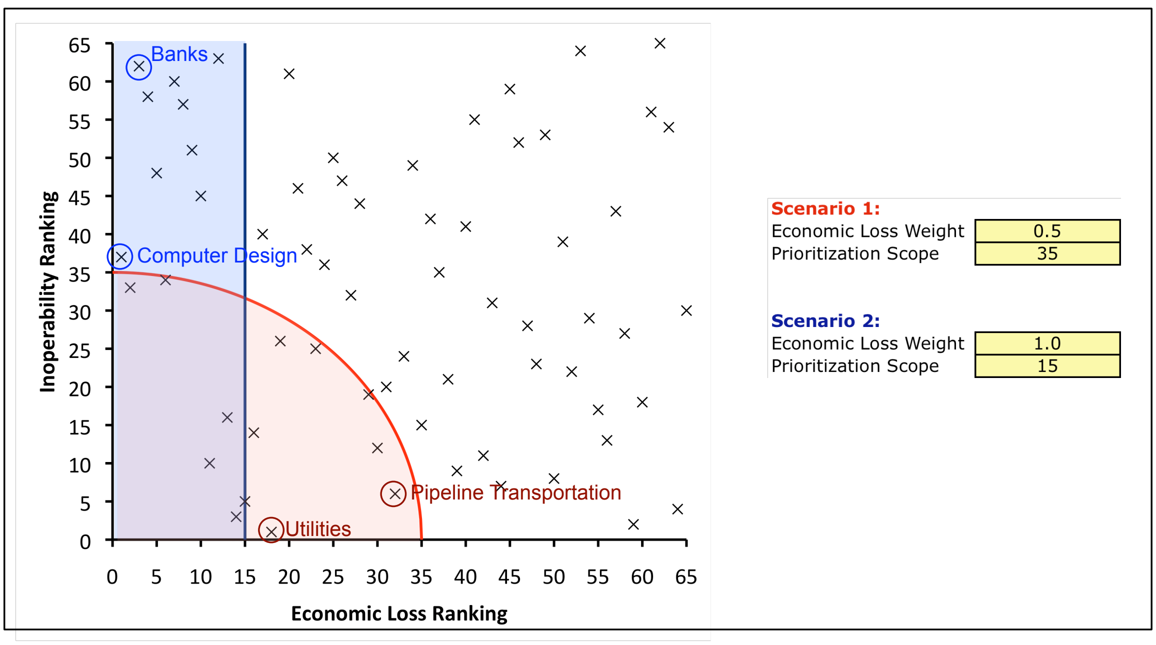

Figure 12. DCPP for Case 2

4.3 Case 3: Infrastructure Disruption with a "Step Function" Recovery

Suppose that Case 1 is expanded such that in addition to the 50% initial workforce inoperability, the electric power recovery is modeled as a step function with the following specifications[7]:

- 80% utility infrastructure disruption for Day 0 to Day 2
- 50% utility infrastructure disruption from Day 3 to Day 5
- 25% utility infrastructure disruption from Day 6 to Day 10

These combined disruption scenarios comprise Case 3, which is explored in this section. The scenario parameters that describe Case 3 are entered into the dynamic IIM and generated the economic loss and inoperability charts in Figure 13. The total economic loss for the simulated scenario is $809 million. From this economic loss, the following losses can be estimated based on the approaches discussed in Section 3.5. Note that the following values encompass the losses incurred within the assumed recovery period of 30 days (or approximately 1 month):

- Tax loss: $7,286,167
- Income loss: $108,475,569
- Equivalent number of jobs lost: 2,475

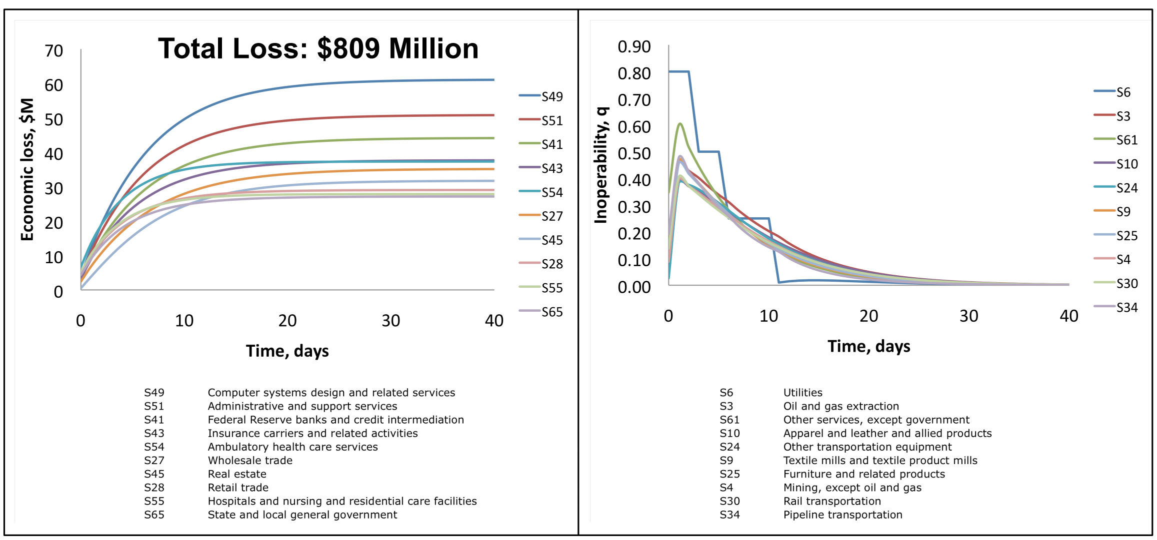

Figure 13. Top-10 critical sectors for Case 3 ranked according to: Economic loss (left) and Inoperability right

For Case 3, the top 10 sectors that suffer the highest economic losses (Figure 13, left panel) are: Computer systems design and related services (S49), Administrative and support services (S51), Federal Reserve banks and credit intermediation (S41), Insurance carriers and related activities (S43), Ambulatory health care services (S54), Wholesale

---

[7] See explanatory notes in footnote #6.

trade (S27), Real estate (S45), Retail trade (S28), Hospitals and nursing and residential care facilities (S55), and State and local general government (S65). The total economic loss for the simulated scenario is $809 million. The top-10 sectors account for 47% of this total economic loss, which is the same as Case 2.

In contrast, the top 10 sectors with highest inoperability values (Figure 13, right panel) are: Utilities (S6), Oil and gas extraction (S3), Other services, except government (S61), Apparel and leather and allied products (S10), Other transportation equipment (S24), Textile mills and textile product mills (S9), Furniture and related products (S25), Mining, except oil and gas (S4), Rail transportation (S30), and Pipeline transportation (S34). In the inoperability charts for Case 3, we can directly observe that the electric power disruption is modeled as a "Utilities" sector disruption, whose recovery is modeled similar to a step function. This type of flexible recovery adjustment is particularly useful for modeling risk management interventions to expedite recovery.

Just like in previous cases, the DCPP tool enables the user to perform sensitivity analysis with respect to how users or decision makers would structure their preference between the economic loss and inoperability objectives. It should be noted that Case 3 is a slight variant of Case 2 (i.e., they only differ with respect to the shape of the recovery function for the "Utilities" sector). Hence the DCPP chart is omitted for this case since the sector priorities are the same as the economic loss and inoperability rankings found in Figure 13.

5. Conclusions and areas for future model improvements

Economic disruptions in the aftermath of a disasters can cascade across interdependent economic sectors, further delaying recovery. This paper develops a recovery model to estimate sector inoperability and economic losses for a disaster scenario in the example region. Two primary IIM metrics for determining critical sectors are presented in this chapter—namely inoperability and economic loss. Inoperability measures the percentage reduction relative to the total output of the sector. Economic loss, on the other hand, corresponds to the decrease in the value of economic output due to the productivity disruptions. From the economic loss values computed by the IIM, other loss categories could be derived such as tax loss, income loss, and equivalent number of jobs lost. Sensitivity analysis of inoperability and loss reduction objectives can provide insights on identification and prioritization of critical sectors. Based on the simulated scenarios, the 10 most critically affected sectors (out of 65) suffer about half of the projected losses. This observation will be particularly useful in informing the regional decision-makers just who will bear the greatest losses.

To show the key features of the IIM tool, three cases are explored. These scenarios involve combinations of disruptions to workforce sectors and to the utility infrastructure sector. Since regional I-O data typically bundle electric power within the general utility sector, further analysis is needed to perform sector disaggregation to analyze direct impacts on the electric power sector. For example, it is possible to take the ratio of electric power output with respect to the total utility sector output. At the national level, utility sector is comprised of three subsectors, namely (i) electric power, (ii) natural gas, and (iii) water and sewerage systems. Such ratio can range from 60-70% based on national data archived by the BEA[8]. Hence, electric power is a significant component of the utility sector. A given value of electric power % outage can be entered to the IIM as a utility sector disruption by applying such ratios.

Finally, the simulated scenarios for the example region showed that the majority of the top-10 sectors based on the economic loss metric are service-oriented. In contrast, the majority of the top-10 sectors based on the inoperability metric are manufacturing-related. Hence, a careful balance must be sought in prioritizing key sectors as different performance measures may indicate a different set of rankings. Given decision-maker preferences, there exists an opportunity to use the Analytic Hierarchy Process (AHP) and other elicitation methods to guide in the prioritization of the key sectors. Although applied specifically to the example metropolitan area, the same methodology can be implemented in other regions. The methodology and decision analysis tool developed in this chapter can also be integrated with other critical infrastructure models.

Acknowledgements:

This work was supported in part by the National Science Foundation (Award #0963718) and U.S. Department of Homeland Security (under U.S. Department of Energy Interagency Agreement 43WT10301). The Department of Management Engineering and Systems Engineering Systems, GWU also provided additional financial support leading to the completion of this paper. The author would like to acknowledge the valuable suggestions offered by Adam Rose and Jerry Brashear. Points of view expressed in this manuscript belong to the authors and do not represent the official positions of NSF, DHS, and GWU.

[8] For examples, GDP and production output data that provide breakdowns of utility sector components are found in http://www.bea.gov/industry/gdpbyind_data.htm.

6 References

Abraham, J.E. and J.D. Hunt, 1999. Policy analysis using the Sacramento MEPLAN land use-transportation interaction model, *Transportation Research Record*, **1685**: 199–208.

Anderson, C.W., J.R. Santos, and Y.Y. Haimes, 2007. A risk-based input-output methodology for measuring the effects of the August 2003 Northeast Blackout. *Economic Systems Research*, **19**(2): 183-204.

Arnold, R., De Sa, J., Gronniger, T., Percy, A., Somers, J., July 2006. A Potential Influenza Pandemic: Possible Macroeconomic Effects and Policy Issues (Washington, DC: Congressional Budget Office).

Barker, K.A., Santos, J.R., July 2010. Measuring the efficacy of inventory with a dynamic input–output model. *International Journal of Production Economics*, **126**(1): 130-143

Bureau of Economic Analysis, 2008, Local Area Personal Income, Available online: <http://www.bea.gov/bea/regional/reis/>

Bureau of Transportation Statistics, 2008. Commodity Flow Survey. Available online: <http://www.bts.gov/programs/commodity_flow_survey/>

Burrus, R.T., C.F. Dumas, C.H. Farrell and W.W. Hall. (2002). The Impacts of Low-Intensity Hurricanes on Regional Economic Activity. Natural Hazards Review, **3**(3):118-125.

Crowther, K.G., Y.Y. Haimes, G. Taub. 2007. Systemic Valuation of Strategic Preparedness with Illustrations from Hurricane Katrina. *Risk Analysis*, **27**(5): 1345–1364.

de la Barra T., 1995. *Integrated Land Use and Transport Modeling: Decision Chains and Hierarchies*. Cambridge University Press, New York, NY.

Department of Homeland Security, 2003a. Homeland Security Presidential Directive-5: Management of Domestic Incidents. Available online: <http://www.fas.org/irp/offdocs/nspd/hspd-5.html>

Department of Homeland Security, 2003b. Presidential Directive-7: Critical Infrastructure Identification, Prioritization, and Protection. Available online: <http://www.fas.org/irp/offdocs/nspd/hspd-7.html>

Department of Homeland Security, January 2008. National Response Framework (NRF). Available online: <http://www.fema.gov/NRF>

Department of Homeland Security, January 2009. National Infrastructure Protection Plan (NIPP). Available online: <http://www.dhs.gov/files/programs/editorial_0827.shtm>

Dietzenbacher E. and M.L. Lahr *Wassily Leontief and Input-Output Economics*, Cambridge University Press, Cambridge, UK, 2004.

Echenique, M.H., 1985. The use of integrated land use transportation planning models: The cases of Sao Paolo, Brazil and Bilbao, Spain. In: M. Florian, Editor, *The Practice of Transportation Planning*, The Elsevier, Hague.

Haggerty, M., J.R. Santos, and Y.Y. Haimes, 2008. A Transportation-Based Framework for Deriving Perturbations to the Inoperability Input-Output Model, *Journal of Infrastructure Systems*, **14**(4): 293-304.

Haimes, Y.Y. and P. Jiang, 2001. Leontief-Based Model of Risk in Complex Interconnected Infrastructures. *Journal of Infrastructure Systems*, **7**(1): 1-12.

Haimes, Y.Y., B.M. Horowitz, J.H. Lambert, J.R. Santos, K. Crowther, and C. Lian, 2005. Inoperability Input-Output Model for Interdependent Infrastructure Sectors. I: Theory and Methodology. *Journal of Infrastructure Systems*, **11**(2): 67-79.

Holling, C. 1973. Resilience and Stability of Ecological Systems. *Annual Review of Ecology and Systematics*, 4: 1–23.

Howe, D., April 2005. "National Planning Scenarios." Available online: <http://media.washingtonpost.com/wp-srv/nation/nationalsecurity/earlywarning/NationalPlanningScenariosApril2005.pdf>

Hunt, J.D. and D.C. Simmonds, 1993. Theory and application of an integrated land-use and transport modeling framework, *Environment and Planning B*, **20**: 221–244.

Isard, W., 1960. Methods of Regional Analysis: An Introduction to Regional Science. MIT Press, Cambridge, MA.

Leontief, W., 1936. Quantitative input and output relations in the economic system of the United States, *Review of Economics and Statistics*, **18**(3): 105-125.

Leontief, W.W. Input-Output Economics, *Scientific American*, pp. 15-21, October 1951a.

Leontief, W.W., *The Structure of the American Economy, 1919-1939, Second Edition.* Oxford University Press, New York, 1951b.

Lian, C. and Y.Y. Haimes, 2006. Managing the Risk of Terrorism to Interdependent Infrastructure Systems Through the Dynamic Inoperability Input-Output Model. *Systems Engineering*, **9**(3): 241-258.

Lian C., Santos, J.R., Y. Y. Haimes, 2007. Extreme Risk Analysis of Interdependent Economic and Infrastructure Sectors, *Risk Analysis, an International Journal*, **27**(4): 1053-1064.

Lowry, I.S., 1964. *Model of Metropolis* (RM-4035-RC), RAND Corporation, Santa Monica, CA.

Miller R.E. and P.D. Blair, 2009. *Input-output Analysis: Foundations and Extensions, 2nd ed*. University Press, Cambridge, UK.

Minnesota IMPLAN Group. 2008. Impact Analysis for Planning (IMPLAN). Available Online: <http://www.implan.com/>

National Cooperative Highway Research Program (NCHRP), 2001. *Report 456: Guidebook for Assessing the Social and Economic Effects of Transportation Projects*. National Academies Press, Washington, DC.

Organisation for Economic Co-operation and Development (OECD). 2001. *OECD Manual: Measuring Productivity; Measurement of Aggregate and Industry-Level Productivity Growth*.

Perrings, C. 2001. Resilience and Sustainability. In H. Folmer, H. L. Gabel, S. Gerking, A. Rose (Eds.), *Frontiers of Environmental Economics*. Cheltenham, pp. 319–41. U.K.: Edward Elgar.

Resurreccion JZ, Santos JR, 2011. Developing an Inventory-Based Prioritization Methodology for Assessing Inoperability and Economic Loss in Interdependent Sectors, *IEEE Proceedings of Systems and Information Engineering Design Symposium*, pp. 176-181.

Rose, A., 2009. Economic Resilience to Disasters: Community and Regional Resilience Institute (CARRI) Research Report 8. CARRI Institute, Oakridge, TN.

Rose, A. and S. Liao, 2005. Modeling Regional Economic Resilience to Disasters: A Computable General Equilibrium Analysis of Water Service Disruptions. *Journal of Regional Science* **45**: 75-112.

Ruiz-Juri, N. and Kockelman, K.M., 2006. Evaluation of the Trans-Texas Corridor Proposal: Application and Enhancements of the Random-Utility-Based Multiregional Input-Output Model, *Journal of Transportation Engineering*, **132** (7): 531-539.

Santos, J.R., 2006. Inoperability Input-Output Modeling of Disruptions to Interdependent Economic Systems. *Systems Engineering*, **9**(1): 20-34.

Santos, J. R., 2008. Inoperability Input-Output Model (IIM) with Multiple Probabilistic Sector Inputs, *Journal of Industrial Management and Optimization*, **4**(3): 489-510.

Santos, J.R. and Haimes, Y.Y., 2004. Modeling the demand reduction input-output (I-O) inoperability due to terrorism of interconnected infrastructures, *Risk Analysis* **24**(6):1437-1451.

Santos, J.R., Y. Y. Haimes, and C. Lian, 2007. A Framework for Linking Cyber Security Metrics to the Modeling of Macroeconomic Interdependencies, *Risk Analysis: An International Journal*, **27**(4): 1283-1297.

Santos, J.R., K. Barker, and P. Zelinke, 2008. Sequential Decision-making in Interdependent Sectors with Multiobjective Inoperability Decision Trees, *Economic Systems Research*, **20**(1): 29-56.

The Infrastructure Security Partnership (TISP), 2006. Regional Disaster Resilience: A guide for developing an action plan. American Society of Civil Engineers, Reston, VA. Available online: <www.llis.gov>, document #19458.

The White House, July 15, 1996. Executive Order 13010: *Establishing the President's Commission on Critical Infrastructure Protection (PCCIP)*. Available online: <http://www.fas.org/irp/offdocs/eo13010.htm>

US Census Bureau, 2007. *Journey to Work and Place of Work*. Available Online: <http://www.census.gov/population/www/socdemo/journey.html>

US Department of Commerce, March 1997. Regional Multipliers: A User Handbook for the Regional Input-Output Modeling System, Washington, DC: U.S. Government Printing Office.

US Department of Transportation (USDOT), 2009. Land Use Compendium, DOT-T-99-03: Enhancement of DVRPC's Travel Simulation Models Task 12: Review of Land Use Models and Recommended Model for DVRPC. Available online: <http://tmip.fhwa.dot.gov/clearinghouse/docs/landuse/compendium/intro.stm>

Zhao, Y. and K.M. Kockelman, 2004. The Random-Utility-Based Multiregional Input-Output Model: Solution Existence and Uniqueness, *Transportation Research B,* **38**(9): 789-807.