Retentive Input-Output Modeling of Complex Systems of Systems for Disaster Planning

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A Thesis

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by

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APPROVAL SHEET

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Abstract:

This thesis develops a methodology to quantify the potential economic and social effects of storm events exacerbated by sea-level rise as a disruptive event. Further, the elements of the infrastructure system of systems, which are most vulnerable to this event, are identified as candidates for investment in its hardening. The existing literature on disaster planning has successfully described the associated cost of not-hardening infrastructure. However, it does not support planners who would wish to compare the risk profiles of alternative investment strategies. This research fills this vital gap by providing a framework to evaluate the tradeoffs that exist among alternative plans. It quantifies the impact of sea-level rise on the southern coastal region of the United States. Sea-level rise has already been observed and is negatively impacting the U.S. economy. Rising seas increase the risk of flooding and wave damage to coastal property. A holistic consideration of the impact of this damage includes many social as well as economic factors, such as temporary displacement, traumatization, particularly of children, disruptions to healthcare, loss of education while schools are closed, or loss of family heirlooms and photographs. For the purpose of this research, we focus on the cascading economic impact of production disruptions. Estimates of increasing sea-level rise and severity of storms are the basis for creating scenarios that communities may face in the future. As infrastructure systems are highly integrated both economically and socially, this analysis considers the interconnectedness and interdependence manifested in the transportation sector as a complex system of systems. Disruption to investment priorities is demonstrated to result from lack of consideration of latent rail transportation network capacity.

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1 Introduction

Three tenths of a meter sea-level rise which has occurred in the past few centuries, is already damaging the reliability and capacity of the US transportation sector (Schwartz 2014). An additional rise of two meters within the next 50 years is considered reasonable. Effectively deploying resources would mitigate the economic damage that will promulgate from this additional sea-level rise requires consideration of the interdependencies and interconnectedness (I-I) of critical infrastructure. The I-I can be characterized through the shared states and essential entities including, decisions, decision-makers, resources, stakeholders, organization, and goals among others (Haimes 2019).

Models that fail to consider the I-I among the subsystems would be unable to capture the impacts of decisions made on one subsystem affecting other interdependent and interconnected subsystems; thus, they would also fail to uncover the intricate complex interdependencies and causal relationships of the economy.

2 The Transportation Sector and Inoperability

Under each proposed scenario of sea-level rise, a degree of transportation inoperability is estimated. This is then used to model the cascading impact from the affected transportation sector to the supply chain, which is the backbone of the global economy. The inoperability is then used as input to the Inoperability Input-Output Model (IIM) which can provide an estimate of the economic damage under each scenario (Haimes et al. 2005). With these results I quantify the value of mitigating climate change and consider the risk to infrastructure, from future sea-level rise. The purpose of this analysis is for these scenarios to provide a disaggregated estimate of the benefits, or utility, that alternative investment plans would provide to the concerned community or business.

The transportation sector within the scope of this thesis consists of critical infrastructure elements, such as bridges or coastal highway segments. NIST (2016) discusses that inoperability of highways caused by flooding can be adequately modeled by considering only the bridges, which are key points of failure. The interdependencies and interconnectedness (I-I) among transportation and the supply chain network Houston is modeled.

Sea-level rise introduces a long-term risk of nuisance flooding, which is low magnitude regular or persistent flooding, of infrastructure and private property near sea-level. The time-scale for nuisance flooding is continuous over decades and relative risk can be interpreted from updated and forecasted flood maps. However, the risk of catastrophic flooding due to storm events is also increased by sea-level rise. The ability of sea-walls and natural structures such as marshes to blunt wave damage and absorb storm surge are diminished. This risk is introduced on an event basis and is much more difficult to model. Thus, I focus on understanding the change in risk that sea-level rise will introduce in extreme weather events.

3 Literature Review

Extensive research has been conducted to understand the potential magnitude and variability effects of sea level rise on both local and global scales (Mitchum 2017). Risk from sea-level rise has been assessed for individual transportation network components, such as railroads (Dawson 2016) and highways (Demirel 2015). The management of supply chains has been an area of great research in the past decades (Christopher 2016). Potential methods to manage supply chain disruptions have also been a focus of research (Snyder 2016). A method to model the economic impact of disruptions to specific economic sectors has been developed with specific applications to Department of Homeland Security (DHS) defined critical infrastructure sectors researched by (Chopra 2015). Combining these fields of study to understand the economic impact of sea-level rise should be of interest to each of the fields represented as the results will significantly increase the direct impact of their own research.

4 Methodology

This research will focus on a case study of the Gulf Coast region. The first step is to create scenarios for sea-level rise. Scenario analysis is necessary as there is uncertainty about the potential state of sea-level rise, which is dependent upon international cooperation, and is beyond the scope of this research. These scenarios are then used as disruptive events to the transportation network using flood maps. The next step, as shown in Figure 1, is to model the disruptions to the transportation sector, which will occur as a result of this potential flooding.

These disruptions are represented as inoperability within the economy with the final financial impact of sea level rise being estimated using IIM. Finally, the contribution of specific transportation infrastructure entities, such as bridges, to economic resilience to flooding events caused by sea-level rise, is assessed. This is accomplished by exhaustively pairing bridges from the list of infrastructure improvement proposals and reassessing the economic impact. As bridges are added in order of greatest change to system resilience and measured in avoided economic loss, the methodology provides a conservative estimate for the value of hardening a specific infrastructure item to a specific flooding threat.

Table 1: Methodology

Modelling Objective	Climate Change	Sea Level Rise	Flooding and Transportation Inoperability	Economic Loss	Future Extension: Human Loss
Modelling Tool	Not Modelled – Beyond Scope	Scenario Analysis	Scenario Analysis	IIM	
Input Data		Reasonable Range of Rise, Degree of International Cooperation, CO_2 Rise	Sea Level Rise, Range of Storm Surge, Failure Estimate Function	Input Output Data from BEA, Mitigation from Retentive IIM	

4.1 Scenario Creation

Climate change will result by 2050 in a large additional rise of sea level. There is epistemic uncertainty surrounding the future actions of countries regarding emissions control and aleatory uncertainty in how the environment will absorb emissions that do occur. Thus, a reasonable point-estimate of long-term sea-level rise would be subject to error as large as 250% (Sweet 2017), and fail to representatively capture the risk of sea-level rise to the transportation sector, supply chain, coastal communities, and the economy. A median estimate of sea-level rise that will be experienced by 2050 is between 1-2m (Mitchum 2017).

This thesis next address the question of how the rise will impact coastal communities. The relationship between sea-level rise and the degree of damage caused to the Gulf Coast is not deterministic, depending on a series of factors such as climate change, weather, local geography, atmospheric state, runoff coefficient, and other human impact. To address these sources of uncertainty we consider four scenarios, the most extreme of which will occur with greater expected frequency as sea-level rise would continue. The selected levels for total transportation sector inoperability are shown in Table 2. Although the selection of scenarios is subjective, it enables the modeler to solicit input from decisionmakers and experts.

Table 2: Scenario Selection

Scenario	**A**	**B**	**C**	**D**
% Inoperability	1	5	10	15
Weeks to Recover	4	6	12	16

4.2 Research Objectives

The key output of this research is a method to consider multiple objectives while planning investment in alternative infrastructure hardening plans. Consider a scenario where federal funds are allocated to a state for mitigating disaster caused failure to infrastructure, the planner would be able to choose among alternative plans on which to spend this money on infrastructure hardening. While it may seem obvious that hardening the bridges with the greatest traffic, or that are nearest the ocean, this would ignore many competing objectives. The planner may also be interested in considering the future state of these objectives, or completely different objectives such as social integration or understanding how development is likely to be affected along the corridor. Metrics for these objectives do not exist in any database and the latter must be modeled. Further, they are not commensurate, thus planners must be able to simultaneously consider the tradeoffs. The methodology provides planners with the ability to rank investment alternatives under such scenarios.

4.3 Input Output Modeling

4.3.1 Traditional Systems Based Input Output Modeling

Inoperability Input-Output Model (IIM) is a method to assess the economic impact of disruptions to net production. It is founded on an inversion of the Leontief I-O model (Haimes 2005). It assumes that the inputs and outputs of each economic sector will be linearly consistent under a disruption. It assumes static economic conditions expressed as below:

$x_j = output\ of\ good\ j,\ j=1,2,\ldots,n$

$r_k = input\ of\ resource\ k,\ k=1,2,\ldots,m$

$x_{ij} = amount\ of\ good\ i\ used\ to\ produce\ good\ j$

$r_{ij} = amount\ of\ resource\ i\ used\ to\ produce\ good\ j$

The assumption of proportionality between input and output is as below:

$$x_{kj} = a_{kj}\, x_j,\quad j,k = 1,2,\ldots,n \tag{1}$$

$$r_{ij} = b_{ij}\, x_j,\quad k = 1, 2, \ldots, m,\ j = 1, 2, \ldots, n \tag{2}$$

Assumes no waste of completed goods

$$x_k = \sum x_{kj} + ck,\quad k = 1, 2, \ldots, n \tag{3}$$

From which the final Leontief equation is derived

$$x_k = \sum a_{kj} x_j + c_k,\quad k = 1, 2, \ldots, n \tag{4}$$

4.3.2 Retentive IIM Model

In this context, retentive is the ability of the model to leverage retained information gathered from previous states of the system. The amount of drift in a sectors inputs and outputs is calculated across time. This change is then assumed to be reversible under the conditions of a long-term disruption. As an intuitive example, consider the various modes of transportation systems. As market prices fluctuate between the cost of rail and truck transportation, it is to be expected that supply chain managers would switch between these modes of transportation as the Pareto-optimal curve between cost and delivery time shifts. Suppose that the American rail system has reached its maximum capacity for carloadings, the industry term for capacity, which is defined as the number of rail cars that are currently loaded with products that are intended for transportation, rail prices would thus increase, making truck transportation more attractive. This would shift transportation demand from the rail to trucks. As this occurs, carloadings will drop.

The Bureau of Economic Analysis data (BEA 2019) used by IIM would assume that this drop in carloadings represents a static change in the capacity of the industry and the relative dependence of the supply chain on the truck over rail transportation. However, when carloadings drop, railroad planners do not immediately respond by removing track, scrapping rolling stock, and laying off workers. Thus, there commonly exists excess capacity of each of these resources within the rail transportation system that is not reflected in the current BEA data, but did exist in past BEA data. The retentive model uses this difference and considers it to be excess capacity that could be used to mitigate some of the disruption caused by bridge failures. By doing so we weaken the dependency of IIM upon the assumption of static conditions and no waste. Excess rail resources are the result of a dynamic economy, and represent wasted capacity. Multiple static models are considered and the system is assumed to perform as it did in the strongest discounted year, which is captured in equations 7 and 8. Modeling excess capacity in this way results in a more realistic, but optimistic (decreased) estimate of the economic loss due to disruptive events. This is consistent with assumptions made throughout the methodology that address uncertainty by considering the less severe result.

To retain information from capacity in past years planners need only look at the BEA data from the desired period. The make-use (A) matrix in equation four is the make-use data generally taken only from the most recently available year. A unique alternative formulation is considered in this methodology creating the retentive I-O model. The existing model is attempting to model economic value, or loss from a sector. The explicit assumption of static economic conditions begets an implicit assumption that demand has been stable resulting in stable capacity. However, demand is not constant and therefore neither is capacity. Capacity is a factor in among other things, infrastructure development and equipment investment. To capture this knowledge, the make-use matrix is replaced with the modified m matrix as below:

$$m_{kj} = \max(z_w \, a_{kjp}), \quad p = 1, 2, \ldots, q \tag{5}$$

Where q is the number of years for which capacity is expected to be retained, and z_w is an industry specific coefficient representing an expected capacity decay rate. The specific case where q=1 is the traditional IIM model. A value of q should be chosen for the specific industries under consideration as the retained capacity of an infrastructure dependent sector, such as freight or rail is expected to be higher than that of sectors less dependent upon infrastructure such as software or other service industries.

5 Demonstration

5.1 Limitations of Empirical Inventory Approach

To motivate the use of a broad scale estimate of economic losses due to bridge collapse, rather than a bridge by bridge inventory-based approach, an analysis of currently available data regarding bridges in the United States is provided below.

5.1.1 Data Availability

The US-DOT Federal Highway Administration (FHWA) freely provides the National Bridge Inventory (US-DOT 1, 2019). The format guidelines published by the FHWA (US-DOT 2, 2019). An inventory of all bridges in Texas was downloaded consisting of 116 attributes for 54,130 structures. Elevation is only provided for bridges crossing a waterway. Future work could include data collection for bridges not over water, but this analysis only considers those bridges crossing water to be the most vulnerable to a storm event. To implement this decision, the data was first filtered by "navigation control" which is labeled "n" if the bridge does not cross water, 0 if no permit is needed to travel below the bridge, and 1 if a permit is needed. Only bridges labeled 0 or 1 were included those labeled n were removed, 44,812 bridges remained. In analyzing this data take care to account for the fact that US-DOT chose not to reserve commas in comma separated data. Next all bridges with a vertical underclearance (the navigable distance between the water surface and the lowest point of the structure) of 0 were removed resulting in 78 remaining bridges. These bridges require a permit to navigate beneath waterways. A value of 0 does not imply that the bridge is at water level, merely that no permit is required to navigate beneath the structure and thus an underclearance is not listed. This analysis could be expanded to consider bridges not requiring a permit if significant resources were dedicated to data gathering. However, this would only alter the hazard function and not the underlying methodology. To select bridges from coastal counties, the final filtering step is to retain those bridges in a coastal county as coded by the Federal Information Processing Standards (FIPS) defined by the Census Bureau (2019) this resulted in a list of 26 bridges which are analyzed below.

5.1.2 Analysis

An empirical hazard function was estimated using the following formula where p(m) is the cumulative failure rate as a function of m, the meters of flooding experienced, xi is the navigable vertical underclearance of bridge i, and n is the total number of bridges. This can be intuitively understood as the negative fraction of bridges that fail as a result of floodwater inundation.

$$p(m) = \frac{1}{n}\sum_{i=1}^{n} min\left(0, \frac{m - x_i}{|m - x_i|}\right) \tag{6}$$

This was replicated for a continuous series of hypothetical floods incrementing by one meter. The resulting values of p are shown in Fig 1.

The graph demonstrates that transportation infrastructure is generally built to withstand minor disturbances, of up to five meters flooding in this particular dataset. As would be expected there is a plateau followed by a relatively sharp uptick in failure between five and seven meters. Another relatively stable state between eight and fourteen meters follows, then another sharp increase in failure. The pattern repeats itself once more in the ranges seventeen to twenty-three and twenty-three to twenty-five respectively. This suggests that once a threshold of flooding is met significant flooding will occur, and a relatively minor increase in sea-level could significantly decrease this threshold. The structure of plateau followed by spike was expected to be observed, but only once rather than the three cycles demonstrated in the data. This may suggest that after the initial threshold is exceeded another stable state with nuisance flooding would be observed, but the set of bridges analyzed was somewhat small so the repeating pattern could be interpreted as an artifact.

As the bridges in this database were only those requiring a permit to navigate beneath, the majority of bridges relevant for transportation operability could not be included. As these bridges are: more numerous, expected to have lower underclearance, and thus higher risk of exposure to flooding; the empirical inventory approach is insufficient for planning purposes.

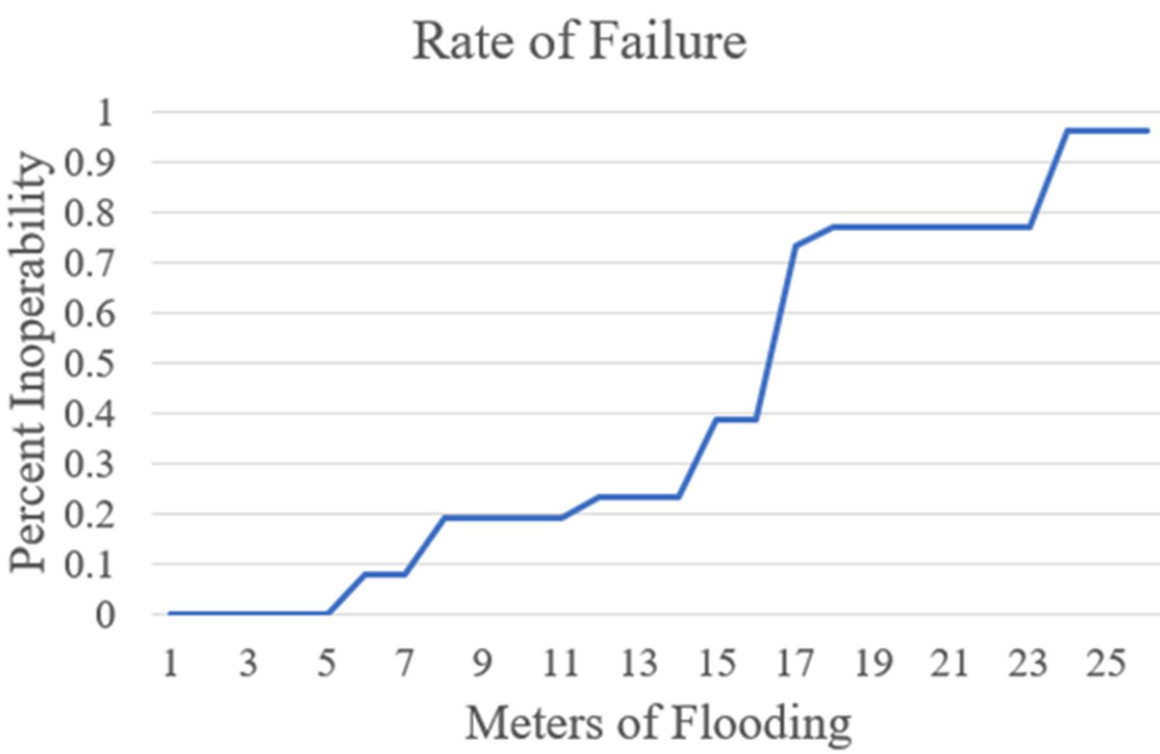

Fig 1: Demonstration of Bridge Failure Rate Using Empirical Data

5.2 Input-Output Approach

Data was collected from BEA.gov for the most recently available year (2017) as well as the two previous years. Since the defined sectors were not consistent throughout the period, the impact of these sectors was removed. The economic damage estimate for each scenario using the traditional IIM approach is summarized in Fig. 2, with a breakdown by sector in Fig. 3.

This demonstrates the key relationship that the timeframe takes as the impacts are not linear as would be predicted if it had not been assumed that more significant damage will require more time to remediate. The most inoperable sectors are shown in Fig. 4.

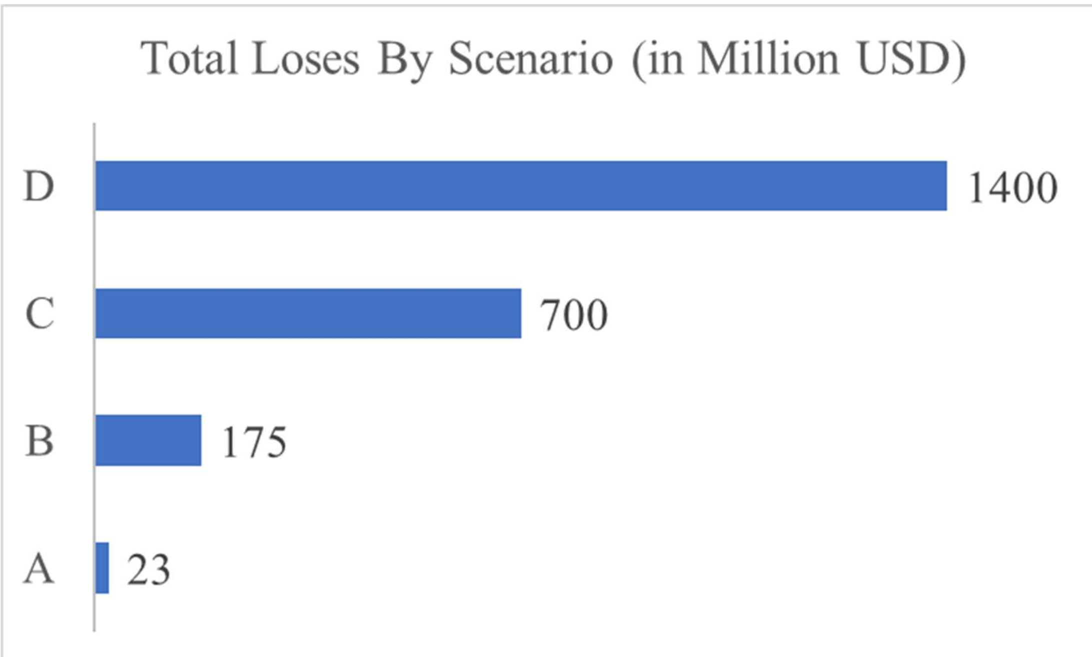

Fig 2: Economic Loss by Scenario

Note that in both Fig. 3 and Fig. 4, the sectors most significantly impacted both as percent inoperability and associated economic loss are related to the petroleum industry. As the results from IIM are for a nationwide inoperability of the selected scenarios, all economic results were scaled to the ratio of Houston to U.S. GDP as reported by BEA. For the purposes of this case study, the linear scaling across sectors is sufficient to demonstrate the approach, though local transportation planners are encouraged to purchase access to the BEA regional multipliers database to scale results to the region under analysis. This will yield results more tailored to the regional economic conditions and unique vulnerabilities that result (Crowther and Haimes, 2009). It is important to note that the IIM does effectively capture the economic damage experienced due to loss of productivity, but it does not model the cost to replace damaged infrastructure. Thus, for planning purposes the estimates provided should be considered to be optimistic regarding the true cost of damages.

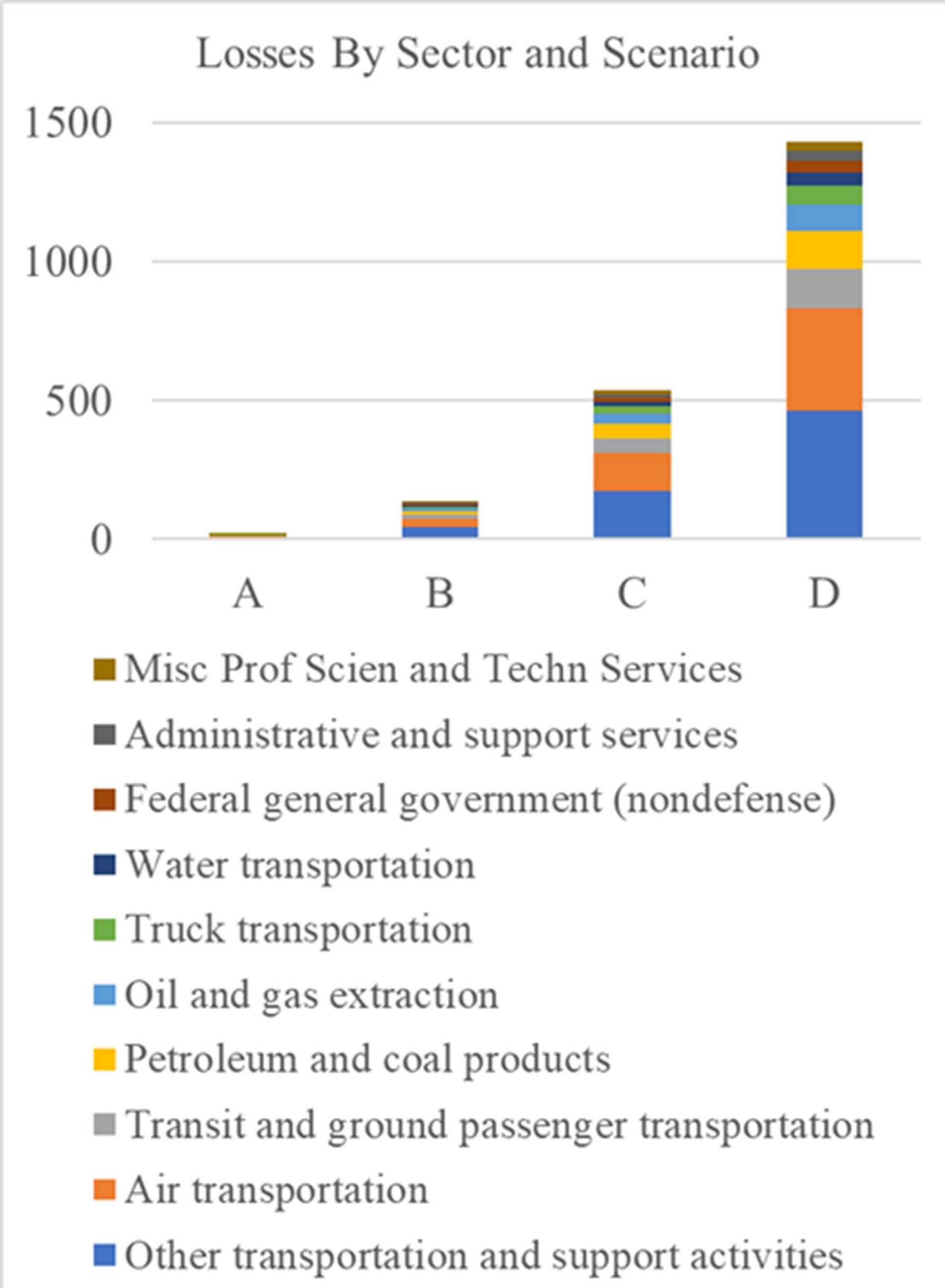

Fig 3: Losses by Sector Categories as Defined by (BEA 2019)

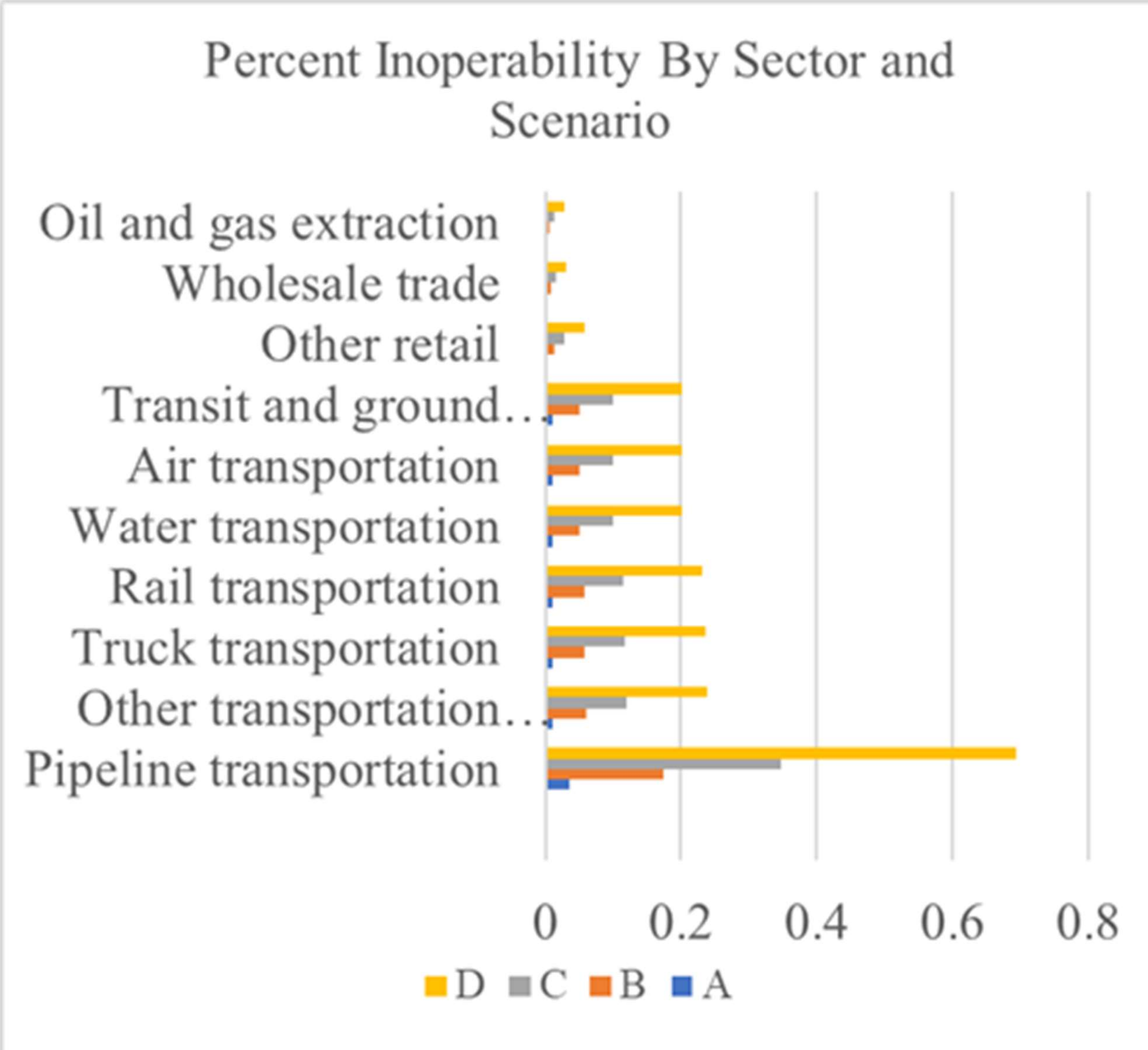

Fig 4: Inoperability Categories as Defined by (BEA 2019)

5.3 Retentive Input-Output Approach

5.3.1 Application to Scenario Analysis

The previous results were calculated using the same value for inoperability as a result of infrastructure damage. This analysis demonstrates the change in results due to latent capacity in rail transportation as a demonstration. While it would not be appropriate for all parts of the economy, a similar analysis could be carried out sector by sector. Each vector in the make matrix (V) is adjusted to account for the latent capacity present in a given sector. There are many justifiable formulaic scaling approaches and the appropriate one must be selected for the given industry, considering: performance, appropriateness to economic sector, and risk acceptance of the decision makers. For this demonstration it was assumed that a decrease in rail demand would result in a linear loss of at most five percent per year as shown in equations 7 and 8 for the appropriate row and column vectors respectively. Where i and j are the relevant sectors and x is the year under consideration.

$$v_{xij} = \max(v_{1ij}, 0.95v_{2ij}, 0.9025v_{3ij}) \quad (7)$$

$$v_{xij} = \max(v_{1ji}, 0.95v_{2ji}, 0.9025v_{3ji}) \quad (8)$$

For this example, a time period of three years was considered. As the BEA data is not reported in a consistent format year after year care must be taken to assure the correct elements are being compared across years. The largest sum change in either of these vectors is the excess latent capacity which is this case is approximately 1.7%. This excess capacity currently out of use is then subtracted from the inoperability of the rail transportation system under each scenario as above and the results are compared. As expected, given the small percent of retained capacity, the total economic loss projections are only slightly lower using RIIM than the traditional IIM method and thus there is not a significant alteration in value to mitigate the disruptive threat as shown in Fig. 5.

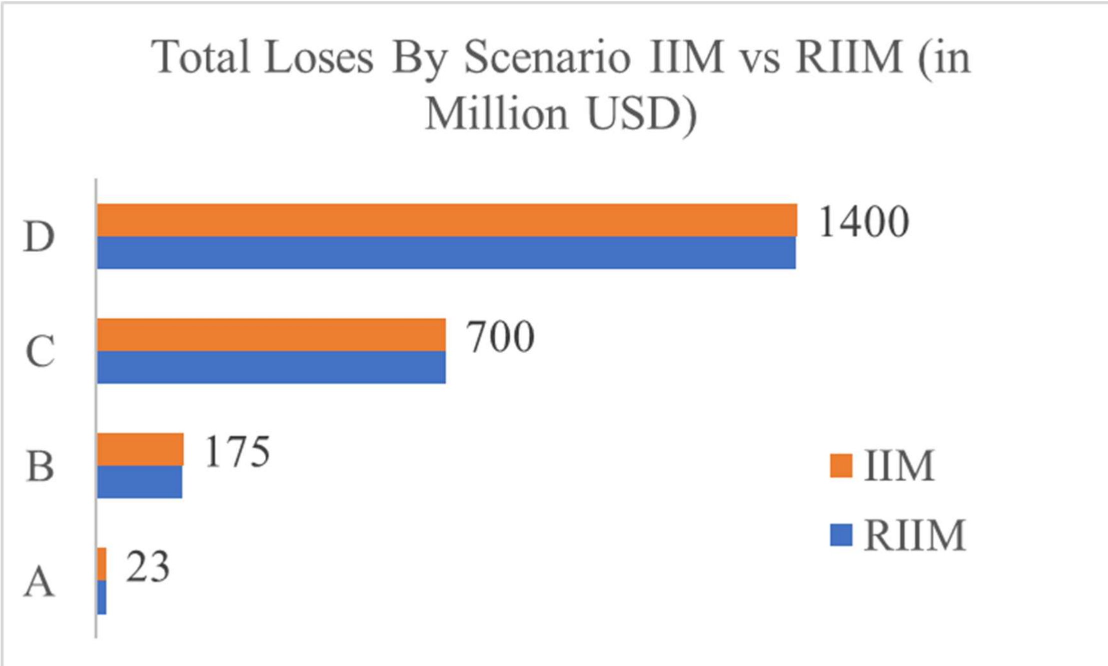

Fig. 5: Comparison of Methods for Estimating Loss

While the budget is thus likely to remain similar, when one investigates the ranking of inoperability by sector it becomes clear that the recommended allocation of this budget is significantly altered. As can be seen in Figure 6, traditional IIM overstates the value of investments that harden rail infrastructure. Conversely air transportation is underemphasized along with a number of other sectors to a lesser degree.

Note that if the rank of a sector was unchanged between solution methods the IIM marker is suppressed in the chart. The rightmost two sectors were the tenth ranked by each method with each dropping out of the top ten when the alternative calculation was employed. In both methods the sector rankings were stable between each of the four scenarios.

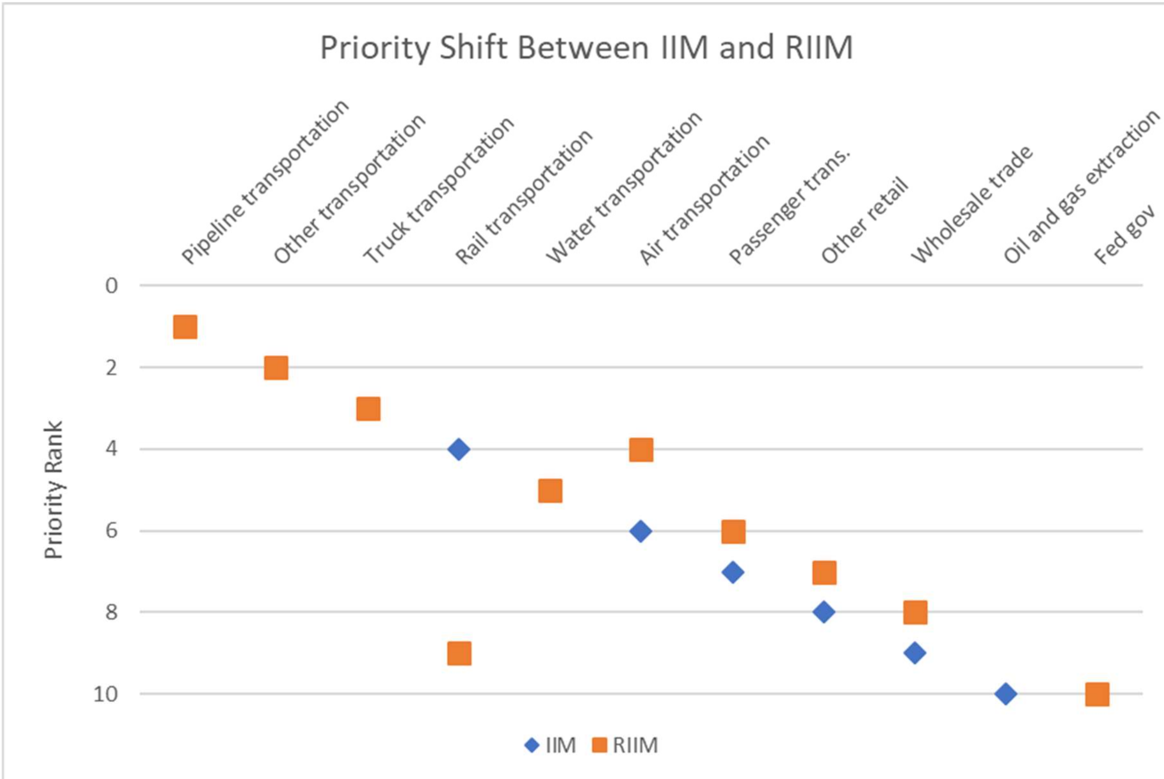

Fig.6: Ranking of sectors using IIM and RIIM

5.3.2 Application to Selecting Among Five Proposed Bridge Hardening Projects

Here I demonstrate the application of RIIM to a hypothetical decision being made by planners for the Texas DOT. A budget of 40 million USD has been set to be allocated for projects that would harden Houston's coastal infrastructure to sea-level rise. After initial screening five projects remain. For each project an estimate of total benefits has been calculated tabulated in Table 3.

Table 3: Cost Benefit Analysis of Proposed Hardening Projects

Bridge	1	2	3	4	5
Benefit (million $)	15	23	8	17	4
Cost (million $)	14	20	4	12	6
B/C Ratio	1.07	1.15	2	1.42	0.67

5.3.2.1 Basic Approach Uninformed by RIIM

The formulation and weighting of components of benefit is specific to any agency that would perform such analysis as well as federal and local legislative regulation and is thus beyond the scope of this research. Projects are ranked by marginal benefit to cost ratio (b/c) and selected in order until the budget is met (Meyer and Miller, 2001). Generally, projects with a b/c below one would be screened out of consideration. The selection algorithm is demonstrated step by step in Table 4, with the final step resulting in a negative remaining budget and thus only bridges 3,4, and 2 are funded.

Table 4a: Marginal B/C

Bridge	1	4	5	3
2	1.33	0.75	1.36	0.94
1		-1.00	1.38	0.70
4			2.17	1.13
5				-2.00

Table 4b: Selection Algorithm

Algorithmic Step	Bridge Selection	Remaining Budget
Column With All alternatives < 1	4	34
Colum With All Alternatives < 1 Excluding Previous Selection	3	30
Lowest Remaining Marginal B/C (Not Shown, Marginal B/C of 2 With Itself is 1	2	10
Lowest Remaining Marginal B/C	1	-4
Lowest Remaining Marginal B/C		

As the intent of this project was to harden the transportation system to sea-level rise the pervious analysis is lacking. An objective to minimize cost of bridge failure was not included. To do so a multiple objective scenario must be considered.

5.3.2.2 RIIM Informed Approach

The hypothetical impact of each bridge becoming inaccessible to the local transportation networks is reported in Table 5. Such data could be modeled using transportation flow models to demonstrate capacity loss or delay.

Table 5: Transportation Sector Inoperability Resulting from Failure of Individual Bridge

Bridge	1	2	3	4	5
Air	0.03	0.1	0.01	0.02	0.02
Rail	0	0.01	0.08	0.1	0.04
Water	0.01	0	0.04	0	0
Truck	0.05	0.09	0.01	0.04	0.02
Transit	0	0.05	0.03	0.01	0.09
Oil Pipelines	0.01	0	0	0.04	0.01
Other and Support	0.02	0.08	0	0.01	0.04

The above data provides input to the RIIM model which is used to calculate expected losses from failure of each bridge individually and reported in Figure 7. These results are reported in dollars so an argument could be made that they are commensurate to the "benefits" in Table 3 and the next step considers this perspective. Inoperability is assumed to persist for one week, though this could be scaled to assume larger damage considering the risk aversion of the planner.

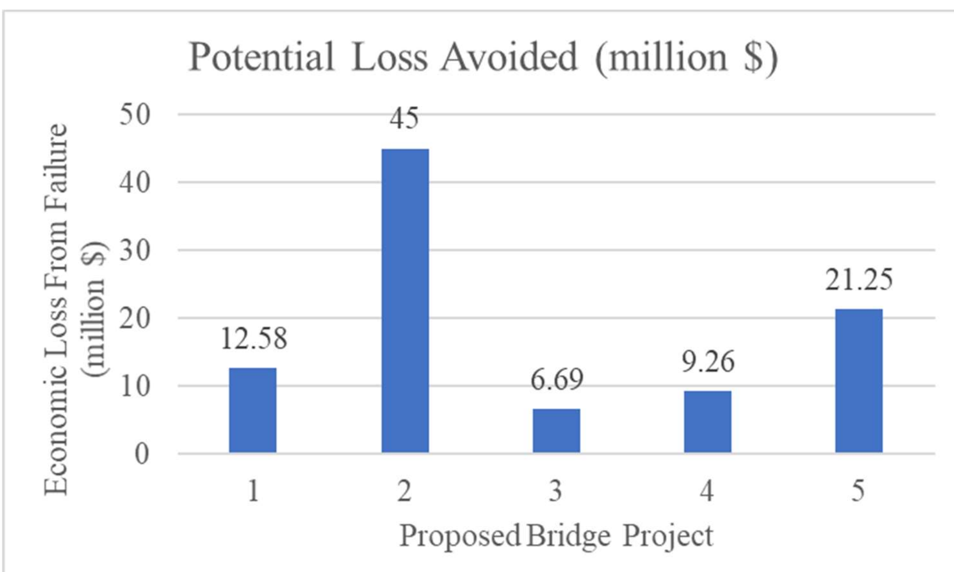

Figure 7: Benefit of Avoiding Loss

5.3.2.2.1 Commensurate Ranking

In this case it is assumed that the benefit of not sustaining economic loss is commensurate to a social benefit as estimated by DOT. These benefits are added to those found in Table 3 and shown in Table 6.

Table 6: Cost Benefit Analysis Updated with Damage Prevention Benefit

Bridge	1	2	3	4	5
Benefit (million $)	27.58	68	14.69	26.26	25.25
Cost (million $)	14	20	4	12	6
B/C Ratio	1.97	3.4	3.67	2.19	4.21

Notice that bridge five now has the highest b/c ratio. This is a manifestation of the interdependence and interconnectedness of the transportation system. The initial analysis did not consider the impacts bridge failure would have on the greater transportation network (sectors other than highway) and thus did not recognize that bridge five was of greater importance than the other bridges in maintaining transportation flow. The same selection algorithm is assumed and demonstrated in Table 7.

Table 7a: Marginal B/C Considering RIIM Results

Bridge	2	1	4	5	3
2		6.73667	5.2175	3.05357	3.33188
1			0.66	0.29125	1.289
4				0.16833	1.44625
5					5.28
3					

Table 7b: Marginal B/C RIIM Selection Algorithm

Algorithm Step	Bridge Selection	Remaining Budget
Column With Most Alternatives < 1	5	34
Remaining Bridge With Alternatives < 1	4	22
Marginal B/C of 1	2	2
Lowest Remaining Marginal B/C	3	-2
Lowest Remaining Marginal B/C	1	

Note that bridges four and two were again funded, but project five was selected instead of project three. This demonstrates that a failure to consider the I-I of the transportation network can lead to misallocation of transportation improvement budgets as well as the ability of RIIM to supplement existing planning processes to improve experienced outcomes of infrastructure investment.

5.3.2.2.2 Non-Commensurate Ranking

A universal statement of commensurability cannot be made regarding benefits and avoided losses as calculated by RIIM, as this would depend upon the method used by the relevant DOT to estimate said benefits or the willingness of the public to consider avoided business losses as equivalent to social gains. Thus, in the following section demonstrates the Pareto-optimal approach to selection of projects for funding wherein these benefits are both objectives to be maximized but cannot be considered of equal scale. The results are shown in Figure 8. Bridges five and one are dominated by the other three projects resulting in the same selection as occurred in Table 4. Note that method is equivalent to dragging a ruler from right to left on Figure 8 which just so happened not to be disrupted by the Pareto frontier. The similarity of outcome is an artifact of the data as the two methods are not conceptually or mathematically equivalent.

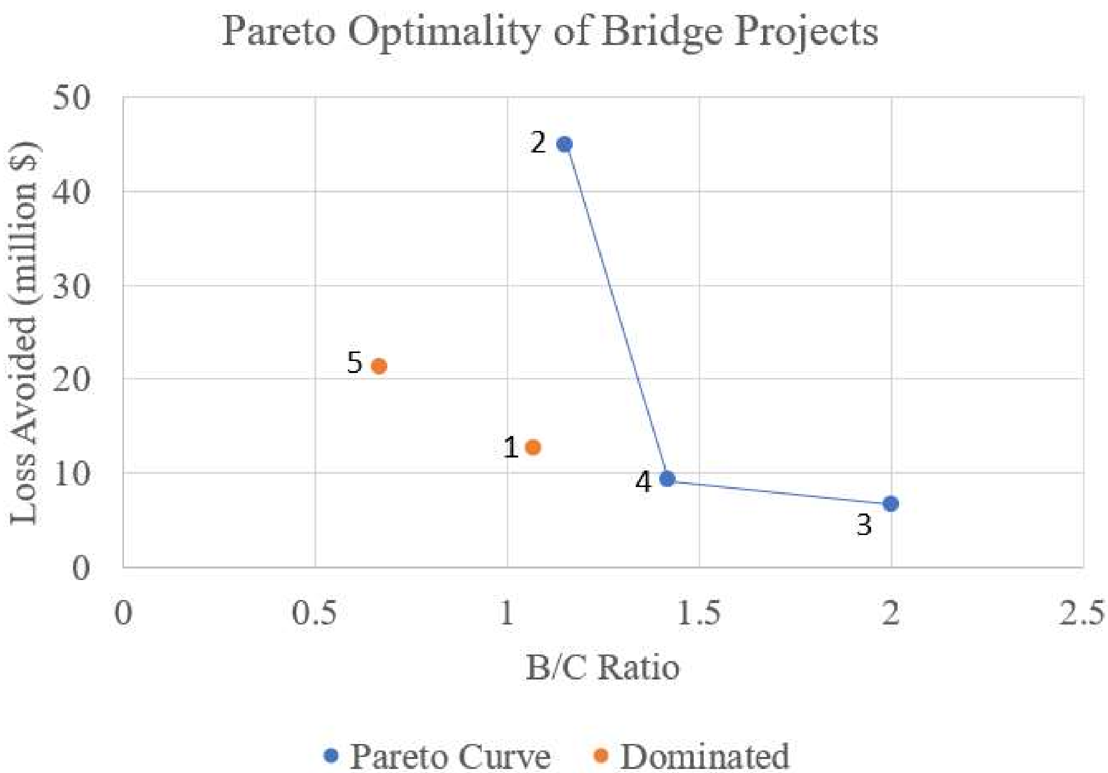

Figure 8: Pareto Curve of Bridge Projects

5.3.2.3 Demonstration of Interdependence Among Five Projects

As it is possible that multiple bridges may become inoperable an analysis of the projects is presented in this section considering the interactions of coupled bridge failure. In a physical transportation system this would require a re-simulation of traffic flow which is beyond the scope of this research; the hypothetical results of such an analysis are shown in Table 8.

This analysis is critical if the planners expected there were any likelihoods of multiple bridges failing. Consider a coastal highway system crossing East-West on the Southern border of Houston. This highway may contain three bridges as shown in Figure 9. As it is a key highway within the transportation network the benefits of hardening any one of these bridges will be high. However, this does not guarantee that all three will be selected. Suppose only bridges A and C are hardened as doing so resulted in the highest b/c ratio.

Table 8: Transportation Network Inoperability Resulting from Coupled Bridge Failures

Coupled Failure	1,2	1,3	1,4	1,5	2,3	2,4	2,5
Air	0.11	0.03	0.03	0.03	0.12	0.1	0.1
Rail	0.01	0.09	0.11	0.05	0.1	0.1	0.04
Water	0.01	0.04	0.01	0.01	0.05	0	0
Truck	0.09	0.05	0.05	0.06	0.11	0.09	0.09
Transit	0.05	0.03	0.01	0.1	0.06	0.05	0.09
Oil Pipelines	0.01	0.01	0.04	0.01	0	0.04	0.01
Other and Support	0.08	0.02	0.02	0.05	0.1	0.08	0.08

	3,4	3,5	4,5	1,2,3	1,2,4	1,2,5	1,3,4
Air	0.02	0.03	0.02	0.13	0.14	0.11	0.04
Rail	0.11	0.11	0.1	0.1	0.14	0.05	0.12
Water	0.04	0.06	0	0.05	0.01	0.01	0.05
Truck	0.04	0.03	0.04	0.12	0.13	0.1	0.06
Transit	0.03	0.13	0.09	0.07	0.07	0.1	0.04
Oil Pipelines	0.04	0.01	0.04	0.01	0.06	0.01	0.05
Other and Support	0.01	0.06	0.04	0.1	0.11	0.09	0.02

Table 8: Continued Transportation Network Inoperability Resulting from Coupled Bridge Failures

Coupled Failure Continued	1,3,5	1,4,5	2,3,4	2,3,5	2,4,5	3,4,5	1,2,3,4
Air	0.03	0.03	0.12	0.15	0.1	0.03	0.14
Rail	0.11	0.11	0.11	0.12	0.1	0.12	0.14
Water	0.06	0.01	0.05	0.06	0	0.06	0.05
Truck	0.06	0.06	0.11	0.14	0.09	0.05	0.13
Transit	0.13	0.1	0.06	0.14	0.09	0.13	0.07
Oil Pipelines	0.01	0.04	0.04	0.02	0.04	0.05	0.06
Other and Support	0.06	0.05	0.1	0.12	0.08	0.06	0.11

	1,2,3,5	1,3,4,5	1,2,4,5	1,2,3,5	2,3,4,5	1,2,3,4,5,
Air	0.15	0.04	0.14	0.15	0.15	0.14
Rail	0.12	0.12	0.14	0.12	0.12	0.14
Water	0.06	0.06	0.01	0.06	0.06	0.06
Truck	0.14	0.06	0.13	0.14	0.14	0.13
Transit	0.14	0.13	0.11	0.14	0.14	0.13
Oil Pipelines	0.02	0.05	0.06	0.02	0.05	0.06
Other and Support	0.12	0.06	0.11	0.12	0.12	0.11

Logically, one might consider the hardening of bridge A to be of limited value given it leads directly to bridge B, which was not hardened, preventing traffic from flowing along the highway between bridges A and C which are expected to remain intact in a storm event. This demonstrates yet another manifestation of the I-I that was not modeled in the single bridge analysis (Table 5). Of course, many of these interdependencies will be far less obvious than the simple example in Figure 9 so a large network would require traffic diversion simulation.

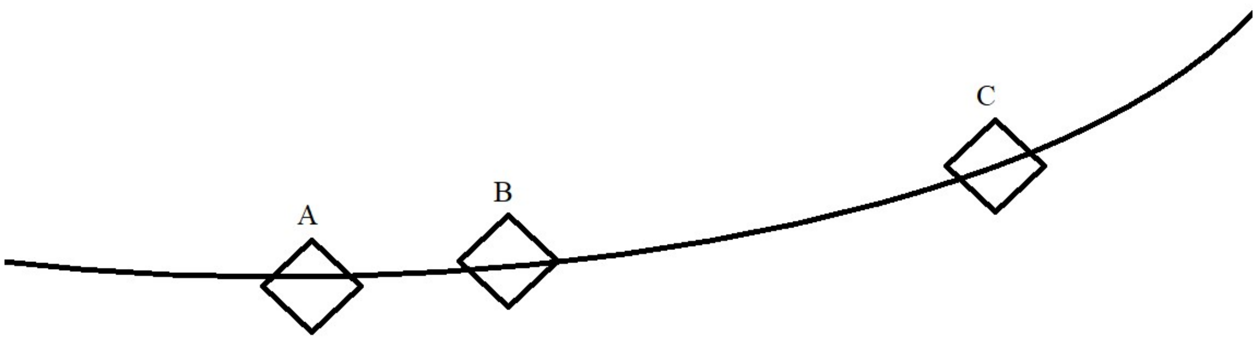

Figure 9: Layout of Hypothetical Highway

5.3.2.3.1 Application of RIIM

Each of the inoperability vectors from Table 8 are an input for one iteration of RIIM. These results, displayed in Table 9, are used to estimate the economic loss that would be avoided by hardening the defined set of bridges. Those combinations resulting in a budget exceedance would be filtered out. It is likely that two different planners and stakeholders would have different tolerances for risk from sea-level rise. One way this would be observed is in their expected timeline for bridges to be repaired. As this operability time curve could be modeled, the expected losses for each set could be adjusted according to the risk tolerance of different decision-makers.

Table 9: Losses Prevented per Week from Paired Investments Costs and Benefits Expressed in Million $

Investement Set	1,2	1,3	1,4	1,5	2,3	2,4	2,5
Economic Loss Avoided	47.63	17.99	15.09	28.28	56.44	47.63	49.32
Benefit	38	23	32	19	31	40	27
Cost	34	18	26	20	24	32	26
Benefit/Cost	1.12	1.28	1.23	0.95	1.29	1.25	1.04
Budget Eceeded	No	No	No	No	No	No	No
Adjusted Benefit	85.63	40.99	47.09	47.28	87.44	87.63	76.32
Adjusted Bemefit/Cost	2.52	2.28	1.81	2.36	3.64	2.74	2.94

Investement Set	3,4	3,5	4,5	1,2,3	1,2,4	1,2,5	1,3,4
Economic Loss Avoided	13.45	32.23	22.52	61.15	64.62	54.78	20.21
Benefit	25	12	21	46	55	42	40
Cost	16	10	18	38	46	40	30
Benefit/Cost	1.56	1.2	1.17	1.21	1.2	1.05	1.33
Budget Eceeded	No	No	No	No	Yes	No	No
Adjusted Benefit	38.45	44.23	43.52	107.15	119.62	96.78	60.21
Adjusted Bemefit/Cost	2.4	4.42	2.42	2.82	2.6	2.42	2.01

Table 9 continued

Investement Set	1,3,5	1,4,5	2,3,4	2,3,5	2,4,5	3,4,5	1,2,3,4
Economic Loss Avoided	34.54	28.81	56.58	75.19	50.84	32.93	65.98
Benefit	27	36	48	35	44	29	63
Cost	24	32	36	30	38	22	50
Benefit/Cost	1.13	1.13	1.33	1.17	1.16	1.32	1.26
Budget Eceeded	No	No	No	No	No	No	Yes
Adjusted Benefit	61.54	64.81	104.58	110.19	94.84	61.93	128.98
Adjusted Bemefit/Cost	2.56	2.03	2.91	3.67	2.5	2.82	2.58

Investement Set	1,2,3,5	1,3,4,5	1,2,4,5	1,2,3,5	2,3,4,5	1,2,3,4,5,
Economic Loss Avoided	75.19	35	67.55	75.19	75.2	70.43
Benefit	44	44	59	50	52	67
Cost	36	36	52	44	42	56
Benefit/Cost	1.22	1.22	1.13	1.14	1.24	1.2
Budget Eceeded	No	No	Yes	Yes	Yes	Yes
Adjusted Benefit	119.19	79	126.55	125.19	127.2	137.43
Adjusted Bemefit/Cost	3.31	2.19	2.43	2.85	3.03	2.45

The RIIM results of Table 9 is compared with the cost of each component project as shown in Table 4 to assess the aggregate benefit and cost of each set and allocate the budget to them first with the commensurate approach in Table 10, then the Pareto approach in Figure 10.

Table 10A: Composite Project Marginal B/C

	2,4	1,4,5	1,3,4	2,3,5	1,4	2,5	2,3	1,3,5	3,4,5	1,5	1,3	4,5	3,4	3,5
1,2	-1	1	-0.5	0.8	0.8	1.4	0.7	1.1	0.8	1.4	0.9	1.1	0.7	1.1
2,4		Infinity	0	2.5	1.3	2.2	1.1	1.6	1.1	1.8	1.2	1.4	0.9	1.3
1,4,5			-2	0.5	0.7	1.5	0.6	1.1	0.7	1.4	0.9	1.1	0.7	1.1
1,3,4				Infinity	2	3.3	1.5	2.2	1.4	2.1	1.4	1.6	1.1	1.4
2,3,5					0.8	2	0.7	1.3	0.8	1.6	1	1.2	0.7	1.2
1,4						Infinity	0.5	2.5	0.8	2.2	1.1	1.4	0.7	1.3
2,5							-2	0	-0.5	1.3	0.5	0.8	0.2	0.9
2,3								Infinity	1	3	1.3	1.7	0.8	1.4
1,3,5									-1	2	0.7	1	0.3	1.1
3,4,5										5	1.5	2	0.7	1.4
1,5											-2	-1	-1.5	0.7
1,3												Infinity	-1	1.4
4,5													-2	1.1
3,4														2.2

Table 10B: Allocation Algorithm

Algorithm Step	Bridge Selection	Remaining Budget
Column With All Alternatives < 1 1,3,4 and 2,4 Second Criteria: Marginal Pairwise = 0, Select Lower Cost Alternative	1,3,4	10
Select Single Bridge Project Within Remaining Budget	5	4

Considering social benefits equivalent to economic losses not sustained results in allocation of the budget to hardening bridges one, three, four, and five.

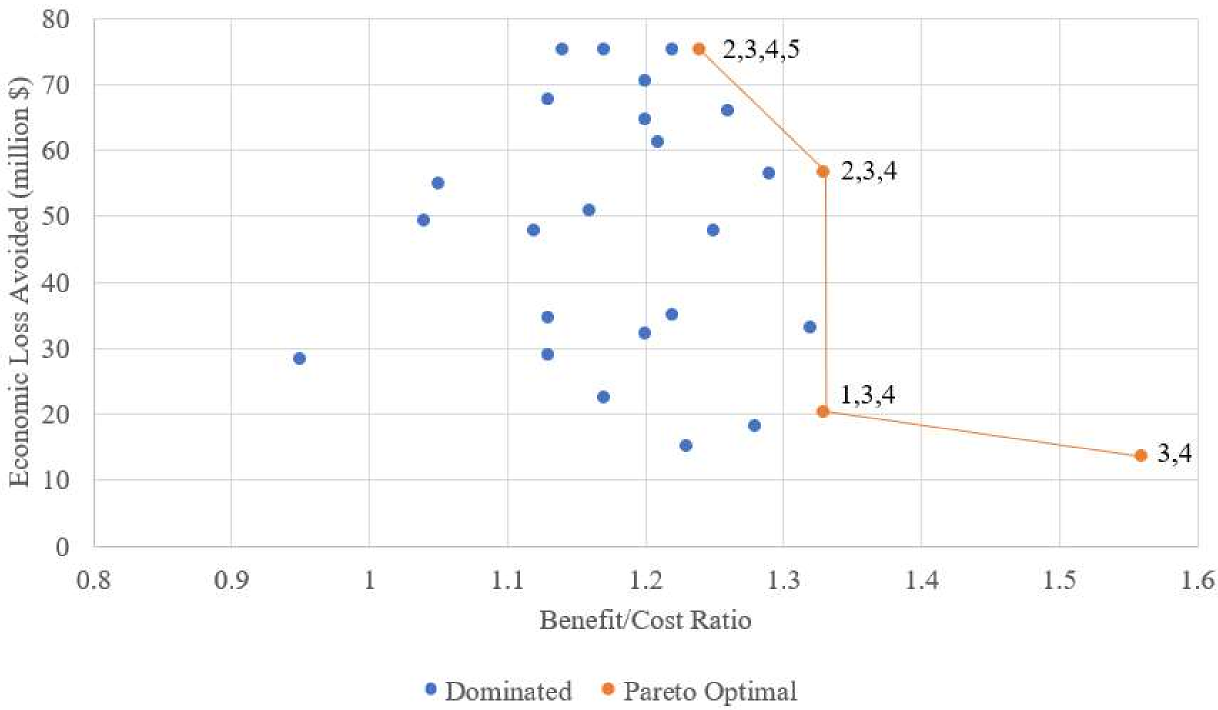

Figure 10: Project Selection Using Pareto Curve

The Pareto-Optimality method is used to select a different set of investements listed in Table 10. The frontier is a set of projects including bridges three and four. Highly pessimistic decision makers would find themselves selecting the set two, three, four, five as this will avoid the largest loss, but at a lower b/c ratio. Conversely, an optimist would select the set three and four. As there would be significant reamaining budget it is likely an optimistic argument could be made for selecting the set one three four, or either of the two sets nearest that point.

5.3.3 Potential For Future Extension

Note that a storm occurring after selecting the project set, which allocates funds to bridges one, two, and three, would result in loss corresponding to not investing in bridge set four and five in Table 9. As the number in Table 9 is per week, the total cost would be multiplied by the number of weeks they both remain inoperable. If bridge four is the first bridge repaired, then the loss is equivalent to that in Table 9 for bridge five multiplied by the number of weeks until its repair. The inverse is true if bridge five were repaired first. The modeling of these repair times is beyond the scope of this thesis, but does present a promising non-trivial extension for future work.

6 Conclusions

The methodology developed in this research enables many stakeholders to improve their decision-making by considering the dynamic tradeoffs among alternative investment strategies that do, or do not, include various sea-level rise mitigation approaches, such as raising bridges. Urban planners have a new method with which to assess the risk from climate change to coastal highway projects. Railroad, port or airport authorities will all find themselves better equipped to compare the long-term risk of investment alternatives. The potential risk involved in locating a warehouse, distribution center, factory, or any other node in the complex supply chains characteristic of modern manufacturing, will be more easily identified. This compounding shift in risk analysis will force America's manufacturing and transportation sectors to adequately consider the potential costs related to future sea-level rise. Shifting these investments decades-before regular flooding will occur, is necessary as these projects have decades-long lifecycles. Creating capacity for informed decision making will enable the economy to mitigate the potential harm from flooding damage before it occurs. This will also lower the burden on public emergency services, as well as transportation agencies, which must budget for repair of damaged infrastructure. These benefits will be gained not through centralized planning dictating where investments are made; rather, through the development of modeling analyses and thus informed decision making.

This thesis develops and refines methodologies to model the interconnectedness and interdependencies of complex systems of systems. These models also enable an integrated assessment of potential public infrastructure and business investments. Assessing and managing risk through these frameworks allows the development of socially integrated infrastructure – designed with an understanding of the multidirectional impacts on the environment, society, and infrastructure of a region. Socially integrated infrastructure in this context is an infrastructure that was planned considering the changes that would result from I-I between infrastructure, the community, and the economy. The most obvious result of this I-I is the increased use of highways and business development along the evolving corridor as well as fluctuations in the population and housing prices. A failure to recognize these I-I relationships could lead to unintended consequences and complete failure of many projects. The methodology can be used to advanced transportation networks in the US, as well as those in developing countries. The relative environmental stability, that societies have enjoyed for centuries, has enabled the development of the advanced global economy we currently enjoy. Continued growth will require more foresight than has been required under the stable conditions that fostered past development.

This paper addresses the following four major contributions: (i) a methodology to measure the impact of climate change related disruptive events; (ii) a new outlook on measuring climate change risk; (iii) a methodology to manage the long-term risks and impact of climate change among alternative proposed infrastructure; and (iv) a methodology for assessing the relative risk of private business investment alternatives in coastal regions.

6.1 Measuring the Impact of Climate-Change-Related Disruptive Events

A methodology is developed for assessing the impact of sea-level rise on the transportation and supply-chain sectors of the economy. Understanding and modeling the interdependence and interconnectedness of these two subsystems is the heart of this contribution, and would enable planners to model the cascading impacts on each of these systems caused by the single disrupting event. The framework could easily be modified to assess the impacts of other related climate-change disruptive events, such as increasing severity of weather or decreasing the reliability of transportation.

6.3 New Outlook on Measuring Climate Change Risk on the Social Environment

The research considers not only first order damages due to sea-level rise, such as immediate infrastructure damage, or damage to private property, but also the cascading social, economic, and technological, impacts of these disruptions on the supply chain and transportation sector. A percentage decrease in operability for any of these key sectors would ripple into a large value loss, which is not captured by traditional methods of assessing damage. These cascading impacts enable a more realistic estimation of the toll that climate change will have on the global economy. Consequently, the potential value of mitigating climate change is increased, justifying increased spending to manage greenhouse gasses.

6.3 Manage the Long-Term Risks and Impact of Climate Change

New or hardened infrastructure would positively alter the interconnectedness and interdependency of the supply-chain, transportation sector, and economy potentially increasing, or decreasing the future impact of sea-level rise. By assessing the change in the I-I that would occur. If for example, a major bridge is hardened, or a new highway were built, then the long-term economic value of these investments can be more accurately estimated. As a result, the limited funds to protect communities from the impact of storms would be more effectively allocated.

6.4 Assessing the Relative Risk to and from Private Business Investments

Private-sector strategists may become increasingly concerned with the potential for climate change that would decrease the return on investment for potential projects. Decisionmakers need only look at past analysis to estimate the inoperability of their sector under a disruptive event to measure the risk to their own projects. Policymakers and steering committees considering investments of scope sufficient to alter the I-I of the local transportation system or economy will have to reanalyze the region using a similar methodology as developed in this thesis.

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