DEVELOPMENT OF AN ANALYTIC BASIS FOR PERFORMING ALL-HAZARDS RISK MANAGEMENT

By

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Dissertation

Submitted to the Faculty of the
Graduate School of Vanderbilt University
in partial fulfillment of the requirements
for the degree of
DOCTOR OF PHILOSOPHY
in
Civil Engineering
May, 2010
Nashville, Tennessee

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CIVIL ENGINEERING

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SAMRAT CHATTERJEE

Dissertation under the direction of Professor Mark D. Abkowitz

Over the past decade, catastrophic events such as the World Trade Center attacks, Hurricane Katrina, and the Minneapolis bridge collapse have affected societal perception of the risks affecting our lives. It has also led to the realization that a more systematic and holistic approach to risk management is needed, one that takes into consideration the risks and potential mitigation strategies associated with natural hazards, man-made accidents, and intentional acts in an integrated all-hazards risk management (AHRM) framework. This would enable the risk manager to prioritize among risks and to make more effective resource allocation and policy decisions. This dissertation includes the development of an AHRM methodology, quantification of risks posed by various hazards, development of a functional relationship between risk mitigation investment and risk reduction, defining and solving an all-hazards risk mitigation resource allocation optimization problem, and application of the methodology to a case study region. Directions for further research are also provided.

To my amazing parents and sister, Chandrika, Bibhav, and Mishtee, always inspiring

and

To my dear wife, Romila, infinitely supportive

ACKNOWLEDGEMENTS

I am grateful to my advisor, Dr. Mark D. Abkowitz, for his guidance, advice, encouragement, understanding, and support throughout this research. My sincere thanks go to Dr. Abkowitz for helping me never lose sight of the big picture. His passion for his work is a source of inspiration for me. I would like to thank my committee members, Dr. James P. Dobbins, Dr. Sankaran Mahadevan, and Dr. Kenneth R. Pence for their advice and help.

I acknowledge the support of Southeastern Transportation Center for funding my project and would like to thank the project monitoring committee. The cooperation of FEMA, FHWA, and USGS staff in providing software, data, and technical information used in this dissertation is also appreciated. Part of this research was conducted during the Young Scientists Summer Program at the International Institute for Applied Systems Analysis, made possible by a grant from the National Academy of Sciences funded by the National Science Foundation. I would like to thank the Risk and Vulnerability group there, especially Dr. Stefan Hochrainer. I appreciate Dr. P.K. Basu's interest in my success as a graduate student.

My heartfelt gratitude goes to my parents, Chandrika and Bibhav Chattopadhyay, for their love, encouragement, guidance, and support at every stage of my life. Special thanks to my sister, Mishtee, for always being caring and loving. Thanks go to my cousins, Auroop R. Ganguly and Swaroop Ganguly, for their guidance and support. I am most grateful to my wife, Romila, for being infinitely supportive, patient, and loving throughout this journey. Thanks go to my parents-in-law, Jayati and Surajit Dasgupta, for welcoming me into their family and hearts. I would like to thank all my family members for their affection and moral support. Thanks go to all my friends for making my Vanderbilt experience a memorable one.

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LIST OF ABBREVIATIONS

AADT	Average Annual Daily Traffic
AHRM	All-Hazards Risk Management
BTS	Bureau of Transportation Statistics
CFS	Commodity Flow Survey
CPI	Consumer Price Index
DHS	Department of Homeland Security
EADL	Expected Annual Direct Loss
EPA	Environmental Protection Agency
FAF	Freight Analysis Framework
FEMA	Federal Emergency Management Agency
FHWA	Federal Highway Administration
GIS	Geographic Information Systems
HAZMAT	Hazardous Materials
HAZUS-MH	Hazards U.S. MultiHazard
HPMS	Highway Performance Monitoring System
MAIS	Maximum Abbreviated Injury Scale
NTAD	National Transportation Atlas Database
RMS	Risk Management Solutions
UASI	Urban Areas Security Initiative
USGS	U.S. Geological Survey
VMT	Vehicle Miles Traveled

CHAPTER I

INTRODUCTION

Problem Statement

Catastrophic events in the past decade have impacted the societal view of risks that affect our lives. The attacks on the World Trade Center led to increased focus on managing security risk. Later, Hurricane Katrina struck and exposed our vulnerability to natural hazards. Three years ago, the Minneapolis Bridge collapsed, reminding us of the perils of man-made accidents. These and other global disasters caused by natural hazards, man-made accidents, and intentional acts along with increase in global interactions of people, goods, and services (Cova and Conger 2004) and climate change, have emphasized the need for an organized study of these events. To be successful, this will require breaking down the “stovepipe” mentality of managing various safety and security risks, to be replaced by adopting an all-hazards approach.

The guiding principle for an all-hazards risk management (AHRM) approach is that all safety and security concerns share a common objective, which is to reduce the likelihood and consequences of undesirable events so as to protect human health, quality of life and the environment. A holistic view of the problem of risk management argues that in order to develop an efficient risk management strategy, the risks posed by natural hazards, man-made accidents, and intentional acts need to be evaluated in a single, integrated framework. This enables the risk manager to make more informed and intelligent decisions about the most important risks to address and what mitigation strategies offer the greatest overall benefit-cost, while feeling confident that the decision-making process is being driven by a complete and systematic approach.

Research Objectives

The overarching objective of this research is to develop a more comprehensive and systematic approach to analyzing operational risks due to multiple hazards. The ultimate goal is to achieve an AHRM approach that can lead to successful investment in risk mitigation, by focusing attention on the most important risks threatening a region of interest and the risk reduction potential of various mitigation strategies, whether applied by a government or industry entity.

The challenges in formulating an AHRM approach lie in establishing a common performance metric to quantify risks posed by various hazards and evaluating risk-based mitigation resource allocation strategies. Utilizing established assessment methods and data sources, an approach is developed wherein relevant risks are expressed in expected annual economic terms (i.e., risk-cost), creating a consistent basis from which one can identify those risks that warrant priority attention. A relationship between mitigation investment and risk-cost reduction is defined leading to the development of an all-hazards risk mitigation resource allocation optimization problem. These techniques are then demonstrated in a case study application.

In order to achieve these research objectives, the following tasks are performed:

1. State-of-the-art literature review of all-hazards risk management methods and practices.
2. Development of methodological design and case study scenario, in terms of geographic

jurisdiction and hazard types of interest, for assessing operational risks on a holistic and systematic basis.

3. Appropriate data and software collection followed by application of methodology to the case study scenario for generating expected annual disaster losses expressed in economic terms (risk-cost).
4. Definition of a functional relationship between risk mitigation investment and reduction in risk-cost.
5. Formulation of an optimization problem for risk mitigation resource allocation, where the objective is to maximize the overall reduction in risk, subject to mitigation budget constraint and risk mitigation return on investment bounds.
6. Development of optimal risk mitigation resource allocation strategies for varying budget levels in the context of a case study application.

Literature Review

"There is a fear that distribution of risk management funds without regard to risks faced by different regions can adversely affect the mitigation strategies of those with greater needs" (Masse et al. 2007; Moteff 2008; Chatterjee and Abkowitz 2010). As a result, the past decade has seen several initiatives aimed at formalizing the concept of an all-hazards risk management approach (Chatterjee and Abkowitz 2009). Following the Indian Ocean catastrophe in 2004, Ambassador Howard Baker, leading the United States delegation to the United Nations World Conference on Disaster Reduction in Kobe, Japan, stated that an all-hazards approach in disaster management is the best way to save lives and money (Baker 2005). Recently, the U.S. President's budget put more than $20 billion annually (based on the statistical probability of emergency related costs) in its budget projections to deal with future emergencies and the costs of natural and man-made disasters (Office of Management and Budget 2009).

All-hazard environmental health risk assessment plans have also been developed, often targeted towards a specific sector, such as the mining industry. The Environmental Protection Agency (EPA) guide to health risk assessment helps government agencies, regulators, and members of the public determine which potential chemical exposures pose the most significant health risks to a broad population, such as city or a community (Davis et al. 2001). In the mining industry, "adequate mine safety and emergency preparedness requires considering all of the possible hazards that could be encountered" (Brnich, Jr. and Mallett 2003). A hazard risk matrix is used to record a risk rating for each potential hazard, in terms of severity levels for likelihood and consequences.

The Federal Emergency Management Agency (FEMA) state and local guide provides emergency planners and personnel with information on FEMA's concept for developing risk-based, all-hazard emergency operations plans (Goss 1996, 2002). Maintaining an all-hazards capability is considered important because there is always a potential for new and unexpected hazards (Goss 1996). The guide provides hazard-specific planning considerations and acknowledges that comparison and prioritization of risks requires the development of a common risk indicator across different hazards. Based on FEMA's guide and with support from federal, state, and local emergency management offices, all-hazard emergency management plans have been developed at the city, county, and state levels.

The City of Livermore's (California) all-hazard vulnerability analysis describes natural and technological (human-made) hazards and serves as a basis for city-level emergency management programs (City of Livermore 2005). Risk prioritization for assets and facilities was established based on numerical scores assigned to categories such as terrorist target, damage, and casualty potential.

The Genesee County (New York) comprehensive emergency management plan outlines the actions to be taken to establish an emergency management capability (Genesee County 2004). The development of this plan includes an investigation and analysis of potential hazards affecting the county that are natural, technological, or human-caused. Each hazard was rated based on a focus group assessment and assignment of a corresponding numerical value.

Alaska's all-hazard risk mitigation plan addresses the risks associated with hazards in the state, discusses hazard mitigation implementation, and identifies and prioritizes mitigation activities (State of Alaska 2007). A multi-hazard risk assessment approach, with risks from natural, technological, human-caused and terrorism hazards is in the process of being implemented and the State is in the early stages of collecting spatial data for statewide risk identification. A hazard and vulnerability matrix has been developed where the hazards affecting different regions have been assigned severity ratings based on their likelihood of occurrence.

Outside the U.S., studies have focused on developing multi-hazard risk assessments at the local and national levels. The multi-hazard risk assessment of the Mackay urban area in Queensland, Australia, focused on risks due to natural hazards (Middelmann and Granger 2000). A range of event scenarios were synthesized and vulnerability and exposure rankings of hazards were determined. These rankings helped evaluate and prioritize the risks posed by natural hazards. Attempts at quantifying the evaluation of risk included building damage comparisons under different hazard scenarios. A recent World Bank study assessed global risks by combining hazard exposure with historical vulnerability for several natural hazards (Dilley et al. 2005). Multi-hazard indices of disaster risks related to mortality (assessed on the gridded population of the world) and economic losses (assessed on a gridded surface of Gross Domestic Product per unit area) were developed. Drought, flood and volcano hazards are characterized in terms of event frequency and severity. Mortality and economic loss related vulnerability coefficients helped develop weights for each hazard for each region. The data were used to identify areas at relatively high risk from a particular natural hazard.

In the post-9/11 era, there have been several research studies that have included terrorism risk within the all-hazards framework (Waugh 2005; Phelps 2005; Propst 2006; Bilal et al. 2007). While terrorism may be considered a "hazard of uncertain probability for most communities and organizations" (Waugh 2005), nonetheless a complete risk analysis should include such intentional acts.

In summary, while substantial progress has been made to formalize the concept of an AHRM approach, its application within an all-hazards context at a regional level has been mostly qualitative in nature. Although efforts have been made to quantify risks from specific hazards within a particular hazard type, doing so effectively in an all-hazards context by using a common risk metric is lacking. Nevertheless, this prior research has provided important insights for developing a more quantitative AHRM protocol. This dissertation research attempts to advance the AHRM concept by developing a common performance metric and corresponding risk assessment techniques to quantify risks posed by various hazards, followed by the development of mitigation resource allocation strategies, thereby enabling decision makers to make more effective policy and risk management resource allocation decisions.

Dissertation Organization

This dissertation is composed of six chapters including this introduction. Chapters II, III, IV, and V are based on manuscripts published, in review or being finalized for submission to refereed journals. Efforts have been taken to keep overlaps in the material that appears in different chapters to a minimum. Chapter II discusses the AHRM methodology and describes a case study region and hazards chosen to implement an AHRM approach. Chapter III discusses the assessment of regional disaster risks posed by truck transportation of hazardous materials, earthquakes, and terrorism in an all-hazards context. Terrorism risk is modeled as a function of attributes of population concentration and critical infrastructure. The terrorism risk assessment methodology incorporates elements of two terrorism risk modeling approaches (event-based models and risk indicators), producing results that can be utilized at various jurisdictional levels. Chapter IV presents the overall AHRM methodological development and presents its application in a case study region. This chapter also discusses how a manager can use risk assessment results to establish risk priorities, but recognizes that to do so, requires a method for identifying mitigation strategies that offer the greatest return on investment. Chapter V focuses on the development of an all-hazards mitigation resource allocation problem. The adopted approach includes defining a functional relationship between risk mitigation investment and reduction in risk-cost, followed by the formulation of a deterministic, nonlinear optimization problem for risk mitigation resource allocation. Using this approach, optimal resource allocation strategies for varying budget levels are discussed in the context of a case study application. Chapter VI provides a summary of the dissertation research with suggestions for future efforts.

CHAPTER II

ALL-HAZARDS RISK MANAGEMENT (AHRM) METHODOLOGY

Conceptual Development

The immediate challenge in formulating an AHRM approach lies in establishing a common performance metric to quantify risks posed by various hazards. The implementation of an AHRM approach as described herein involves the evaluation of each relevant risk in expected annual economic (monetary) terms for the area of concern, hereafter referred to as the *risk-cost*. Risk-cost as expressed in this dissertation includes both event likelihood and consequences associated with a particular hazard. The region of interest could be a political jurisdiction, such as a city, county or state. It could also represent a specific facility or a collection of facilities, possibly situated in diverse locations. Because the likelihood and consequence of each hazard is taken into consideration prior to aggregating to an all-hazard risk cost, there is already an implicit probability weighting. An all hazards risk-cost can be computed by aggregating the risk-costs due to different hazard types that threaten the region of interest:

$$Risk_{ah}^{c} = Risk_{n}^{c} + Risk_{m}^{c} + Risk_{i}^{c} \tag{2.1}$$

where:

$Risk_{ah}^{c}$ = all-hazards risk-cost

$Risk_{n}^{c}$ = natural hazards risk-cost

$Risk_{m}^{c}$ = man-made accidents risk-cost

$Risk_{i}^{c}$ = intentional acts risk-cost

For example, a hypothetical all hazard risk-cost for the region of interest, expressed in terms of the percentage attributed to natural hazard, man-made accident, and intentional act hazard types, could have natural hazard not only as the largest contributor to the all hazard risk-cost but also present the majority of the risk-cost. It would therefore be reasonable for these concerns to dominate the risk manager's attention and resources.

Each of these sub-categories includes more specific hazards, whose risk-costs would be aggregated to reach the category amounts. The risk-cost of each specific hazard can be added to generate the risk-cost for a particular hazard type:

$$Risk_n^c = \sum_{k=1}^{N} Risk_{n_k}^c \tag{2.2}$$

where:

n_k = specific natural hazard k

$$Risk_m^c = \sum_{k=1}^{M} Risk_{m_k}^c \tag{2.3}$$

where:

m_k = specific man-made accident k

$$Risk_i^c = \sum_{k=1}^{I} Risk_{i_k}^c \tag{2.4}$$

where:

i_k = specific intentional act k

For example, a hypothetical natural hazard risk-cost for an area of concern, expressed in terms of the percentage attributed to volcanoes, hurricanes, floods and earthquakes, could have flood and volcano risk stand out as the major contributors to natural hazard risk-cost. These concerns should justifiably be the focal point of risk management attention.

Although relatively simple in concept, the implementation of an all-hazards risk assessment methodology is a formidable task. The number of specific hazards to be considered, the development of an accepted risk assessment technique for each specific hazard, and the availability of the necessary data to implement each technique all contribute to this challenge. Moreover, the necessary data required to implement an all hazards risk assessment methodology are collected by multiple agencies, leading to consistency issues and resulting in multi-step computations for extracting desired information.

Case Study

In bringing this conceptualization to light, this research focused on developing and applying an AHRM methodology to three major hazard categories (accident, natural disaster, and intentional act), and deriving its corresponding risk-cost for a geographical area of interest. The hazards chosen for AHRM methodological development were an accident involving truck transport of hazardous materials, earthquakes, and terrorist acts.

Many local governments in the United States suffer enormous disaster losses annually. Most local governments transfer the burden of losses to higher levels of government leading to funding delays (Burby et al. 1991). To overcome the inefficiencies and inequities in federal disaster relief and to get back on the road to recovery in a prompt manner, local governments need to develop and implement disaster risk management plans (Burby et al. 1991). To examine potential differences in risk-cost within and across regions of interest, the development process considered three counties located in the State of Tennessee: (1) Hamblen, (2) Shelby, and (3) Smith (see Figure 2.1). The basis for selecting these counties was their varying hazardous materials (hazmat) truck transportation patterns, seismicity, population characteristics, and number of critical infrastructure elements (see Table 2.1).

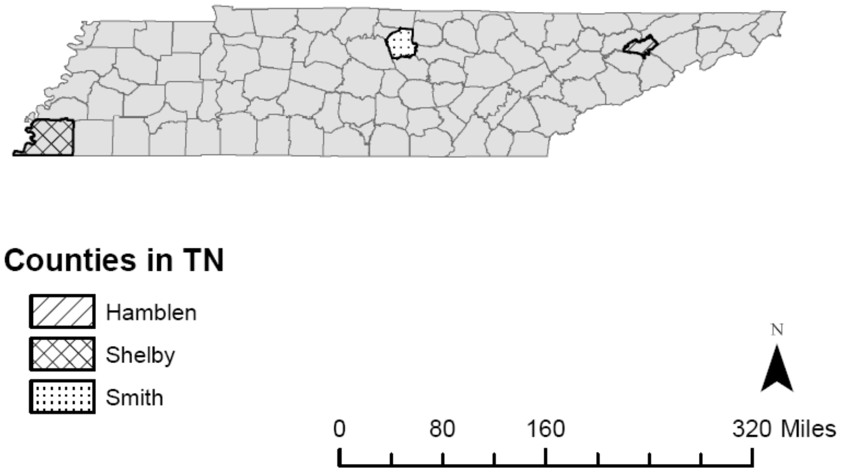


Figure 2.1: Counties in Tennessee selected for case study.

Table 2.1: Characteristics of the selected counties

Characteristic	Hamblen County	Shelby County	Smith County
Annual hazmat truck vehicle-miles traveled (VMT) (in millions)	3.96	41.30	7.17
Maximum peak ground acceleration with 10% probability of exceedance in 50 years (in %g)	8	25	4
Population, 2000 census	58,128	897,472	17,712
Population density (per square mile), 2000 census	361	1,189	57
Number of critical infrastructure elements (national historic landmarks, dams, nuclear reactors, bridges, and tunnels)	3	75	6

CHAPTER III

REGIONAL DISASTER RISK ASSESSMENTS

Truck Transportation of Hazardous Materials

Two major tasks were associated with performing the risk assessment for truck transportation of hazmat in the areas of concern: (1) estimating the percentage of trucks carrying hazmat from the total truck population at the state level, and (2) using this information to calculate hazmat truck transport risk-cost at the highway segment level. The data sources utilized in performing the hazmat truck transportation risk assessment were:

(1) Federal Highway Administration (FHWA), 2002 Highway Performance Monitoring System (HPMS) data (FHWA 2006)
(2) U.S. Census Bureau, 2002 Commodity Flow Survey (CFS) (U.S. Census Bureau 2007)
(3) FHWA, Freight Analysis Framework (FAF) for Tennessee (FHWA 2008)
(4) Bureau of Transportation Statistics (BTS)- National Transportation Atlas Database (NTAD) (BTS 2008).

Data compatibility is essential in performing this type of analysis, especially when it encompasses different agencies. Fortunately, linear referencing systems were available to integrate spatial data from these sources at the highway segment level.

Percentage of trucks carrying hazmat

The steps in this process involved estimating: (1) the average trip length and number of trucks carrying hazmat to derive annual hazmat truck vehicle-miles, and (2) estimating the annual truck vehicle-miles in Tennessee. By combining this information, the percentage of truck vehicle-miles carrying hazmat cargo could be determined.

Figure 3.1 shows a flowchart of the calculations performed to determine annual hazmat truck vehicle-miles. To derive the average hazmat truck vehicle-miles per shipment, the percentage of all freight shipments utilizing the truck mode and the average hazmat vehicle-miles per shipment to and from Tennessee were used (FHWA 2008). To derive the number of truck hazmat shipments, the percentage of all freight shipments utilizing the truck mode and the total hazmat weight (all modes) from and to Tennessee were used to calculate the weight of hazmat transported by trucks (FHWA 2008). To convert this to the number of hazmat truck shipments, based on data availability and for illustrative purposes, a "typical" shipment was defined as a loaded gasoline truck with a maximum weight of 40 tons (Tennessee Department of Safety 2008). Based on the assumptions of 9,000 gallon truck capacity and 87 percent maximum carrying capacity (taking into consideration the effect of sloshing), the maximum weight of a hazmat shipment was calculated to be 26.2 tons. This compares favorably with general practice, where it has been reported that a 40 ton truck can deliver 26 tons of gasoline to a conventional gasoline filling station (Bossel et al. 2005). The number of hazmat truck shipments (from and to TN) was then calculated by dividing the weight of hazmat transported by trucks by the maximum weight of a hazmat shipment. To determine the total hazmat vehicle-miles by truck (from and to TN), the hazmat truck vehicle-miles per shipment was multiplied by the number of hazmat truck shipments.

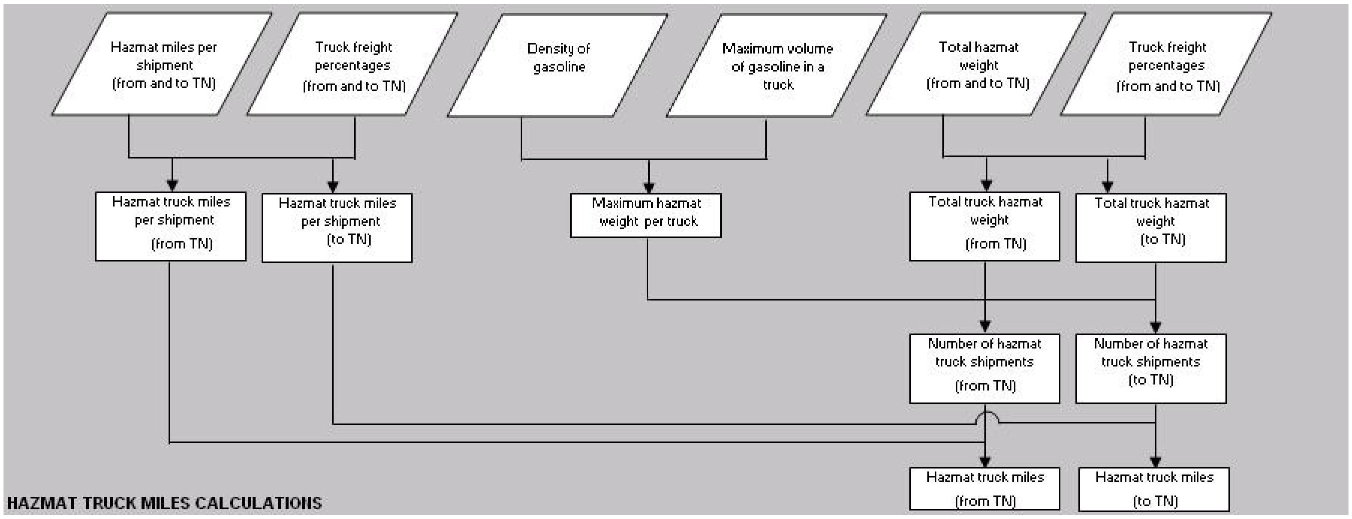


Figure 3.1: Flowchart for estimating hazmat truck vehicle-miles in Tennessee.

Figure 3.2 shows a flowchart of the calculations performed to determine the total truck vehicle-miles (from and to TN). The total truck shipment weight (all shipments) was divided by the maximum weight per truck (40 tons was used to generate a conservative estimate of the percentage of trucks carrying hazmat) to determine the total number of truck shipments (from and to TN). The truck vehicle-miles per shipment were then multiplied by the total number of truck shipments to compute a measure of total vehicle-miles by truck (from and to TN).

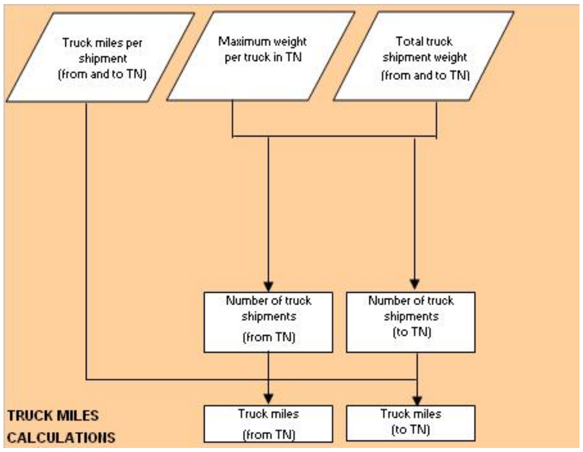


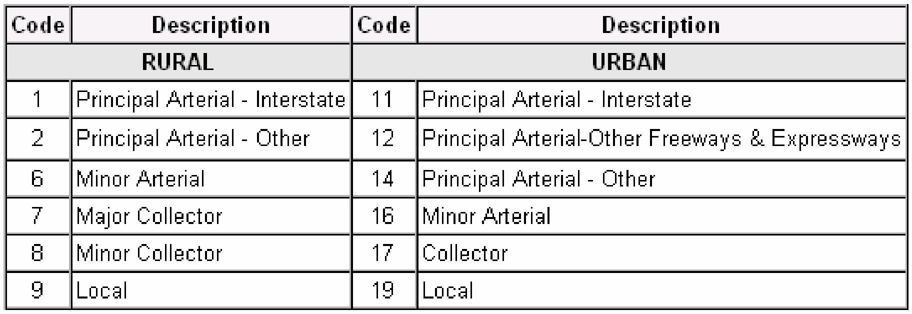
Figure 3.2: Flowchart for determining total truck vehicle miles in Tennessee.

To determine the percent of truck shipments in Tennessee carrying hazardous materials, the percentage of trucks carrying hazmat from and to Tennessee was determined by using the total hazmat vehicle-miles by truck and the total vehicle-miles by truck. The two cases where Tennessee is the state of origin and the state of destination were combined to generate a weighted average (by number of shipments). This resulted in a final estimate that 8.1 percent of truck shipments in Tennessee are carrying hazardous materials. This compares favorably with an estimated 8 percent of all large trucks carrying hazardous materials in Tennessee in the year 2002 (U.S. Census Bureau 2004). However, due to data unavailability, the estimation of percent trucks carrying hazmat does not include hazmat trucking movements where Tennessee was not the state of origin or destination.

Hazmat truck transport risk-cost

The risk-cost computation for hazmat truck transport in each of the selected counties was performed at the highway segment level. HPMS attributes include the segment length and the segment average annual daily traffic (AADT). This information led to the calculation of daily segment VMT and then annual segment VMT. For a sample of roughly 8 percent of the HPMS segments in Tennessee, additional information is collected from which one can derive the average percentage of AADT attributed to single unit and combination trucks by highway functional class (see Table 3.1). The average truck percentages in each functional class were subsequently assumed to apply to the remaining HPMS highway segments in the State of Tennessee belonging to the same functional class. This enabled computation of annual truck VMT for each highway segment in Tennessee (see Figure 3.3). The percent of trucks carrying hazmat in Tennessee (computed earlier as 8.1%) was then used to compute the annual hazmat truck VMT for each highway section in each of the case study counties.

Table 3.1: Highway Functional System Code (FHWA 2006)



Code	Description	Code	Description
RURAL		URBAN	
1	Principal Arterial - Interstate	11	Principal Arterial - Interstate
2	Principal Arterial - Other	12	Principal Arterial-Other Freeways & Expressways
6	Minor Arterial	14	Principal Arterial - Other
7	Major Collector	16	Minor Arterial
8	Minor Collector	17	Collector
9	Local	19	Local

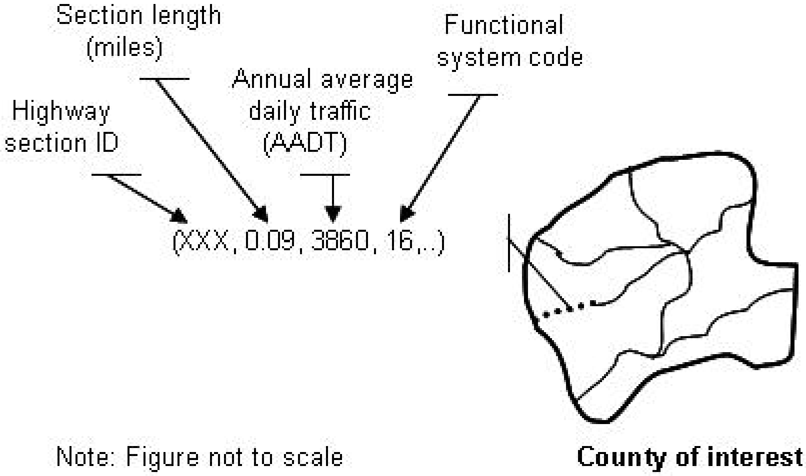


Figure 3.3: Information used to derive segment level annual truck VMT.

Transforming annual hazmat truck traffic to a risk-cost was accomplished by referring to a recent Federal Motor Carrier Safety Administration study (Battelle Memorial Institute 2001). In that project, the average hazmat truck accident/incident cost per mile was calculated to be $ 0.14 (across all hazmat categories). The data used in the aforementioned study corresponded to calendar year 1996. A recent U.S. Department of Transportation study (U.S. Department of Transportation 2008) estimated the economic value of preventing a human fatality as $5.8 million and also provided economic values of preventing varying degrees of injury severity. The updated economic values of a fatality/injury and the Consumer Price Index (CPI) calculator were used to revise the hazmat truck accident/incident cost per mile to $0.46 (across all hazmat categories) i.e. 2006 terms, the reference year for this study (Bureau of Labor Statistics 2008). The hazmat truck accident/incident cost per mile, when multiplied by the annual hazmat truck VMT, produced the annual hazmat truck transport risk-cost by highway segment. The annual hazmat truck transport risk-cost was calculated for the counties of Hamblen, Shelby, and Smith by aggregating the segment level data for highways located in each respective jurisdiction. Table 3.2 shows the results of this effort. As expected, Shelby County has the highest hazmat truck transport risk-cost, by virtue of having considerably more hazmat transport activity occurring within the region. Figure 3.4 presents the spatial distribution of county-level annual hazmat truck transport risk-cost in the State of Tennessee. The three case study counties are indicated and are placed in different annual hazmat truck transport risk-cost intervals.

Table 3.2: County-level annual hazmat truck transport risk-cost

County	Annual hazmat truck transport risk-cost ($)
Hamblen	1,820,000
Shelby	19,000,000
Smith	3,300,000

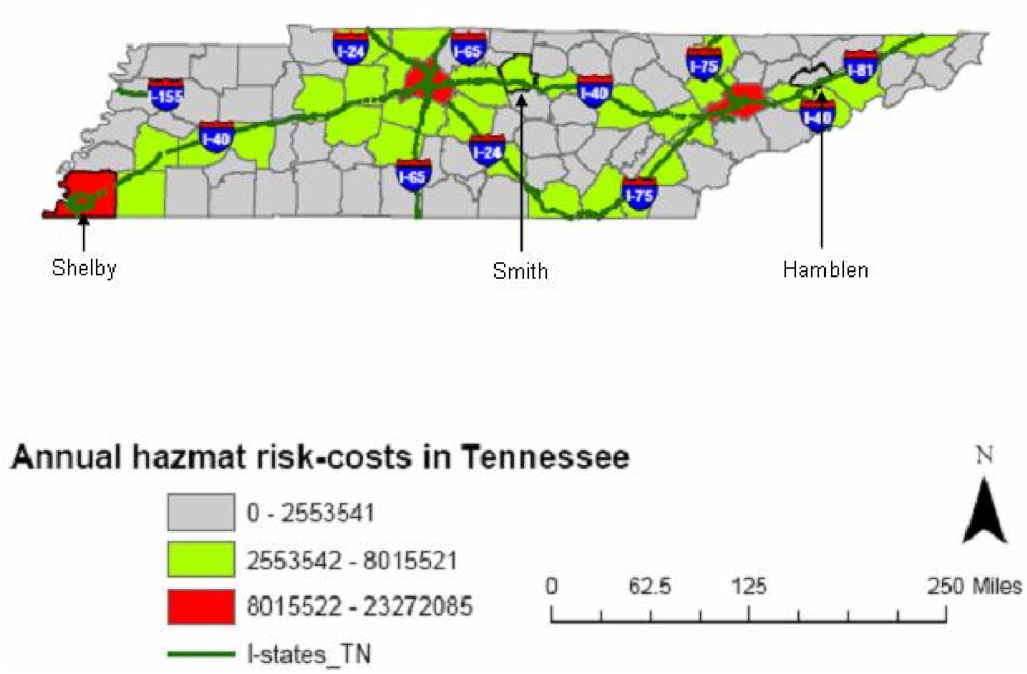


Figure 3.4: County-level annual hazmat truck transport risk-cost in Tennessee.

Earthquakes

Discussion of the earthquake consequence estimation procedure can be found in a recent publication (Chatterjee and Abkowitz 2009). Earthquake consequence estimation was derived using the HAZards U.S. MultiHazard (HAZUS-MH) software, a product developed by FEMA (HAZUS-MH MR3 Technical Manual 2003). HAZUS-MH uses geographic information systems (GIS) to model the built environment against the backdrop of possible natural hazards. The HAZUS-MH methodology involves three basic components: (1) classification of different systems for inventory, (2) methods for evaluating the damage and calculating losses, and (3) databases characterizing demographics, building inventory and the regional economy (Tantala et al. 2001; Kircher et al. 2006). The HAZUS-MH version used in this study (v.1.3) contained building valuations and commercial data corresponding to calendar year 2006. For earthquakes, based on a user-specified moment magnitude and earthquake return period, HAZUS-MH uses

U.S. Geological Survey (USGS) probabilistic ground motion maps, ground motion attenuation models, building capacity curves, and fragility curves to estimate damages and losses (USGS 2002). The HAZUS-MH methodology is outlined in Figure 3.5.

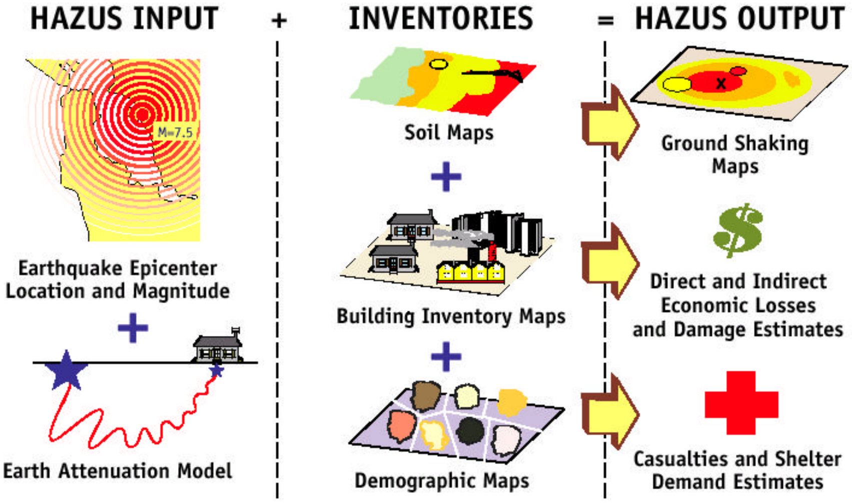


Figure 3.5: Earthquake loss estimation using HAZUS-MH (Tantala et al. 2001).

HAZUS-MH separates consequential impacts into economic losses and human casualties at three different times of the day. For worst-case scenario analysis or maximum consequential impact, human losses corresponding to the time of the day that yielded the maximum total human loss were chosen. There are other consequential impacts (acute and long-term) that are not accounted for in the methodology (e.g., business continuity; evacuations; traffic disruptions; investor, supplier and customer relations; increased cost of regulation; security hardening etc.). The lack of uncertainty quantification of consequences, absence of model calibration to specific economic situation of a region of interest, and the design of HAZUS-MH as a closed-source, stand-alone, single-user desktop system are some of the other limitations of using HAZUS-MH for consequence analysis (Scott 2006; Mofatt and Laefer 2010).

For the purposes of an AHRM approach, it is desirable to convert human casualties into monetary terms. In a recent study, the U.S. Department of Transportation estimated that a fatality was equivalent to a loss of $5.8 million (U.S. Department of Transportation 2008). To convert this estimate to 2006 terms, the CPI calculator was used by taking into consideration the impact of inflation (Bureau of Labor Statistics 2008). Fractions of the economic value of a statistical life, corresponding to Maximum Abbreviated Injury Scale (MAIS) levels, were used to calculate the economic values of HAZUS casualty levels 1 (MAIS level 1), 2 (average of MAIS levels 2 and 3) and 3 (average of MAIS levels 4 and 5) (U.S. Department of Transportation 2008).

In applying HAZUS-MH for earthquake loss estimation, a moment magnitude of 6.0 was used, which represented a point at which damages level off irrespective of whether the earthquake is of higher intensity. The justification for using a moment magnitude of 6.0 was based on a sensitivity analysis conducted for Shelby County (which has a relatively high seismic hazard), using varying moment magnitudes and return period levels. The sensitivity analysis results show that irrespective of earthquake return periods (100, 250, 500, 750, 1000, 1500, 2000, and 2500 years were used), moment magnitude variations above 6.0 do not have a significant effect on consequence. On the contrary, return period does have a positive impact on the losses due to scenario earthquakes. The positive relationship between return period and losses is intuitive, since the longer the period of time between occurrences, the more undamaged infrastructure and population that is exposed.

To generate earthquake risk-cost, probability distributions of earthquake losses in monetary terms were used. These functions are cumulative distributions where the horizontal axis represents the annual loss and the vertical axis represents the probability that losses do not exceed a certain level (Hochrainer 2006). The probability that losses do not exceed a certain level is calculated below:

$$F_X(x) = P(X \leq x) = 1 - \left(\frac{1}{r_e}\right) \tag{3.1}$$

where:

x = annualized earthquake loss level

r_e = earthquake return period

The earthquake loss distribution for a region of interest is displayed in Figure 3.6. In formulating this function, it was assumed that the losses corresponding to an earthquake event with a return period of 10 years are negligible. In the figure, the shaded area above the curve is defined as the expected annual direct loss (EADL) and is used as the estimate of earthquake risk-cost in the AHRM methodology.

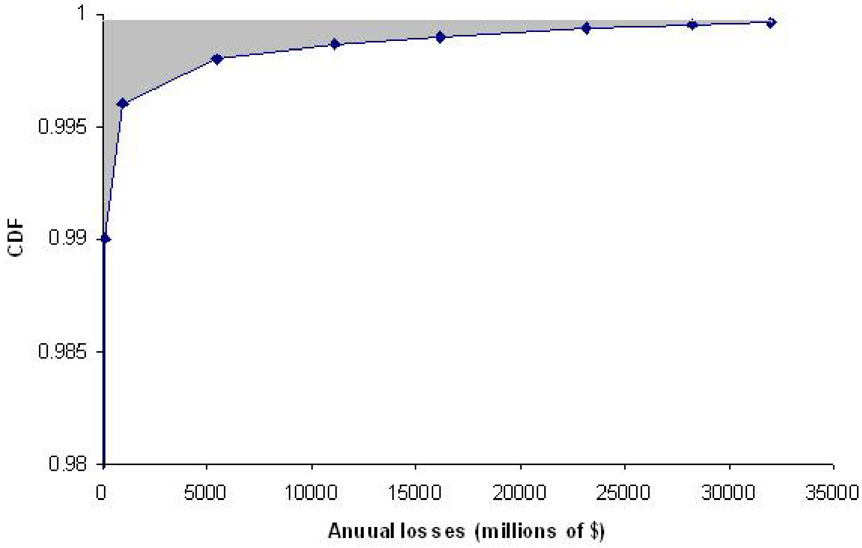


Figure 3.6: Earthquake loss distribution for a region of interest.

Table 3.3 shows the annual earthquake risk-cost for the selected counties in Tennessee. Note that the earthquake risk-cost for Shelby County dwarfs the other two counties. The reason for this disparity is the fact that the City of Memphis, a major population center located within Shelby Country, lies near a major geological fault.

Table 3.3: County-level annual earthquake risk-cost

County	Annual earthquake risk-cost ($)
Hamblen	790,000
Shelby	36,310,000
Smith	120,000

Terrorism

The approach taken to estimate terrorism risk-cost was to develop a regression model with terrorism risk-cost as the dependent variable, and the attributes of density-weighted population and critical infrastructure as the independent variables (Chatterjee and Abkowitz 2010). The model development is discussed below.

Introduction

The attacks on the World Trade Center demonstrated the dangers associated with terrorism risk and heightened interest in performing terrorism risk assessments. Modeling approaches for assessing terrorism risk have been an outgrowth of this interest. While an important development, there is also a concern that terrorism risk has occupied a disproportionate amount of attention with resources subsequently placed on mitigating terrorism risk having been done so at the expense of managing societal risks posed by accidents and natural hazards (Chatterjee and Abkowitz 2009). To address this consideration, the notion of an integrated, all-hazards approach has been introduced as a preferred risk management paradigm in order to save lives and money (Baker 2005; Phelps 2005; Propst 2006). The ability to quantify risk using a common performance metric across different hazards allows the risk manager to prioritize risks and to make informed and effective resource allocation and policy decisions.

Although generally accepted practices exist for estimating the likelihood and consequence of natural disasters and man-made accidents, security aspects are more complex to understand and measure. For example, a variety of attack scenarios exist where a transportation vehicle itself or the cargo contained therein could be used as a weapon, and the target could be an element of the infrastructure system (i.e., bridges, tunnels, etc.) or an area of heavily concentrated population.

This section discusses the development and application of a regional terrorism risk assessment model, with impacts expressed in monetary terms (i.e., risk-cost), that can be used as a basis for comparison of terrorism risks among different regions, as well as with man-made accident and natural hazard risks. The adopted methodology incorporates elements of two terrorism risk modeling approaches (event-based models and risk indicators), producing results that can be utilized at various jurisdictional levels.

Literature Review

The Department of Homeland Security (DHS) was created in November 2002 with the mission of "preventing terrorist attacks, reducing vulnerability to such attacks, and providing emergency response in the event of an attack" (Moteff 2008). In comparison to insurance and financial industries, terrorism risk analysis is considered less developed due to the dynamic nature of terrorism and the lack of a historical database of terrorist attacks (Masse et al. 2007).

Unlike other risk assessments that focus on event likelihood and consequence, components of terrorism risk are three-fold: (1) threat to a target, (2) target vulnerability, and (3) consequence of a successful attack. The first two components of terrorism risk are considered to be probabilistic in nature, while consequence, as for other risk assessments, is considered to be deterministic. The product of threat, vulnerability, and consequence is used by DHS for assessing risk and making funding allocation decisions. However, difficulties in differentiating vulnerability values across areas has resulted in the compression of vulnerability and consequence into a single variable, one that includes weighted effects of population, infrastructure and the economy (Masse et al. 2007).

One important component of terrorism risk assessment is the identification of critical assets, a list that contained 77,069 entries as of January 2006 (Moteff 2008). The existence of such a large database has drawn criticism that too much emphasis has been placed on assets of local rather than national importance, making resource allocation decisions difficult to determine. In response, DHS has established a list of about 600 high priority sites (Stephan 2006), and has classified urban areas in tiers, allocating risk management resources based "not only on risk, but also on need" (Moteff 2008). The absence of a systematic methodology to evaluate terrorism risk has led some DHS observers to suggest the continuation of disbursement of a minimal level of funds to all states (Masse et al. 2007).

FEMA's state and local guide for all-hazards emergency operations planning includes an attachment on managing terrorism consequences (Goss 2002). The guide provides a framework for coordinating local, state and federal terrorism consequence management activities. Using this guide, all-hazard emergency management plans, including consideration of terrorism hazards, have been developed at the city, county, and state levels. Some examples are provided below.

The City of Seattle's all-hazards risk management plan aims to develop an integrated hazard mitigation strategy (City of Seattle 2004). Hazard frequency, expected (most likely) effects, and potential (maximum credible) effects were assigned numerical scores from 1 (low) to 5 (high) for different hazards. A subjective evaluation of terrorism risk was conducted, where risk was expressed as the product of frequency, expected effects, and potential effects.

As mentioned in chapter one, the Genesee County (New York) comprehensive emergency management plan evaluates terrorism risk based on a focus group assessment (Genesee County 2004).

Also mentioned in chapter one, Alaska's all-hazard risk mitigation plan includes risk from terrorism hazard. A hazard and vulnerability matrix has been developed where terrorism hazard affecting different regions has been assigned a severity rating based on the likelihood of occurrence (State of Alaska 2007).

In the post-9/11 era, there have also been several research studies focused on quantifying terrorism risk by itself and within an all-hazards framework. Pate-Cornell and Guikema adopted a systems approach and developed a theoretical probabilistic model for prioritizing terrorist threat and counterterrorism strategies (Pate-Cornell and Guikema 2002). Woo's work includes the development of a theoretical stochastic terrorism risk model providing the framework for probabilistic risk analysis (Woo 2002a), as well as the use of event-trees for estimation of success probabilities of attacks and development of terrorism loss exceedance curves (Woo 2002b). In September 2002, Risk Management Solutions (RMS) released the first version of its "Terrorism Risk Model" (RMS 2003). The RMS model calculates expected annual consequences (human and economic) from varied terrorist threats. The methodology relies on the elicitation of particular attack scenarios at different targets using expert judgment, and assessing the capabilities for different attack modes, overall likelihood of attack, and ability to stage multiple coordinated attacks (RMS 2003; Willis 2007).

Garrick et al. identified the importance of processing intelligence information and developed a framework for scenario-based probabilistic terrorism risk assessments for assets and facilities (Garrick et al. 2004). In a RAND study, terrorism risk and its components were defined, uncertainty quantification in terrorism risk assessment was discussed, two approaches for estimating terrorism risk in urban areas were presented, and risk-based resource allocation recommendations were made (Willis et al. 2005). Using the results from the RAND study, Willis also suggested that dividing risks into categories in terms of individual and population may help in making risk management decisions (Willis 2007).

Bilal et al. developed a mathematical formula within an all-hazards framework for asset-level and portfolio-level risk analysis (Bilal et al. 2007). The formula resembles the "traditional security risk model where risk is the product of consequence, vulnerability, and threat." The data for the analysis was based on historical information and expert opinion, with accommodations made for the associated uncertainties. Depending on the needs of the decision maker, model parameters were chosen and benefit-cost analysis of risk mitigation investments was conducted. More recently, Ezell and von Winterfeldt acknowledged the use of probabilistic risk analysis and event trees for terrorism risk assessment (Ezell and von Winterfeldt 2009).

In summary, while substantial progress has been made to quantify terrorism risk, when considered within an all-hazards context at a regional level, terrorism risk assessment methodologies have been qualitative in nature. Nevertheless, this prior research has provided important insights for developing a more quantitative regional terrorism risk model.

Terrorism Risk Assessment Approach

One way of quantifying terrorism risk is to define it in expected annual economic (monetary) terms, referred to as *risk-cost*. Based on the recent RAND study (Willis et al. 2005), two approaches to terrorism risk assessment have emerged, event-based models and simple risk indicators. Event-based models examine specific attack scenarios, of which there can be many, and generally require access to comprehensive information. On the other hand, risk indicators use proxy measures to estimate corresponding risks, using more readily available data. One such indicator is "density-weighted population" (i.e., the product of a region's population and its population density), which recognizes the desire for a terrorist to attack locations where mass casualties are more likely. Importantly, in work that has been done to date, this indicator has been shown to be correlated with the distribution of terrorism risk across the United States, as estimated by event-based models (Willis et al. 2005).

The RAND study used the RMS Terrorism Risk Model to estimate expected annual terrorism consequences, in terms of property damage, fatalities and injuries, in forty-seven urban areas in the United States as part of the Urban Areas Security Initiative (UASI) of the DHS (Willis et al. 2005). This program is designed to mitigate acts of terrorism by allocating funds towards equipment, planning, training and technical assistance. The model developed herein utilized each of these UASI urban areas as individual observations, resulting in a database of forty-seven records.

Modeling Approach

The dependent variable in this model is considered to be terrorism risk-cost. Recall that the RAND study estimated expected annual terrorism consequences (i.e., terrorism risk) in terms of property damage, fatalities, and injuries in each urban area (Willis et al. 2005). To conform to the units of the dependent variable, it was necessary to convert fatalities and injuries into monetary terms, and to bring all costs into a common reference year (i.e., 2006). The property damage risk-cost was converted to 2006 terms using the Consumer Price Index (CPI) inflation calculator (Bureau of Labor Statistics 2009). In a recent study, the U.S. Department of Transportation estimated that a fatality was equivalent to a loss of $5.8 million (U.S. Department of Transportation 2008), which corresponded to a value of $5.32 million in 2006 terms.

Conversion of injuries into economic terms required a more complex calculation because of significant variations in cost associated with different injury severity levels. Since the RAND study reported only total injuries, the approach taken was to assume a uniform distribution of injury across this domain, and to utilize the average of the fractions of the economic value of a statistical life corresponding to MAIS levels. This resulted in an average cost of $1.09 million per injury in 2006 terms (Bureau of Labor Statistics 2009; U.S. Department of Transportation 2008). The sum of property damage, fatality, and injury risk-costs resulted in the estimation of annual terrorism risk-costs for each of the forty-seven urban areas.

One of the independent variables included in the model formulation was the density-weighted population (defined as the product of a region's population and population density). This metric for the 47 UASI urban areas was based on the census in 2000 and obtained from the RAND Corporation study (Willis et al. 2005).

Information for the other independent variable, critical infrastructure[1], was more difficult to obtain. A recent Federal Motor Carrier Safety Administration study on hazmat routing safety

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[1] In this study, critical infrastructure refers to critical assets including national historic landmarks (that include infrastructure elements of national significance), dams, operating nuclear reactors, bridges, and tunnels.

and security risk analysis assumed that "areas with important cultural, economic, and symbolic resources such as historic sites and monuments, government offices, stadiums, convention centers, schools, bridges, and tunnels might be designated as having iconic structures/critical infrastructure" (Battelle Memorial Institute 2008). Although DHS has been developing and maintaining a National Asset Database containing critical assets associated with twelve sectors of the economy and five groups of key resources (i.e., dams, commercial assets, government facilities, national monuments, and nuclear resources), this information is not publicly available (Moteff 2007). However, there exists a publicly available national historic landmarks database that contains buildings, sites, districts, objects or infrastructure elements that are considered nationally significant and readily recognized (2,489 entries as of January 2009) (National Park Service 2009a; National Park Service 2009b).

In addition to utilizing the national historic landmark database, supplemental information on dams, operating nuclear reactors (including power reactors and research and test reactors), bridges, and tunnels located in each of the 47 UASI urban areas was collected (U.S. Nuclear Regulatory Commission 2007; U.S. Hometown Locator 2009). The unweighted sums (providing equal importance to each asset) of the number of these critical infrastructure elements were subsequently used in model estimation.

Model Estimation

In order to estimate annual regional terrorism risk-costs (without allowing for negative values), a natural logarithmic transformation of annual terrorism risk-cost and density-weighted population was performed. Using a stepwise regression approach (Statistics.com 2010), the first version of the regression model yielded the following results:

$$\ln(Risk_t^c) = -13.02637 + (1.38327 \times \ln(p_{dw})) + (0.00016 \times \ln(p_{dw}) \times s_{ci}) \qquad (3.2)$$

where:

$Risk_t^c$ = annual terrorism risk-cost in dollars

p_{dw} = density-weighted population in population^2/mile^2

s_{ci} = unweighted sum of number of critical infrastructure elements

The above model generated an R^2 of 0.717 and a standard error of 1.29 dollars. Table 3.4 lists the corresponding t-statistics and p-values. These results indicate that at a 95% confidence level, each of the variables has a significant effect on the terrorism risk-cost. The F-statistic of 55.743 and significance of 8.683E-13 indicates that at a 95% confidence level, the variables also have a joint significant effect on the terrorism risk-cost. The positive variable coefficients indicate that as the population concentration and/or the number of critical infrastructure elements increase, the annual terrorism risk-cost increases, as one would expect.

Table 3.4: Initial model results: t-statistics and p-values

Parameter	t statistic	p-value
Intercept	-4.184	1.348E-04
$\ln(p_{dw})$	9.238	7.265E-12
$\ln(p_{dw}) \times s_{ci}$	2.124	3.934E-02

Satisfaction of all regression model assumptions result in approximately 68% of the standardized residuals between -1 and +1, approximately 95% between -2 and +2, and approximately 99.7% between -3 and +3 (Dean and Voss 1999). While reviewing these assumptions, one apparent outlier (corresponding to the Las Vegas urban area) with standardized residual value of 4.398 was observed. This suggests that there may be unique factors for the Las

Vegas urban area that have not been properly accounted for in the model. This can be explained by the significant involvement of the gaming industry and resort casinos in Las Vegas, resulting in a large number of visitors (non-resident population) occupying a confined space. Due to these unusual characteristics that are site-specific, data corresponding to the Las Vegas urban area was dropped from the model and a revised estimate was performed.

Using data for the remaining 46 UASI urban areas resulted in the following model estimate:

$$\ln(Risk_t^c) = -18.45559 + (1.63299 \times \ln(p_{dw})) + (0.00017 \times \ln(p_{dw}) \times s_{ci}) \quad (3.3)$$

This model produced an R^2 of 0.856 and standard error of 0.93 dollars. Table 3.5 lists the corresponding t-statistics and p-values. At a 95% individual confidence level, each variable has a significant effect on terrorism risk-cost. With an F-statistic of 127.79 and significance of 8.049E-19, the variables also have a joint significant effect on terrorism risk-cost at the 95% confidence level. Once again, the positive coefficients for the variables are intuitively appealing. This revised version of the regional terrorism risk model was adopted for application consideration.

TABLE 3.5: Revised model results: t-statistics and p-values

Parameter	t statistic	p-value
Intercept	-7.701	1.261E-09
$\ln(p_{dw})$	14.244	6.928E-18
$\ln(p_{dw}) \times s_{ci}$	3.075	3.653E-03

Model Application

The aforementioned model was subsequently used in a case study to estimate the terrorism risk-cost for three counties in the State of Tennessee: (1) Hamblen, (2) Shelby, and (3)

Smith. The terrorism risk-cost model was applied to the case study counties using county-specific values for the independent variables. Table 3.6 shows the annual terrorism risk-costs in 2006 terms as derived for the three counties. As with the previous hazards, Shelby County (which includes the City of Memphis) dominates in terms of terrorism risk-cost, whereas terrorism does not appear to be a cause for concern in Hamblen and Smith counties.

Table 3.6: County-level annual terrorism risk-cost

County	Annual terrorism risk-cost ($)
Hamblen	8,810
Shelby	6,970,000
Smith	62

In the absence of actual data to validate the results from applying the regional terrorism risk model, a heuristic approach was adopted, using Shelby County due to its annual terrorism risk-cost falling within the range of annual terrorism risk-costs for the 46 UASI urban areas. The model estimate of annual terrorism risk-cost for Shelby County was compared to the annual terrorism risk-cost of the UASI urban area that was closest overall to Shelby County in terms of population, population density, and unweighted sum of number of critical infrastructure elements. The validation procedure is shown in Figure 3.7. This procedure resulted in identifying the Phoenix-Mesa urban area as most closely resembling the characteristics of Shelby County. This urban area had a calculated annual terrorism risk-cost of $5,832,000, a difference of $1,134,000 or 16.3%, when compared to the estimated risk-cost for Shelby County. This would appear to be a reasonable outcome.

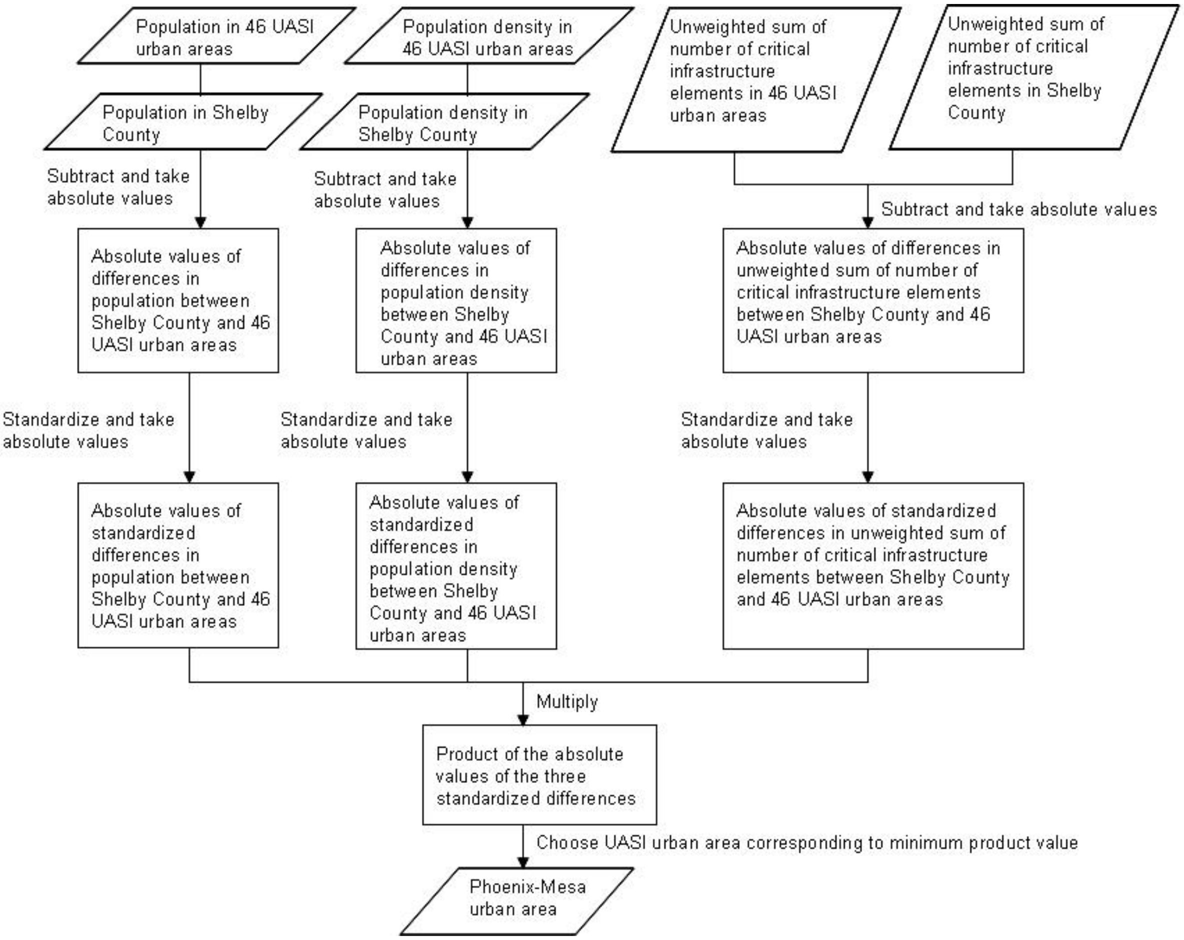


Figure 3.7: Flowchart of regional terrorism risk model validation procedure.

Further Discussion

The aforementioned regional terrorism risk model, given its statistical significance and reasonable case study application results, suggests that it could serve as a meaningful first-generation approximation of annual terrorism risk-cost at the regional level. This suggests that it could provide value as both a screening tool for comparing terrorism risk in different locations and as applied in an all-hazards context where the risk-cost of other hazards facing a jurisdiction are considered. Since terrorism risk is expressed in economic terms, similar to what has been done with risks associated with other hazards (Chatterjee and Abkowitz 2009), it can assist in establishing risk management priorities and in making informed policy and resource allocation decisions.

A limitation of this modeling approach, however, is that it does not fully reflect the interactions of threat, vulnerability, or consequence (Willis et al. 2005). However, the use of expected terrorism risk consequences (estimated from the event-based RMS model) as the response variable and the use of a popular risk indicator (density-weighted population) as one of the predictor variables incorporates elements of both terrorism risk modeling approaches available in literature. The inclusion of critical infrastructure as a predictor variable also contributes positively to measuring terrorism risk. Including additional infrastructure elements like schools, government facilities, stadiums, convention centers and airports in the model, may increase the influence of critical infrastructure on terrorism risk-cost estimation.

As with any regression model, prediction outside of the data range used to develop the model can lead to an increase in uncertainty. Such is the case when the model was applied to Hamblen and Smith counties. In these instances, results from extrapolation need to be viewed with caution and should be used judiciously. Also, results from application of the terrorism risk model to non-urban jurisdictions need to be viewed with caution. Since results from the RMS model for several urban areas are used to develop the regional terrorism risk model, some of the assumptions and limitations of the RMS model could also extend to the regional terrorism risk model. For example, the RMS model's use of expert opinion could bias the likelihood of attack modes and targets in different cities (Willis 2007).

CHAPTER IV

OVERALL AHRM METHODOLOGICAL DEVELOPMENT

Risk Prioritization

The ability to estimate a risk-cost for truck hazmat transportation, earthquake and terrorism hazards presents a framework for a decision-maker to compare among risks threatening a region of interest and make a determination as to the risk(s) warranting priority attention. As this opportunity applies to the case study described herein, the summary analysis results presented in Table 4.1 would be utilized.

Table 4.1: Summary of annual risk-costs by county

County	Annual hazmat truck transport risk-cost ($)	Annual earthquake risk-cost ($)	Annual terrorism risk-cost ($)	Total annual risk-cost ($)
Hamblen	1,820,000	790,000	8,810	2,618,810
Shelby	19,000,000	36,310,000	6,970,000	62,280,000
Smith	3,300,000	120,000	62	3,420,062

From a policy perspective, these results can support decisions at two different levels: (1) how a state's risk management resources should be apportioned to respective counties, and (2) how a county's risk management resources should be allocated towards hazard types and specific hazards. For the purposes of the following discussion, it is assumed that the State of Tennessee is comprised of only Shelby, Hamblen and Smith counties, and that the truck transportation of hazardous materials, earthquakes and terrorism are the only hazards threatening the state. In a simplistic scenario, used for illustrating the AHRM approach in the following discussion, the allocation of resources is in proportion to the risk contribution from each hazard source.

Resource allocation at the state level

An inter-county assessment of risks can provide a basis for the state risk manager to allocate risk management resources among respective counties. Referring to Table 4.1, from an overall risk management resource allocation perspective, based on total annual risk-cost, Shelby County would command the vast majority of the risk management resources (91%) distributed by the state. Similarly, Hamblen and Smith counties would receive 4% and 5% of the state allocation, respectively.

Resource allocation at the county level

The intra-county assessment of risks can provide the county risk manager with a means for allocating risk mitigation resources due to hazards afflicting the particular county. Again referring to Table 4.1, and assuming that the allocation of resources is in proportion to the risk contribution from each hazard source, the following decisions would be made. For Hamblen County, nearly 70% of the risk management resources would be applied toward mitigation of hazmat truck transport risks, with 30% allocated to earthquake risk management and the remainder apportioned to terrorism risk mitigation. By contrast, the risk management resources in Shelby County would be allocated as 58% of the budget to earthquake risk management, 31% to hazmat truck transport risk mitigation and 11% to fight terrorism risk. In Smith County, nearly all (96%) of available risk management resources would be utilized on hazmat truck transport, with the remainder allocated to earthquakes and a negligible amount dedicated to terrorism risk management.

Risk Mitigation

In reality, the functional relationships between resource allocation and risk reduction are complex. As a result, the apportionment of resources depends on the cost-effectiveness of risk mitigation measures that might be applied in each region of interest. In a more realistic scenario, resource allocation for risk mitigation is an optimization problem where the objective is to maximize the overall risk-cost reduction subject to constraints arising from the functional relationships between the investment and the return on investment (risk-cost reduction) for each hazard in each region of interest. Other constraints would include the available risk mitigation budget, as well as any requirements to spend a minimum amount of mitigation funds on designated hazards.

In most instances, a variety of risk mitigation strategies could be considered for potential implementation. These may include investments in infrastructure maintenance or rehabilitation, law enforcement technology or training, emergency response preparedness, and public education and awareness. In practice, any of the mitigation measures or a combination of them may contribute towards controlling or reducing risk from one or more hazards.

Moreover, the success of any particular strategy may be highly dependent on the size of the investment. For example, lack of a critical level of funding may lead to only marginal improvement in risk-cost. As shown in Figure 4.1, an investment in excess of x_0 would be required before an attractive risk-cost return on investment could be achieved. Conversely, too large an investment may lead to diminishing risk-cost return, such that the extra resources may be more wisely spent on other mitigation strategies (Abkowitz and Chatterjee 2010). Figure 4.2 depicts this relationship, where it can be seen that an investment in excess of x_1 brings a declining marginal reduction in risk-cost than prior investment levels (Abkowitz and Chatterjee 2010). In Figures 4.1 and 4.2, it is assumed that the reduction in risk-cost increases with greater investment, starting from an initial state of reduction in risk-cost which is greater than zero and may be representative of mitigation measures that are already in place.

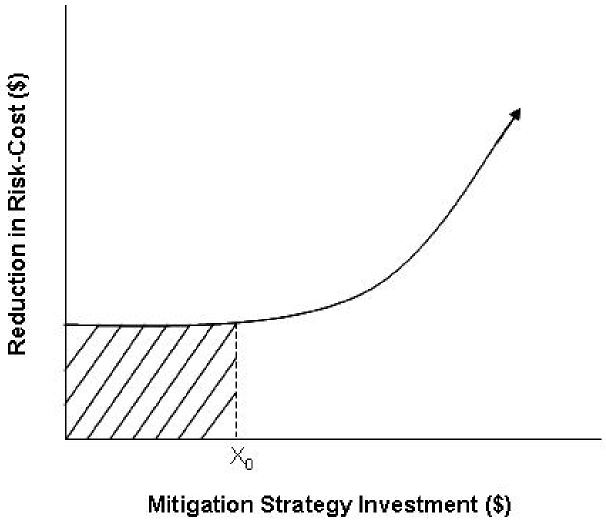


Figure 4.1: Underinvestment in mitigation strategy.

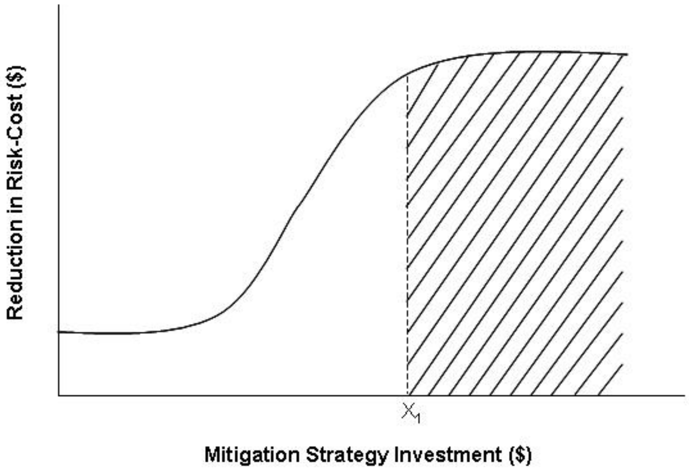


Figure 4.2: Overinvestment in mitigation strategy.

The risk manager will need to define the functional relationship between the level of investment in each mitigation strategy and its return on investment for different hazards facing the region of interest. Typically, but not always, one would expect the marginal rate of mitigated risk-cost (return) with respect to hazard mitigation investment increases up to an inflection point and then decreases. However, the shape of the function may also depend on the risk preferences of the decision maker (RMS 2003). When a risk is considered large, one may tend to exhibit risk-averse behavior, leading to over-investment in risk mitigation, whereas for smaller risks, a more risk-neutral posture may be more likely (Masse et al. 2007).

CHAPTER V

RESOURCE ALLOCATION FOR REGIONAL DISASTER RISK MITIGATION

Introduction

This chapter describes the development of an all-hazards risk mitigation resource allocation problem. The approach begins by defining a functional relationship between risk mitigation investment and reduction in disaster risk-cost (expected annual loss in monetary terms), followed by the formulation of a deterministic nonlinear optimization problem for mitigation resource allocation. Optimal resource allocation strategies for varying budget levels are discussed in the context of a case study application.

Background

Concerns have been expressed that the distribution of risk management funds has been made without regard to the magnitude of risks and risk reduction opportunities within a region and across different regions (Moteff 2008; Masse et al. 2007; Chatterjee and Abkowitz 2010). This is slowly beginning to change. For example, recently the U.S. President's proposed budget allocated more than $20 billion annually, based on the statistical probability of emergency related costs, to deal with future emergencies and the costs of natural and man-made disasters (Office of Management and Budget 2009). In parallel, several initiatives have been aimed at formalizing concepts to help guide these decisions. FEMA has developed mitigation planning guides that include procedures for conducting benefit-cost analysis and mitigation prioritization using qualitative (listing and relative rating) and quantitative (scoring and weighted scoring) methods (FEMA 2007). Dodo et al. (2007) developed and applied a linear program and efficient solution algorithms to identify buildings that should be upgraded to minimize the present value of the total mitigation and expected post-earthquake reconstruction expenditures, occurring over time, subject to mitigation budget constraints. The U.S. Department of Homeland Security (DHS) has established a list of high priority sites and has classified urban areas in tiers, allocating risk management resources based on both risk and need (Stephan 2006; Moteff 2008). Overall, one can conclude that while measured progress has been made to formalize the concept of an AHRM approach and risk mitigation resource allocation, its application at a regional level using a common risk metric is lacking.

The implementation of an AHRM approach and risk mitigation resource allocation as described in this study involves the evaluation of disaster risks in expected annual economic (monetary) terms (both human casualties and other economic losses) for a region of interest, referred to as *risk-cost*.

The ability to derive a risk-cost for any particular hazard, and the aggregation of individual hazard risk-costs into an all-hazards risk-cost is an important development. By exercising this approach, a risk manager has the ability, using risk-cost as a common metric, to identify which risks pose the greatest concern. However, it does not necessarily follow that allocating risk mitigation resources to the most threatening risks offers the best use of these resources. Much of that depends on the level of reduction in risk-cost that can be achieved for every dollar spent on a particular mitigation strategy. It is for this reason that the disaster risk resource allocation problem must be formulated and solved.

Disaster Risk Mitigation

Investment in managing disaster risk generally falls into two categories, either financing losses after the event occurs, or opting to implement prevention strategies prior to event occurrence (Hochrainer 2006). The focus of this research is on monetary investment in pre-disaster risk mitigation. A variety of pre-disaster risk mitigation measures are available, for example investments in infrastructure protection, law enforcement, emergency response, or public education and awareness. The functional relationship between risk mitigation investment and reduction in total risk-cost proposed herein is based on the economic concept of diminishing marginal returns. This implies that at some expenditure threshold, additional investment will lead to declining marginal risk-cost return, highlighting the potential to spend the excess resources on another mitigation strategy that offers a greater risk-cost return-on-investment (Abkowitz and Chatterjee 2010). Mathematically, as the mitigation investment increases, the marginal rate (slope of tangent) of reduction in risk-cost increases until reaching an inflection point, beyond which increasing investment would yield a decreasing marginal rate of reduction in risk-cost. This nonlinear relationship can be represented by a sigmoid function or an *S-shaped* curve (Carreño et al. 2005).

A logistic function is a common sigmoid function used to model the growth of some parameter of interest (see Figure 5.1). The initial stage of growth is approximately exponential; then, as saturation begins, the growth continues to slow down. The logistic model of population growth is a suitable representation of the nonlinear relationship between risk mitigation investments and reduction in risk-cost (Anderson 2006). The rate of growth of reduction in risk-cost with respect to mitigation investments is proportional to the existing reduction in risk-cost and the amount of available resources, the competition for which tends to limit the reduction in risk-cost growth. Therefore, each hazard affecting a region of interest could have corresponding risk mitigation investment and reduction in risk-cost relationships which can be used to make resource allocation and policy decisions.

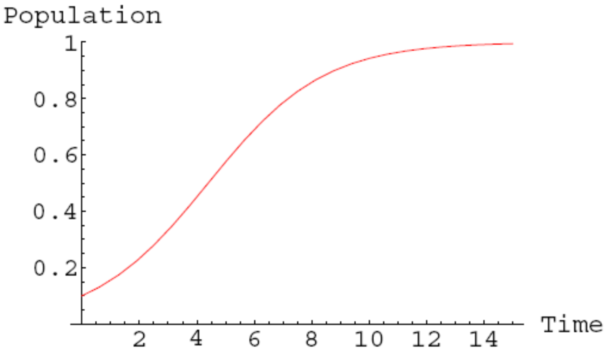


Figure 5.1: Sample population growth using logistic model (Anderson 2006).

Risk Mitigation Logistic Model

The logistic model, a first-order nonlinear differential equation, when applied to the problem of risk mitigation is:

$$\frac{dR}{di} = r\,R\left(1 - \frac{R}{M}\right) \tag{5.1}$$

where:

R = reduction in risk-cost

i = risk mitigation investment

r = growth rate of reduction in risk-cost

M = maximum reduction in risk-cost

Solution of the above equation and interpretation of the results is discussed below.

Using equation (5.1) and substituting R/M = k and dR = M×dk results in the following differential equation:

$$\frac{M \times dk}{di} = r\,M\,k\left(1-k\right)$$

$$\Rightarrow \frac{dk}{k\left(1-k\right)} = r\,di$$

Integration under limits yields the following problem:

$$\Rightarrow \int_{\frac{R_0}{M}}^{\frac{R}{M}} \frac{dk}{k(1-k)} = \int_0^i r\,di$$

where:

R_0 = initial reduction in risk-cost

$$\Rightarrow \int_{\frac{R_0}{M}}^{\frac{R}{M}} \frac{dk}{k} + \int_{\frac{R_0}{M}}^{\frac{R}{M}} \frac{dk}{1-k} = \int_0^i r\,di$$

Solving the above equation yields:

$$\Rightarrow \left[\ln\left(\frac{k}{1-k}\right)\right]_{\frac{R_0}{M}}^{\frac{R}{M}} = r \times i$$

$$\Rightarrow \ln\left(\frac{R}{M-R} \times \frac{M-R_0}{R_0}\right) = r \times i$$

$$\Rightarrow \frac{R}{M-R} = \frac{R_0 \times e^{ri}}{M-R_0}$$

$$\Rightarrow R(i) = \frac{M \times R_0}{e^{-ri}\left(M-R_0\right)+R_0} \tag{5.2}$$

where:

R(i) = reduction in risk-cost at investment level i

$\lim_{i \to \infty} R(i) = M$; or M is the limiting value of reduction in risk-cost that can be achieved with an infinite amount of investment.

Growth Rate of Reduction in Risk-Cost

To compute the reduction in risk-cost at an investment level using equation (5.2), the maximum reduction in risk-cost (M), the initial reduction in risk-cost (R_0), and the growth rate (r) are needed. The maximum reduction in risk-cost is the value of the disaster risk-cost and the initial reduction in risk-cost is assumed as 1% of the maximum reduction in risk-cost. The underlying assumption for the initial reduction in risk-cost to be greater than zero is the form of the risk mitigation logistic function used, where reduction in risk-cost increases with greater investment, starting from an initial state of reduction in risk-cost which may be representative of mitigation measures that are already in place. The growth rate is a positive variable with values greater than zero. To compute the growth rate using equation (5.1), the slope of reduction in risk-cost at an investment level, the corresponding risk-cost, and the maximum reduction in risk-cost are needed. Based on the properties associated with the point of inflection, the risk-cost at the point of inflection can be derived mathematically. Therefore, the growth rate can be expressed in terms of the slope of reduction in risk-cost at the point of inflection and the maximum reduction in risk-cost.

An inflection point is a location at which a function’s curvature or concavity changes signs. For a risk mitigation logistic function R(i), R'(i) is $r\,R\left(1-\frac{R}{M}\right)$, where r >0, R >0, and $\left(1-\frac{R}{M}\right)$>0, meaning that R'(i) is always greater than zero and implying that R(i) may have an inflection point at some investment level i. A necessary condition for investment level i to be at an inflection point is R"(i) =0. A sufficient condition of R"(i+ε) and R"(i-ε) having opposite signs in the neighborhood of i was checked to be satisfactory. The computations for the necessary condition for the point of inflection and the expression for growth rate in terms of the slope of reduction in risk-cost at the point of inflection are described below.

From equation (5.1):

$$\frac{dR}{di} = r\,R\left(1 - \frac{R}{M}\right) = rR - r\frac{R^2}{M}$$

Differentiating R'(i) with respect to i:

$$\frac{d^2R}{di^2} = r\frac{dR}{di} - \frac{r}{M} \times 2R\frac{dR}{di}$$

Substituting dR/di = $r\,R\left(1 - \frac{R}{M}\right)$ above yields:

$$\Rightarrow \frac{d^2R}{di^2} = r^2 R\left(1 - \frac{R}{M}\right)\left(1 - \frac{2R}{M}\right)$$

Substituting R"(i) = 0 generates three possible solutions:

$\Rightarrow R = 0$ (infeasible solution; R_0 >0 for theoretical and practical applications)

$\Rightarrow R = M$ (infeasible solution; $\lim_{i \to \infty} R(i) = M$)

$$\Rightarrow R = \frac{M}{2} \quad \text{(feasible solution)} \tag{5.3}$$

Substituting the expression for R at the point of inflection from equation (5.3) in equation (5.1):

$$\left(\frac{dR}{di}\right)_{POI} = r \times \frac{M}{2} \times \left(1 - \frac{1}{2}\right)$$

where:

$\left(\frac{dR}{di}\right)_{POI}$ = slope of reduction in risk-cost at the point of inflection

$$\Rightarrow r = \frac{4 \times \left(\frac{dR}{di}\right)_{POI}}{M} \tag{5.4}$$

Marginal Return on Investment Threshold

A risk manager defines the return on investment threshold before deciding to invest funds in a mitigation strategy. This threshold varies depending on the risk preferences of the decision maker. By nature of the logistic function, the marginal slope of reduction in risk-cost with respect to mitigation investment increases up to the inflection point and then decreases. Therefore, there are two investment levels where the slope of reduction in risk-cost values are the same, one below and one above the investment level at the inflection point.

Based on psychophysical models, Tversky and Kahneman (1979) developed prospect theory to describe the combination of risk and loss aversion and how decisions are made (see Figure 5.2) (OpenLearn 2010; McDermott 1998). Risk behavior will depend on proximity to a particular reference point, creating a domain of losses on one side of the reference point and a domain of gains on the other (OpenLearn 2010). Prospect theory and the *S-shaped* utility curve suggest that risk-averse behavior in the domain of gains and risk-seeking in the domain of losses (McDermott 1998).

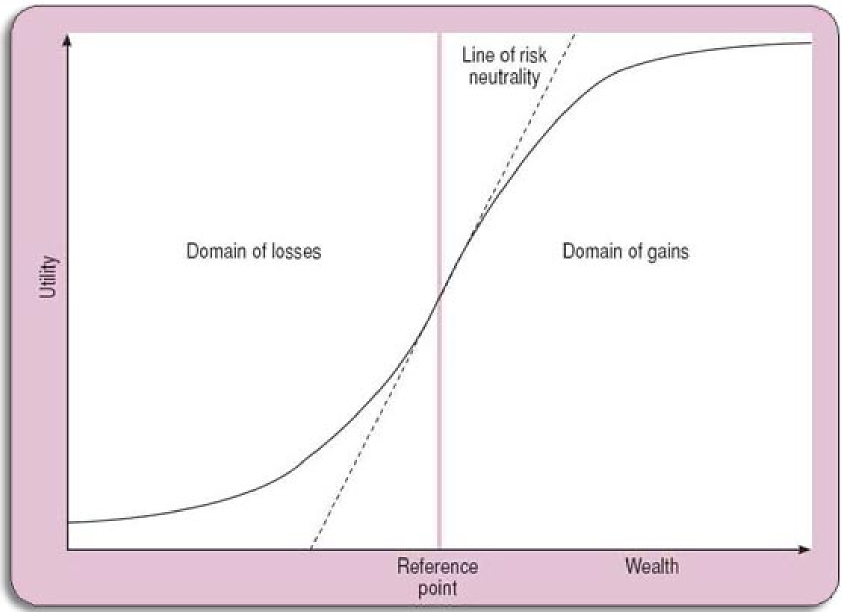


Figure 5.2: Sample utility function according to prospect theory (OpenLearn 2010).

Risk preference in government policy depends on the effect of specific risks threatening its jurisdiction (Mechler 2003). As potential consequences become more significant, government tend to become more risk-averse, as evidenced by the budgeting process used by the U.S. in financing loss prevention associated with future emergencies (Office of Management and Budget 2009).

Under such risk-averse behavior in the context of mitigation planning, as per the concept of prospect theory, the marginal return of investment threshold should be at the investment level that is greater than the investment level at the point of inflection on the logistic curve. The relationship between investment level and marginal return on investment threshold is derived below.

From equation (5.1):

$$\frac{dR}{di} = r\,R\left(1-\frac{R}{M}\right) = rR - r\frac{R^2}{M} = t$$

where:

t = marginal return on investment threshold

$$\Rightarrow r\frac{R^2}{M}-rR+t=0$$

Multiplying both sides by M/r yields:

$$\Rightarrow R^2-MR+\frac{t\times M}{r}=0$$

Two solutions for this quadratic equation are:

$$R=\frac{M\pm\sqrt{M^2-4\times 1\times\frac{t\times M}{r}}}{2}$$

Since marginal return on investment threshold, as per the concept of prospect theory, should lie at a reduction in risk-cost level greater than that at the point of inflection:

$$R_T=\frac{M+\sqrt{M^2-\frac{4\times t\times M}{r}}}{2} \tag{5.5}$$

where:

R_T = reduction in risk-cost at marginal return on investment threshold

Using equation (5.2) to express mitigation investment in terms of reduction in risk-cost yields:

$$R(i)=\frac{M\times R_0}{e^{-ri}(M-R_0)+R_0}$$

$$\Rightarrow e^{-ri}(M-R_0)=\frac{M\times R_0}{R}-R_0$$

$$\Rightarrow -ri=\ln\left(\frac{R_0}{R}\times\frac{M-R}{M-R_0}\right)$$

$$\Rightarrow i=\frac{1}{r}\ln\left(\frac{R}{R_0}\times\frac{M-R_0}{M-R}\right)$$

$$\Rightarrow i_T = \frac{1}{r}\ln\left(\frac{R_T}{R_0}\times\frac{M-R_0}{M-R_T}\right) \tag{5.6}$$

where:

i_T = risk mitigation investment at marginal return on investment threshold

Resource Allocation Problem Formulation

The need for a proactive loss financing approach is recognized in the literature (Office of Management and Budget 2009; Hochrainer 2006; Mechler 2003). However, investment in disaster risk mitigation comes at the cost of not putting these resources into alternative programs. Moreover, within a disaster risk mitigation program itself, various mitigation strategies are competing for available resources. Therefore, the apportionment of resources depends on benefit-cost analysis of each potential initiative (Abkowitz and Chatterjee 2010).

In this study, resource allocation for risk mitigation is modeled as a deterministic, nonlinear optimization problem, where the objective is to maximize the overall reduction in total risk-cost subject to a mitigation budget constraint, marginal return-on-investment upper bound constraint, and investment non-negativity constraint. The optimization problem is deterministic because risk-costs or annual expected losses are used, and is nonlinear due to the use of logistic functions for explaining the risk mitigation and investment relationship. The resource allocation problem formulation under these conditions is defined below:

Maximize $$\sum_{h=1}^{H} R(i)_h \tag{5.7}$$

subject to: $$\sum_{h=1}^{H} i_h \le x \times \sum_{h=1}^{H} Risk_h^c \quad \text{(mitigation budget constraint)} \tag{5.8}$$

$$i_h \leq \min\left(i_{T_h}, Risk_h^c, x \times \sum_{h=1}^{H} Risk_h^c \right) \forall\, h = 1, ..., H \text{ (upper bound constraint)} \quad (5.9)$$

$$i_h \geq 0 \ \forall\ h = 1, ..., H \quad \text{(non-negativity constraint)} \quad (5.10)$$

where:

$R(i)_h$ = reduction in risk-cost at investment level i

i_h = risk mitigation investment (decision variable)

H = number of hazards under consideration

$Risk_h^c$ = hazard risk-cost

x = fraction between 0 and 1

i_{T_h} = risk mitigation investment at marginal return on investment threshold

For the case where the mitigation budget is assumed to be a fraction of the total risk-cost, there is a possibility that the budget might be less than an individual hazard risk-cost. In order to deal with the effect of varying budgets on the mitigation investment upper bound, the minimum of the risk mitigation investment at marginal return on investment threshold, individual hazard risk-cost and the budget used was chosen as the risk mitigation investment upper bound.

In a constrained, nonlinear resource allocation optimization problem, the issue of local versus global optimal solution arises. Optimization software for nonlinear programming models generate local optimal solutions and cannot guarantee that the local optimal is also the global optimal. To manage the local versus global optimal solution issue, within the bounds of the hazard mitigation investment (decision variable), different values can be chosen as initial estimates for solving the optimization problem. The maximum value of the overall reduction in hazard risk-cost (objective function) among the different solutions can then be chosen as the best feasible or optimal solution. Thereafter, the values of the decision variables corresponding to the best feasible solution are used as initial estimates for another optimization run to observe any improvements to the best feasible solution.

The optimization problem was implemented in MATLAB (The Mathworks, Inc. 2010a), using the *fmincon* function for constrained nonlinear optimization. This function is typically used when the objective and constraint functions are both continuous and have continuous first derivatives (The Mathworks, Inc. 2010b).

Optimal Resource Allocation Strategies

The all-hazard risk mitigation resource allocation optimization model developed in this study aims to be a screening-level tool to help decision makers in prioritizing among different risks and corresponding mitigation strategies. In previous chapters, a case study was performed in which risk-costs for three hazards (earthquakes, truck transportation of hazardous materials, and terrorism) were derived for three regions (Hamblen, Shelby, and Smith counties) in the State of Tennessee (Chatterjee and Abkowitz 2009; Abkowitz and Chatterjee 2010). This was used as the basis for extending the case study application to include formulating and solving the risk mitigation resource allocation problem.

The development of a logistic curve for a disaster risk mitigation strategy would begin with the estimation of maximum reduction in risk-cost (chosen hazard risk-cost), initial reduction in risk-cost (assumed to be 1% of the maximum reduction in risk-cost), and the growth rate of reduction in risk-cost with mitigation investment. The growth rate depends on the value of the slope of reduction in risk-cost at the point of inflection. This would be established based on prior experience and expert opinion of decision makers. An example of risk mitigation logistic curves and marginal return on investment upper bounds for Shelby County is presented in Figure 5.3, corresponding to separate relationships for hazmat truck transport accidents, earthquakes and terrorist events, respectively. The figure shows that, for the same slope of reduction in risk-cost at the point of inflection and marginal return on investment threshold, the rate of growth of reduction in risk-cost can be different for each hazard.

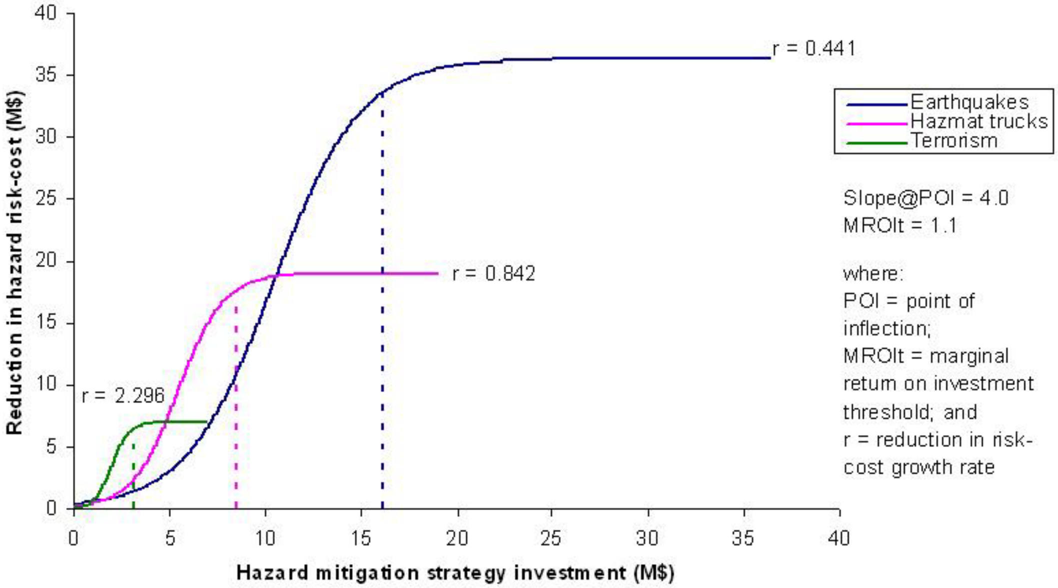


Figure 5.3: Sample risk mitigation logistic curves for Shelby County.

To understand the effect of slope of reduction in risk-cost at the point of inflection on the risk mitigation logistic curves and corresponding resource allocation strategies for the risks within the case study counties, optimization runs were performed for two different sensitivity analysis scenarios. The numerical values of slope of reduction in risk-cost at the point of inflection were based on Congressional Budget Office and the National Institute of Building Sciences issued reports suggesting that, for every dollar spent on pre-disaster risk mitigation, future losses are reduced by $3 to $4 (Govtrack.US 2009).

In the first sensitivity analysis, the slope of reduction in risk-cost at the point of inflection was assumed to be equal across different risks and its numerical value was varied from 1.2 to 4.0

at increments of 0.2 (or 15 scenarios). The optimization runs were performed for two marginal return on investment thresholds of 5% and 10% above the initial mitigation investment. This county level analysis was performed under two different budget scenarios: 1) equal to the total risk-cost and 2) one-half of the total risk-cost. This resulted in 60 (15×2×2) optimization runs for each county.

In the second sensitivity analysis, the slope of reduction in risk-cost at the point of inflection was varied across different hazards and its numerical value was fixed at three levels of 1.2, 2.6, and 4.0. All possible combinations of varying slope of reduction in risk-cost at the point of inflection across different hazards were assessed, resulting in 27 (3×3×3) scenarios. The optimization runs were performed for marginal return on investment threshold of 1.1 (or 10% above the initial mitigation investment). This county level analysis was performed under two different budget scenarios: 1) equal to the total risk-cost and 2) one-half of the total risk-cost. This resulted in a total of 54 (27×1×2) optimization runs for each county.

Results for the sensitivity analyses performed on Shelby County are discussed below. It should be noted that depending on the risk-cost values, similar trends were observed for the other two case study counties.

Equivalent Slope of Reduction in Risk-Cost at the Point of Inflection

Reduction in risk-cost increases with a rise in the slope of reduction in risk-cost at the point of inflection, for both cases where the allocation budget is equal to one-half or all of the total risk-cost (see Figures 5.4 and 5.5). This result is intuitive because a logistic curve with a higher slope of reduction in risk-cost at the point of inflection will have a higher growth rate and result in a greater reduction in total risk-cost for the same mitigation investment. For slope of reduction in risk-cost at the point of inflection values of less than 3.4, the reduction in total risk-cost is higher when the budget is equal to the total risk-cost. This indicates that, depending on the effectiveness of mitigation investment in reducing disaster risk-cost, limited resource availability can lead to limited risk reduction opportunity. The reduction in total risk-cost for a marginal return on investment threshold of 5% above the mitigation investment is equal to or greater than the reduction in total risk-cost for a marginal return on investment threshold of 10% above the mitigation investment. Since a lower marginal return on investment threshold indicates a greater relative degree of risk aversion, the result is intuitive.

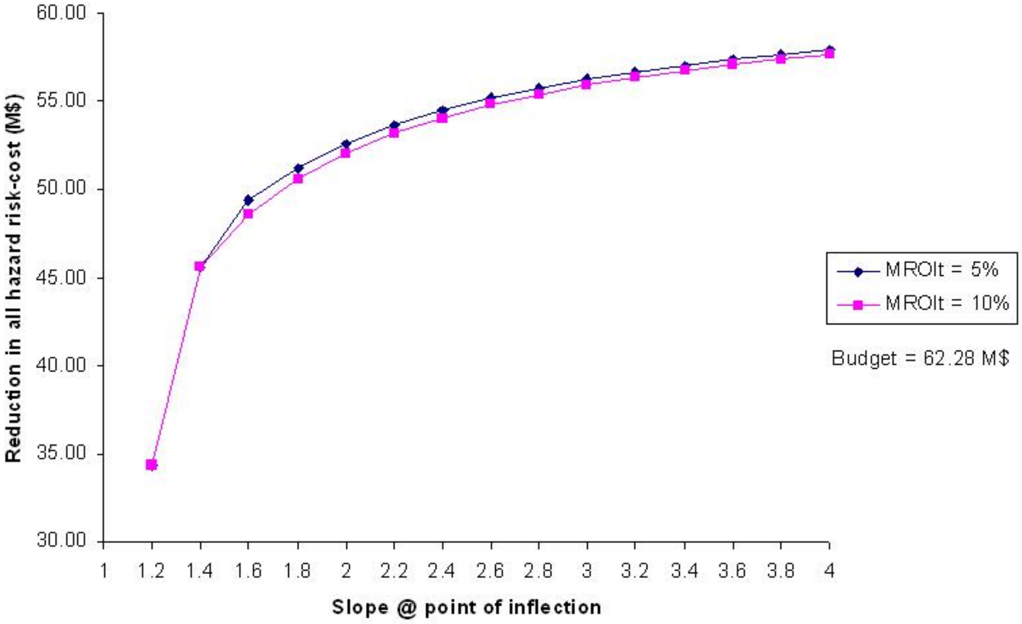


Figure 5.4: Reduction in total risk-cost with budget equal to total risk-cost.

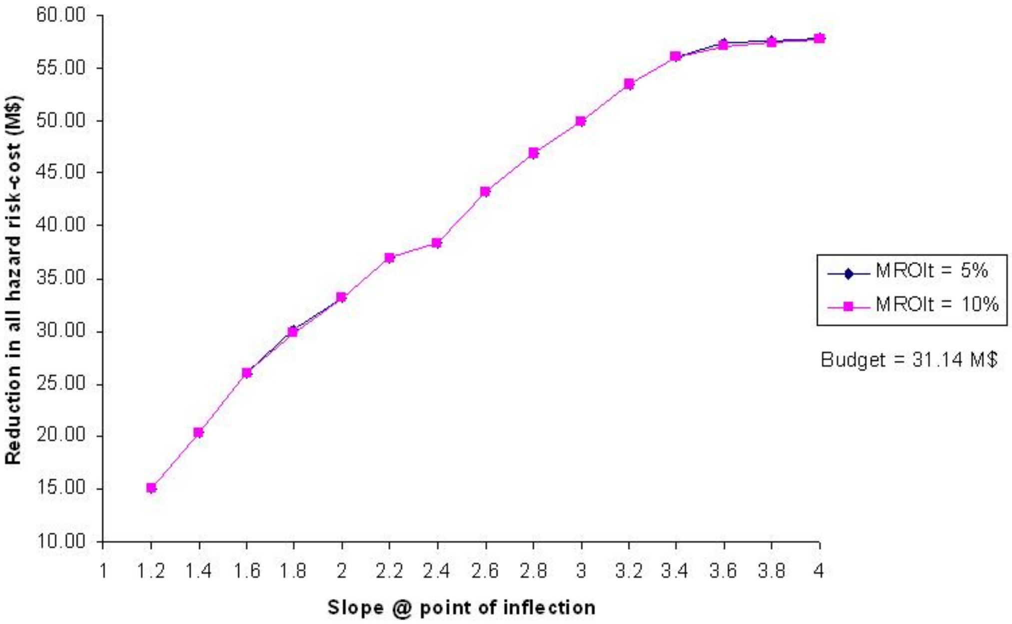


Figure 5.5: Reduction in total risk-cost with budget as one-half of total risk-cost.

The portion of the budget allotted for risk mitigation stays equal to the budget or decreases as the slope of reduction in risk-cost at the point of inflection increases because logistic curves with a higher slope of reduction in risk-cost at the point of inflection have higher growth rates and lower values of investment upper bounds (see Figures 5.6 and 5.7). This indicates that, depending on the effectiveness of mitigation investment in reducing risk-cost, spending an entire mitigation budget is not justified if available mitigation strategies do not provide a threshold return on investment. For slope of reduction in risk-cost at the point of inflection values of greater than 3.4, the budget used for risk mitigation falls below one-half of the total risk-cost, resulting in the same reduction in total risk-cost for both budget cases. The budget used for total risk mitigation for a marginal return on investment threshold of 5% above the mitigation investment is equal to or greater than the budget used for total risk mitigation for a marginal return on investment threshold of 10% above the mitigation investment, because a greater relative degree of risk aversion implies a larger risk mitigation investment.

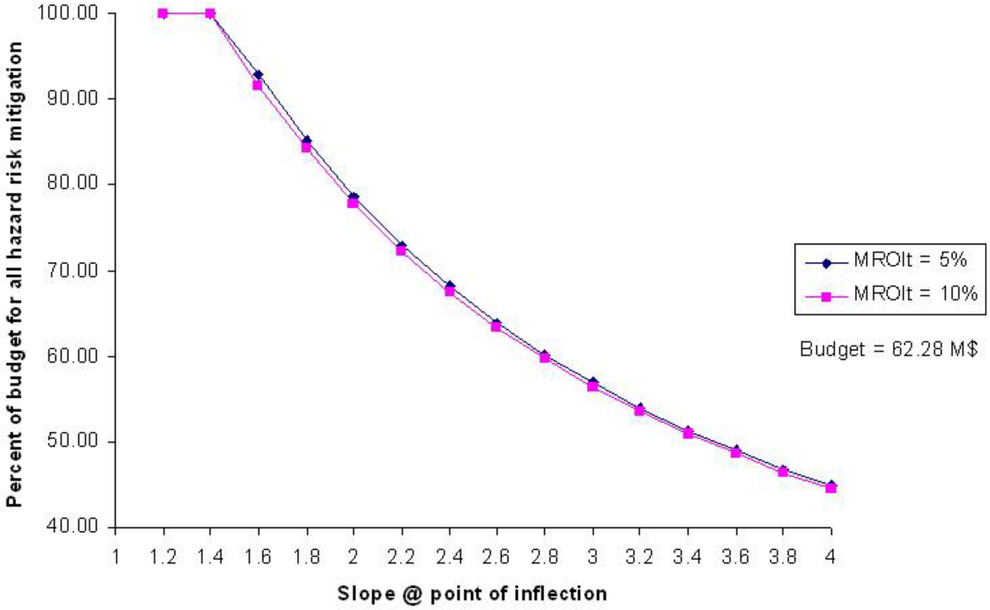


Figure 5.6: Investment in total risk mitigation with budget equal to total risk-cost.

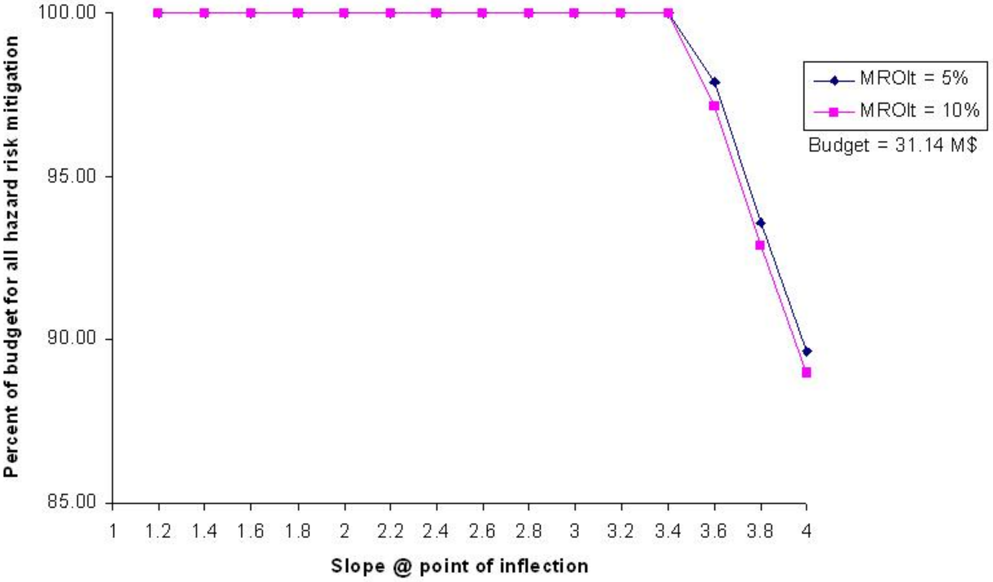


Figure 5.7: Investment in total risk mitigation with budget as one-half of total risk-cost.

Proportions of the budget allotted for risk mitigation were computed for all three hazards. The results for earthquake risk mitigation are discussed here. The earthquake risk mitigation budget decreases with increase in the slope of reduction in risk-cost at the point of inflection values for the case where the risk mitigation budget is equal to the total risk-cost (see Figure 5.8). When the risk mitigation budget is equal to one-half of the total risk-cost, the decrease in earthquake risk mitigation budget with increasing slope of reduction in risk-cost at the point of inflection is stepwise initially and gets smoother for a slope of reduction in risk-cost at the point of inflection of greater than 3.0 (see Figure 5.9). In both budget scenarios, the earthquake risk mitigation budget for a marginal return on investment threshold of 5% above the mitigation investment is equal to or greater than the earthquake risk mitigation budget for a marginal return on investment threshold of 10% above the mitigation investment.

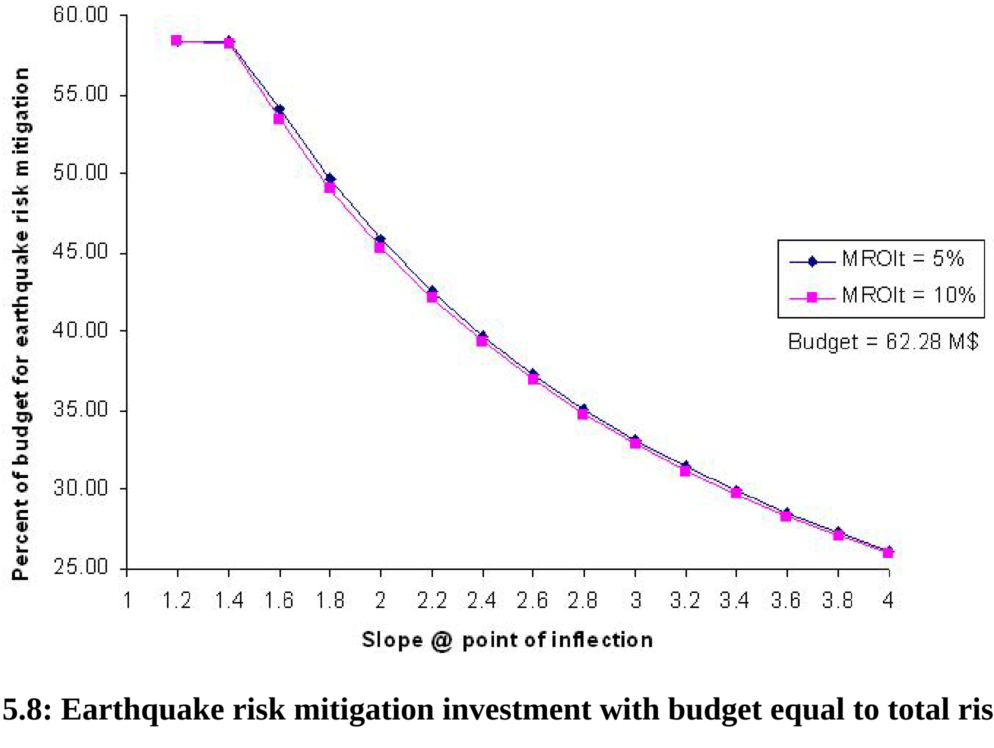


Figure 5.8: Earthquake risk mitigation investment with budget equal to total risk-cost.

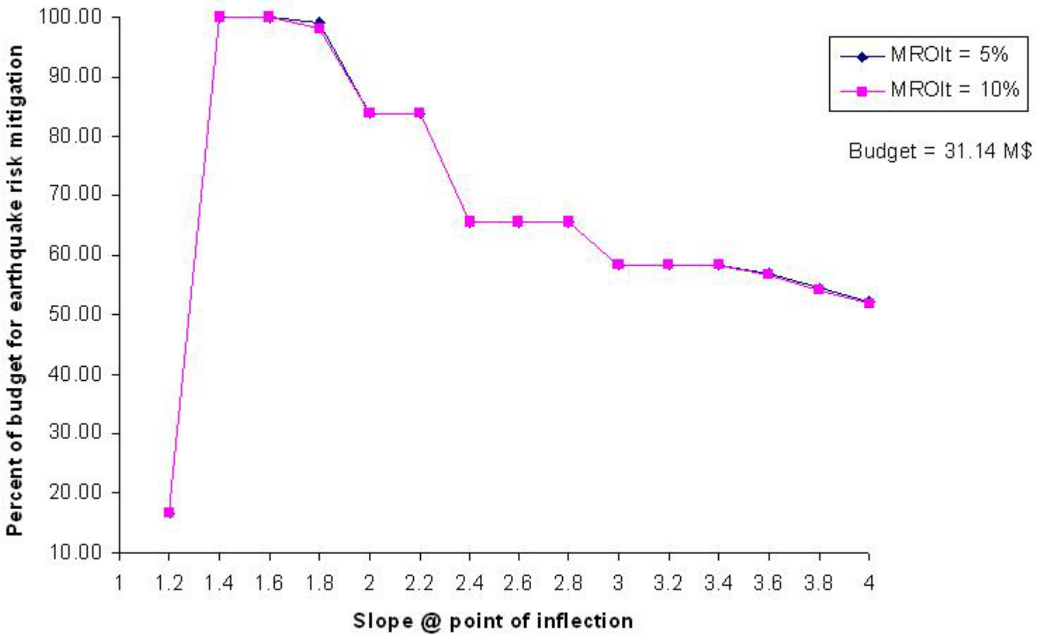


Figure 5.9: Earthquake risk mitigation investment with budget as one-half of total risk-cost.

Varying Slope of Reduction in Risk-Cost at the Point of Inflection

The results for a scenario where the earthquake slope of reduction in risk-cost at the point of inflection is equal to 1.2 are discussed here. As the slope of reduction in risk-cost at the point of inflection increases for hazmat transportation by trucks and terrorism, the reduction in total risk-cost increases for both budget cases (see Figures 5.10 and 5.11). This result is intuitive because a logistic curve with higher slope of reduction in risk-cost at the point of inflection will have a higher growth rate and greater reduction in total risk-cost for the same mitigation investment. Since the reduction in total risk-cost is greater when the budget is larger and, depending on the effectiveness of mitigation investment in reducing risk-cost, the availability of only limited resources can lead to limited risk reduction opportunity.

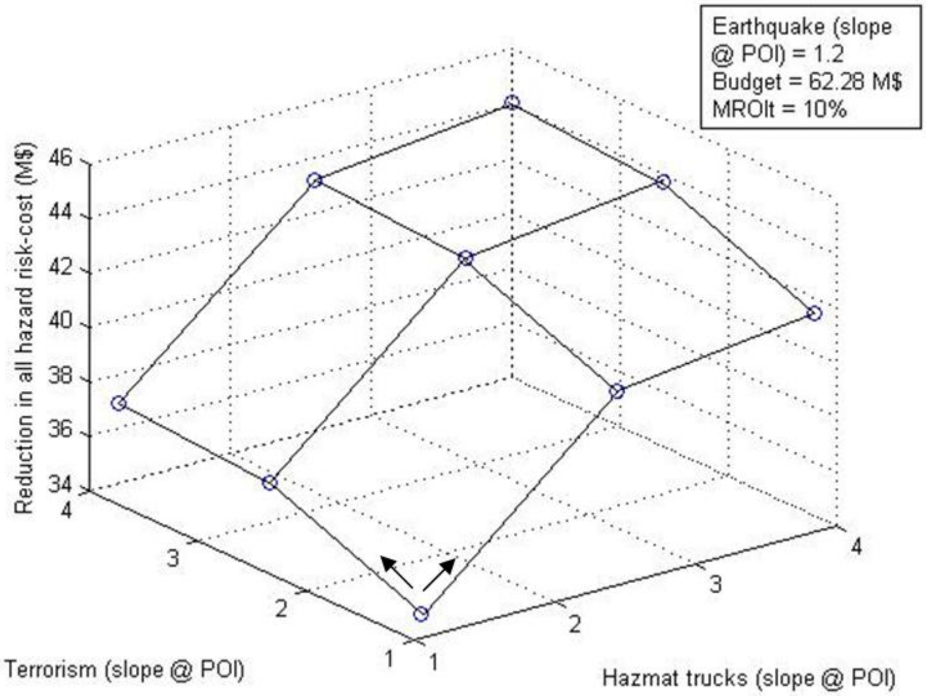


Figure 5.10: Reduction in total risk-cost with budget equal to total risk-cost and varying slope of reduction in risk-cost at the point of inflection.

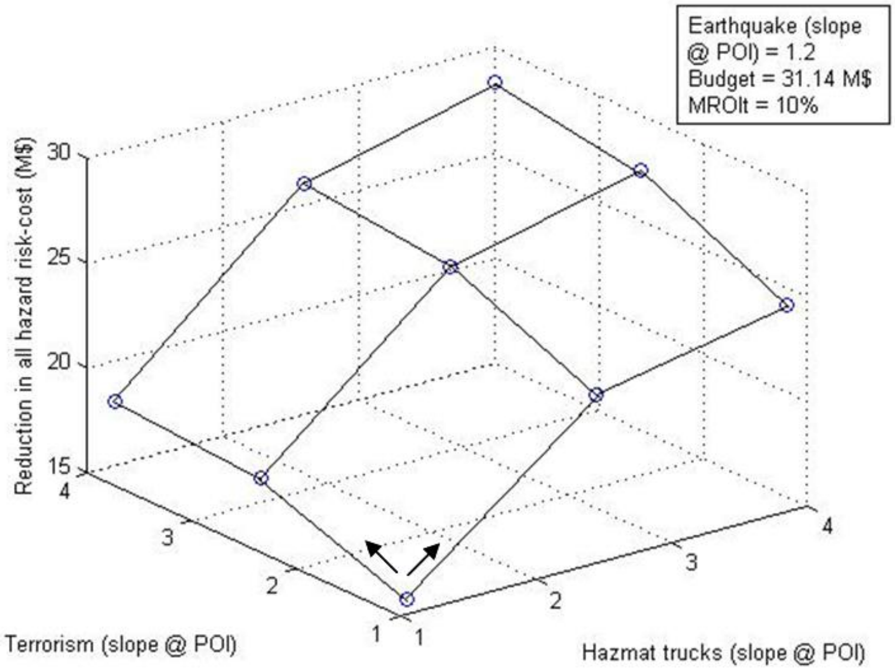


Figure 5.11: Reduction in total risk-cost with budget as one-half of total risk-cost and varying slope of reduction in risk-cost at the point of inflection.

When the budget is equal to the total risk-cost, the portion of the budget allotted for risk mitigation decreases as the slope of reduction in risk-cost at the point of inflection increases for hazmat transportation by trucks and terrorism. This result is intuitive because logistic curves with a higher slope of reduction in risk-cost at the point of inflection have higher growth rates and lower values of investment upper bounds (see Figure 5.12). This indicates that, depending on the effectiveness of mitigation investment in reducing risk-cost, spending an entire mitigation budget is not justified if available mitigation strategies do not provide a threshold return on investment. For the case where the earthquake slope of reduction in risk-cost at the point of inflection is equal to 1.2, the budget used for risk mitigation stays above one-half of the total risk-cost, resulting in the entire budget being used for total risk mitigation in the case where the budget is equal to one-half of the total risk-cost.

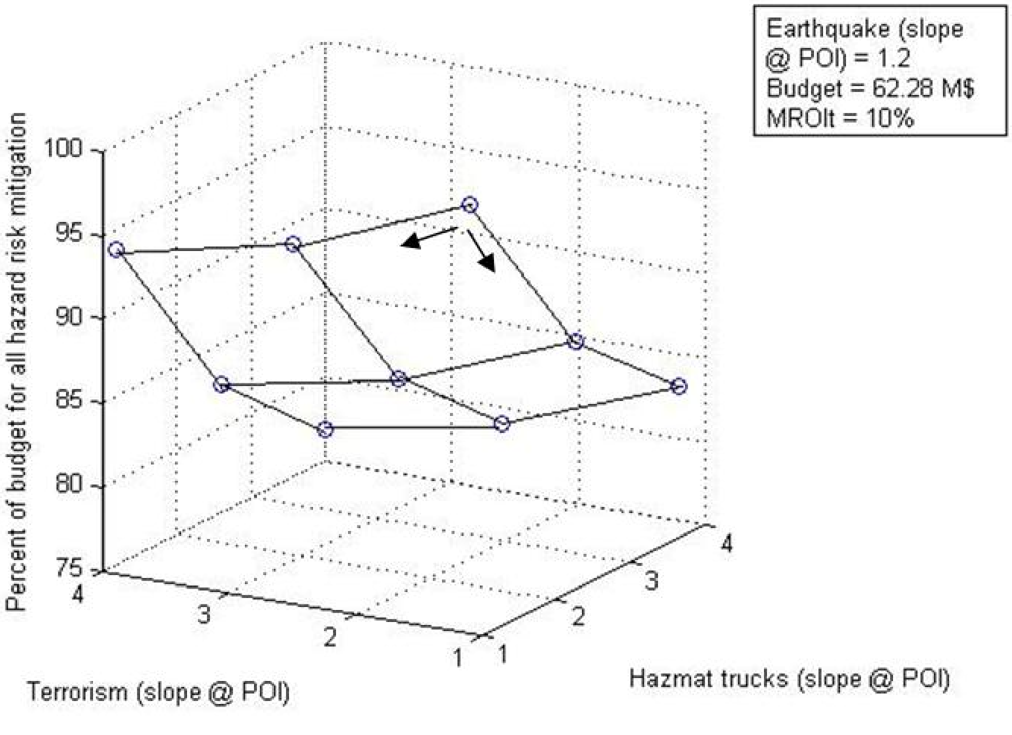
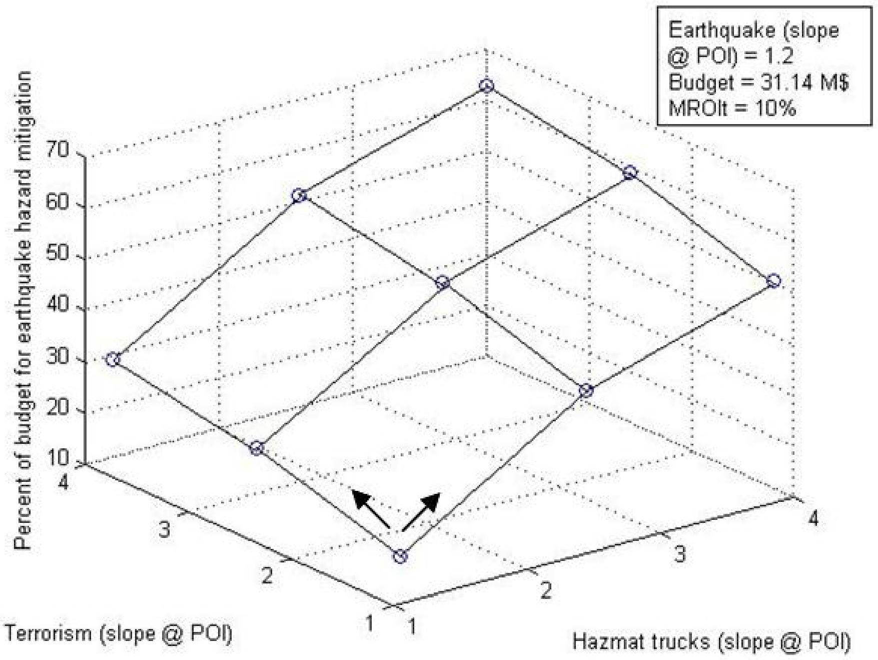
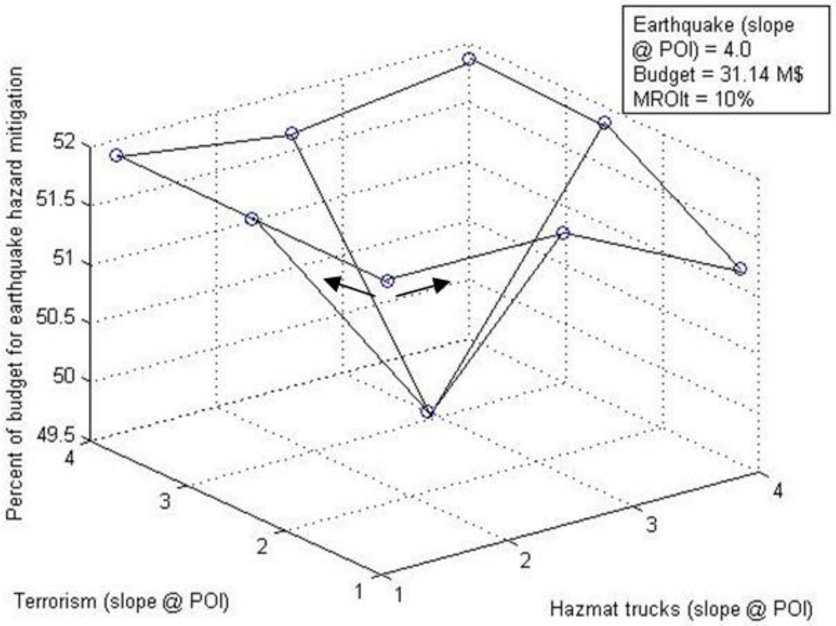


Figure 5.12: Investment for total risk mitigation with budget equal to total risk-cost and varying slope of reduction in risk-cost at the point of inflection.

Proportions of the budget allotted for risk mitigation were computed for all three hazards. The results for earthquake risk mitigation are discussed here. When the budget is equal to the total risk-cost and the earthquake slope of reduction in risk-cost at the point of inflection is equal to 1.2, 58.3% of budget is allotted for earthquake risk mitigation with varying slope of reduction in risk-cost at the point of inflection values for other hazards. When the budget is one-half of the total risk-cost, the percent of budget allocated to earthquake risk mitigation increases with increase in slope of reduction in risk-cost at the point of inflection values for the other hazards, only when the earthquake slope of reduction in risk-cost at the point of inflection is low (see Figure 5.13a). When the budget is one-half of the total risk-cost, its value falls below the earthquake risk-cost. Also, increasing values of earthquake slope of reduction in risk-cost at the point of inflection leads to logistic curves with higher growth rates of reduction in risk-cost. The combined effect of low budget and high growth rates of reduction in risk-cost can cause rapid variations in percent of budget for earthquake risk mitigation (see Figure 5.13b).



(a) Earthquake slope of reduction in risk-cost at the point of inflection equal to 1.2



(b) Earthquake slope of reduction in risk-cost at the point of inflection equal to 4.0

Figure 5.13: Earthquake risk mitigation budget with budget as one-half of total risk-cost and varying slope of reduction in risk-cost at the point of inflection.

CHAPTER VI

CONCLUSIONS AND FURTHER RESEARCH

This dissertation has focused on the development of an all-hazards operational risk management approach. This research was motivated by the occurrences of catastrophic events over the past decade and the realization that there is a need for developing a comprehensive (all-hazards) risk assessment and management framework. The ultimate goal is to achieve an AHRM approach that can lead to successful investment in risk mitigation strategies, by focusing attention on the most important risks threatening a region of interest and the risk reduction potential of various mitigation strategies, whether applied by a government or industry entity.

This research effort began with a review of all-hazards risk management methods and practices. The described AHRM methodology and its subsequent case study application represented a preliminary step towards development of a more comprehensive and systematic approach to analyzing societal risks due to multiple hazards. As a starting point, the application was limited to evaluating the risk-cost of earthquake and truck hazmat transportation hazards in three counties within the State of Tennessee. The proof of concept study demonstrates the potential of implementing a holistic and systematic framework for analyzing risks due to multiple hazards.

Continuing this effort, a regional terrorism risk assessment model was developed by adopting a stepwise regression approach, incorporating the effects of population concentration and critical infrastructure on the risk from terrorism. The model produced statistically significant results in terms of overall goodness of fit as well as the explanatory power of the independent variables, both individually and jointly. The model utilizes readily available data, as demonstrated in a case study application.

The aforementioned effort also emphasized the need to develop formal procedures for solving the resource allocation problem as it relates to investment in risk mitigation strategies. The apportionment of resources depends on the cost-effectiveness of risk mitigation measures that might be applied in each region of interest. Resource allocation for risk mitigation is an optimization problem where the objective is to maximize the overall risk-cost reduction subject to constraints arising from the functional relationships between the investment and the return on investment (risk-cost reduction) for each risk in each region of interest. Other constraints include the available risk mitigation budget, as well as any requirements to spend a minimum amount of mitigation funds on designated risks. Examples of mitigation strategies are investments in infrastructure maintenance or rehabilitation, law enforcement technology or training, emergency response preparedness, and public education and awareness.

In practice, any of the mitigation measures or a combination of them may contribute towards reducing risk from one or more hazards. Moreover, the success of any particular strategy may be highly dependent on the size of the investment. The lack of a critical level of funding may lead to only marginal improvement in risk-cost. Conversely, too large an investment may lead to diminishing risk-cost return, such that the extra resources may be more wisely spent on other mitigation strategies. The risk manager will need to define the functional relationship between the level of investment in each mitigation strategy and its return on investment for different risks facing the region of interest.

The all-hazards mitigation resource allocation problem was formulated and applied in a case study involving three hazards and three regions of interest. A logistic function was defined to explain the functional relationship between risk mitigation investment and reduction in risk-cost. Risk mitigation resource allocation was defined as a deterministic, nonlinear optimization problem where the objective is to maximize the overall reduction in risk-cost subject to a mitigation budget constraint and risk mitigation return on investment bounds. Using this approach, optimal resource allocation strategies for varying budget levels (equal to and one-half of total risk-cost) were considered in the case study. Depending on the effectiveness of mitigation investment in reducing risk-cost, the availability of limited resources can lead to limited risk reduction opportunity; spending an entire mitigation budget is also not justified if available mitigation strategies do not provide a threshold return on investment.

Development of an all-hazards risk mitigation resource allocation problem represents a meaningful screening-level step in supporting a comprehensive risk management approach. This can lead to more effective resource allocation and policy decisions, by investing in risk mitigation strategies for the most important hazards threatening a region of interest, while taking into consideration the effectiveness of various risk reduction strategies.

From a practical standpoint, an AHRM methodology when applied to a region of interest would begin with the identification of the most important hazards based on historical and potential for future occurrence. The next step would involve the assessment of disaster risk-costs to establish the budget parameters for mitigation purposes. Thereafter, based on prior experience and expert opinion of decision makers, a portfolio of logistic curves (explaining mitigation investment effectiveness in reducing disaster risks) would be specified for different disaster risk mitigation alternatives. Based on these logistic curves, different all-hazards risk mitigation resource allocation optimization problems would be formulated and evaluated. Optimal solutions to the risk mitigation resource allocation problems would help prioritize among hazards and provide mitigation resource allocation guidelines based on the effectiveness of various risk reduction strategies, thereby serving as a means for making more effective policy decisions. It is hoped that the results of this research can help advance the adoption of an all-hazards approach to risk management, by motivating more effective resource allocation and policy decisions.

To advance the AHRM methodology from a screening to a more comprehensive risk management tool, further research steps are needed. This could include introducing uncertainty in the risk-cost estimates (or data), introducing uncertainty in the risk mitigation logistic model, introducing uncertainty in formulating the resource allocation optimization problem, accounting for effects of correlation regarding the risk-cost reduction potential of different mitigation strategies, development of resource allocation strategies over extended time periods, and incorporating other types of natural hazards, man-made accidents, and intentional acts into the AHRM decision framework.

APPENDIX A

MATLAB CODE

opt.m (MATLAB M-file)

```
% deterministic nonlinear optimization for all-hazards resource allocation

% data preparation
M = [0.79; 1.82; 8.81E-3];
R_LL = M*0.01;
s= [4; 4; 4];
t= 1.1;
r = M.\(s*4);
I_LL = zeros(3,1);
R_UL = (M + sqrt(M.^2 - (r.\(M*4*t))))/2;
I_UL = r.\(-log((R_UL.*(M-R_LL)).\(R_LL.*(M-R_UL))));

%optimization
A = [1 1 1];
b = [1.309405];
bfo=zeros(1,8);
u = min(M(1),I_UL(1));
u_new = min(b,u);
v = min(M(2),I_UL(2));
v_new = min(b,v);
w = min(M(3),I_UL(3));
w_new = min(b,w);
I_ULuse = [u_new; v_new; w_new];
for e=0:u_new*0.1:u_new
   for h=0:v_new*0.1:v_new
      for te=0:w_new*0.1:w_new
         x0 = [e; h; te];
         [x,fval,exitflag,output]= fmincon(@myfun,x0,A,b,[],[],I_LL,I_ULuse);
         computation = struct2cell(output);
         iterations = cell2mat(computation(1));
         fncalls = cell2mat(computation(2));
         bfo = [bfo; [-fval (x(1)*100)/b (x(2)*100)/b (x(3)*100)/b sum(x) exitflag iterations
                  fncalls]];
      end
   end
end
[c d]=size(bfo);
```

```
bfo=bfo(2:c,:);
bfo=sortrows(bfo,1);

% check with optimal solution as initial guess
e_check = (bfo(end,2)*b)/100;
h_check = (bfo(end,3)*b)/100;
t_check = (bfo(end,4)*b)/100;
x0_check = [e_check; h_check; t_check];
[x,fval,exitflag,output] = fmincon(@myfun,x0_check,A,b,[],[],I_LL,I_ULuse);
computation = struct2cell(output);
iterations = cell2mat(computation(1));
fncalls = cell2mat(computation(2));
bfo_check = zeros(1,8);
bfo_check = [bfo_check; [-fval (x(1)*100)/b (x(2)*100)/b (x(3)*100)/b sum(x) exitflag iterations
fncalls]];
bfo_check= bfo_check(2,:);
```

myfun.m (MATLAB M-file)

```
% calculation of objective function
function f = myfun(x)
M = [0.79; 1.82; 8.81E-3];
R_LL = M*0.01;
s= [4; 4; 4];
r = M.\(s*4);
f = -sum((exp(-r.*x).*(M-R_LL)+ R_LL).\(M.*R_LL));
```

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