Development of a Fuzzy Linear Programming Model for Allocation of Inoperability in Economic Sectors Due to Loss of Natural Resource Inputs

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The inoperability input-output model (IIM) has recently been proposed as an extension of conventional input-output analysis for assessing the vulnerability of interdependent infrastructures to various perturbations, such as natural disasters, industrial accidents, and deliberate attacks. The IIM framework makes use of a dimensionless risk metric called *inoperability*, which quantifies the degree of failure of a system on a scale ranging from 0 (normal state) to 1 (total failure). This inoperability is then assumed to propagate through any given industrial network after being induced by initial demand or supply-side perturbations. This work presents a fuzzy linear programming (FLP) model to allocate inoperability in a complex industrial network caused by a loss of natural resource inputs. Such losses may either be "rapid-onset" (e.g., seismic events) or "slow-onset" (e.g., climate change). The model seeks to maximize a dimensionless variable, γ, which modulates the distribution of inoperability across the sectors, as governed by input-output relationships and *a priori* inoperability limits for each of the sectors. We illustrate the use of this model with two illustrative cases based on scenarios of hypothetical loss of agricultural land due to climate change.

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INTRODUCTION

The impact of climate change manifests through socio-economic and environmental channels. These effects can be observed through increased incidence of natural disasters, variations in rainfall levels, changes in temperature, among others. The Asian Development Bank (2013) highlighted the vulnerability of sectors such as agriculture, fisheries, tourism, coral reefs, and human health, which involve the lower income strata of developing economies. Their inability to harness economies of scale renders a more vulnerable state. Food security is threatened with the global emergence of smallholder farming (Fan, Brzeska, Keyzer, & Halsema, 2013). Beyond the traditional indications of climate change, the development and mutation of new diseases and pests further increase the vulnerability of smallholders (Morton, 2007). Hence, climate change can essentially induce aberrant variations in weather patterns. Consequences of climate change can manifest, for example, in the form of drought (Santos, Pagsuyoin, Herrera, Tan, & Yu, 2014) or storms (Stromberg, Esteban, & Gasparatos, 2011), which then cause damage to agriculture and other economic sectors.

The inoperability input-output model (IIM) was first proposed by Haimes and Jiang (2001) for predicting the indirect effects of disruptive events such as natural disasters. Their work proposed the concept of inoperability, a dimensionless index in the interval [0, 1] for quantifying the degree of failure of physical infrastructure, where the limiting values of 0 and 1 signify states of normal operation and total collapse, respectively. Structurally, the original IIM was an extension of Leontief's celebrated input-output model (Leontief, 1936), but it used a system of linear equations to describe the physical propagation of inoperability through a complex system composed of interdependent components. One of the main drawbacks of the original concept was the problem of calibrating the coefficients for physical dependencies; for example, agent-based modeling techniques have been proposed (Oliva, Panzieri, & Setola, 2010).

Santos and Haimes (2004) proposed an alternative interpretation of IIM based on demand reduction; this alternative allowed IIM models to be calibrated based on standard input-output data which is routinely recorded in most countries as a matter of economic monitoring. This development led to the rapid growth of IIM (Greenberg et al., 2012), leading to applications for quantifying the ripple effects of such notable historical events as the 9/11 terrorist attacks (Santos & Haimes, 2004), the 2003 Northeast blackout (Anderson, Santos, & Haimes, 2007), Hurricane Katrina (Crowther, Haimes, & Taub, 2007) and the Great East Japan earthquake (MacKenzie, Santos, & Barker, 2012). In addition, other published applications have looked at potential future disasters, including managing risks from influenza pandemics (Orsi & Santos, 2011), biofuel supply failure (Santos, Barker, & Zelinke, 2008), and energy shortage (Khanna & Bakshi, 2009). The methodology is particularly useful for estimating the sectorwise vulnerability assessment, which may be essential for allocating resources and priorities for risk management (Barker & Santos, 2010a).

The IIM methodology itself has also seen significant development in the form of various extensions of the basic, deterministic, and static form originally proposed by Haimes and Jiang (2001). The development of the dynamic form of IIM has allowed temporal aspects of disasters to be integrated into the analyses (Lian & Haimes, 2006; Orsi & Santos, 2010), and in particular has led to the exploration of the effect of inventory as a mitigation measure (Barker and Santos, 2010b; Resurreccion & Santos, 2011). Leung, Haimes, and Santos (2007) proposed an extension where the initial system perturbation comes in the form of supply reduction, as opposed to demand reduction. In addition, the assumption of determinicity has been relaxed through the use of probabilistic (Santos, 2008), fuzzy (Setola, De Porcellinis, & Sforna, 2009), and interval (Barker & Rocco, 2011) IIM variants. In addition, there have been attempts to integrate IIM within an optimization framework to allow for prescriptive, rather than descriptive, modelling. Kananen, Korhonen, Wallenius, & Wallenius (1990) proposed a multi-objective input-output model that preceded the inoperability concept; they demonstrated the use of the model for identifying Pareto optimal solutions for hypothetical crisis scenarios in Finland. A rudimentary optimization-based IIM variant was first proposed by Haimes and Jiang in their seminal paper (Haimes and Jiang, 2001). The concept was developed further in a subsequent article (Jiang and Haimes, 2004). More recently, inoperability was used as a measure of risk in a source-sink model for optimal energy resource allocation (Tan, 2011).

In this work, we propose an optimization model for determining appropriate actions in response to disasters where initial disruptions manifest as loss of natural resources. Such losses are of particular importance in assessing how climate change may cause economic damage through both fast and slow-onset disruptions. For example, reduced rainfall may cause drought which in turn leads to crop failure and hydroelectric power shortage. Desertification may also cause loss of arable land resource that is needed for agriculture, while the damage to marine ecosystems may result in the collapse of fisheries. Such effects are easily integrated through an extended form of the basic input-output model (Chen, 1973). The rest of the paper is organized as follows. The development of the model is discussed in the next section. The main contribution of this work is the methodological development associated with the integration of fuzzy modeling and input-output analysis. Two case studies are then presented to illustrate the use of the resulting methodology. Finally, conclusions and prospects for future work are discussed.

MODEL DEVELOPMENT

We begin with a general input-output model with an environmental extension to account for natural resources drawn from the environment:

$$(\mathbf{I} - \mathbf{A})\mathbf{x} = \mathbf{y} \qquad (1)$$

$$\mathbf{B}\mathbf{x} = \mathbf{z} \qquad (2)$$

where **I** is an identity matrix, **A** is the technical coefficient matrix, **x** is the total output vector, **y** is the final demand vector, **B** is the environmental coefficient matrix and **z** is the total resource usage matrix. The coefficients of **B** represent the direct usage of natural resources per unit of output of each sector. Note that **B** is not necessarily a square matrix, and as there may be fewer resources of concern than there are economic sectors, in practice, **B** will often have fewer rows than columns.

Eq. 1 may be inverted to give:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\,\mathbf{y} \qquad (3)$$

Subtitution into Eq. 2 then gives:

$$\mathbf{B}(\mathbf{I} - \mathbf{A})^{-1}\,\mathbf{y} = \mathbf{z} \qquad (4)$$

Eq. 4 thus yields the total natural resource used by the economic system (**z**) in order to produce its final output (**y**). Then, it can be seen that changes in **y** and **z** are related as follows:

$$(\mathbf{I} - \mathbf{A})^{-1}\,\delta\mathbf{y} = \delta\mathbf{z} \qquad (5)$$

In the case of disaster-induced loss of natural resources, the problem is to determine $\delta\mathbf{y}$ given a disruption $\delta\mathbf{z}$. Since, as previously stated, $\delta\mathbf{y}$ has more rows than $\delta\mathbf{z}$, Eq. 5 exhibits excess degrees of freedom, which allows for optimization of the system. Next, Eq. 5 may be modified so that disruptions are normalized into dimensionless form. We define the fractional loss of final demand as:

$$\mathbf{u} = \mathbf{Q}\delta\mathbf{y} \qquad (6)$$

$$\mathbf{Q} = (\mathrm{diag}(\mathbf{y}))^{-1} \qquad (7)$$

Likewise, we define fractional loss of natural resource as:

$$\mathbf{v} = \mathbf{R}\delta\mathbf{z} \qquad (8)$$

$$\mathbf{R} = (\mathrm{diag}(\mathbf{z}))^{-1} \qquad (9)$$

Then, Eq. 5 can be modified to give:

$$\mathbf{RB}(\mathbf{I} - \mathbf{A})^{-1}(\mathbf{Q}^{-1}\mathbf{Q})\delta\mathbf{y} = \mathbf{R}\delta\mathbf{z} \qquad (10)$$

Substituting Eq. 6 and 8 into Eq. 10 gives:

$$\mathbf{RB}(\mathbf{I} - \mathbf{A})^{-1}\mathbf{Q}^{-1}\mathbf{u} = \mathbf{v} \qquad (11)$$

This may then be expressed as:

$$\mathbf{Pu} = \mathbf{v} \qquad (12)$$

$$\mathbf{P} = \mathbf{RB}(\mathbf{I} - \mathbf{A})^{-1}\mathbf{Q}^{-1} \qquad (13)$$

where matrix **P** characterizes the economic system's internal input-output connectivity, its interaction with the natural environment, and its baseline level of activity. Given that the fractional loss of natural resource inputs into the system, **v**, is exogenously defined, and given that Eq. 12 has excess degrees of freedom, the following vector optimization problem arises:

$$\min \mathbf{u} \qquad (14a)$$

$$\text{s.t.} \quad \mathbf{Pu} = \mathbf{v} \qquad (14b)$$

The optimization may be done using various approaches. For example, the Pareto frontier for the system may be traced via the ε-constraint method (Haimes, Hall, & Freedman, 1975). Alternatively, a linear weighted objective function may be used:

$$\min \mathbf{w}^T\mathbf{u} \qquad (15a)$$

$$\text{s.t.} \quad \mathbf{Pu} = \mathbf{v} \qquad (15b)$$

where **w** is the vector of priority weights of the various sectors. If the Pareto frontier is continuous, it may also be traced by solving Eq. 15a and 15b for various values of **w**. Note that the problem yields the minimum GDP loss if the elements of **w** are proportionate to the baseline sectoral final demands before the disruption occurred. Since the vector **u** represents the fractional loss of final demand for the economic sector, relative to the baseline state of the system, applying a weight vector **w** which is comprised of sector-specific GDP contributions results in $\mathbf{w}^T\mathbf{u}$ being equivalent to the total reduction in GDP, as measured in monetary units. Alternatively, **w** may be elicited from stakeholder value judgments, for example using the Analytic Hierarchy Process (AHP) (Saaty, 1980).

Alternatively, a fuzzy optimization approach may be used (Zimmermann, 1978). This technique requires that predefined limits for each element of **u** to be specified. Note that the lower limit is more desirable as it represents lower magnitude of output loss. A linear scale may then be defined for u_j signifying the desirability of its value in the interval [0, 1]; this is known as the fuzzy membership function, corresponding to a fuzzy goal where partial degrees of satisfaction are possible. It then becomes possible to define the optimization model as:

$$\max \lambda \qquad (16a)$$

$$\text{s.t.} \quad \mathbf{Pu} = \mathbf{v} \qquad (16b)$$

$$(u_j - u_j^{max})/(u_j^{min} - u_j^{max}) \geq \lambda \quad \forall j \qquad (16c)$$

$$0 \leq \lambda \leq 1 \qquad (16d)$$

where λ is the overall index of satisfaction of fuzzy goals, and u_j^{min} and u_j^{max} are the lower and upper limits of fraction loss of final demand of each sector j. This formulation is based on max-min aggregation (Zimmermann, 1978), which ensures that the optimal solution gives the best value for the *least satisfied* fuzzy goal. In other words, the model maximizes λ, which in turn represents the minimum degree of satisfaction of all the constraints defined by Eq. 16c, hence the term max-min aggregation. We also note that this model is linear, and can thus be solved to global optimality without major computational difficulties.

In the succeeding section, the model is illustrated using two demonstration case studies and implemented using the commerical optimization software LINGO 12.0 (Lindo Systems, 2010). The first case study is a didactic example, which is selected to be simple enough to facilitate understanding of the modelling framework itself. The second case study is a hypothetical but plausible example, illustrating how the model may be applied in a tropical country when production of a major commerical crop is threatened by climate change.

Sample Case Study 1

This case study is adapted from a stylized two-sector illustrative example from Miller and Blair (2009); the data has been modified by adding 100 units of a hypothetical natural resource input stream into the economic system, with one-fifth of the resource being drawn directly by Sector 1, and the balance by Sector 2. The simplicity of this example is deliberately used in order to facilitate the illustration of the key features of the optimization model. Table 1 shows the economic and environmental flows for this economic system at the baseline state.

Next, it is possible to determine the intersectoral flow of goods as well as the natural resource usage, per unit of production output from each sector. The resulting figures are shown in Table 2.

Table 1
Economic and Environmental Flows in Case 1

	Sector 1	**Sector 2**	**Final Demand**	**Total Output**
Sector 1	150	500	350	1000
Sector 2	200	100	1700	2000
Resource	20	80	100	n/a

*Total resource drawn by economy

Table 2
Coefficients of A and B in Case 1

	Sector 1	**Sector 2**
Sector 1	0.15	0.25
Sector 2	0.20	0.05
Resource	0.02	0.04

It can be seen that the first two data rows comprise matrix **A**, while the last row corresponds to **B**. The coefficients for both **A** and **B** are obtained by dividing the associated element in Table 1 by the total output of the corresponding column sector.

We then consider a disruptive event that causes a 10% loss in availability of the natural resource. It can easily be seen that such a loss can result in all economic flows being scaled down by a similar proportion (i.e., total output and final demand of each sector contracts by 10%). However, if we suppose that the natural resource in question can be reallocated between the two sectors, appropriate damage control measures can be determined based on specified optimization criteria. Suppose that the fuzzy limits for fractional loss of final demand for the two sectors are specified, as shown in Table 3.

Table 3
Limits for Fractional Loss of Final Demand in Case 1

	u_j^{min}	u_j^{max}
Sector 1	0.05	0.10
Sector 2	0.04	0.12

Solving Eq. 16 gives the optimal level of fractional final demand losses of the two sectors, as shown in the first data column of Table 4. Note that both sectors lose approximately 10% of their respective final demands, but Sector 2 absorbs a slightly larger proportion of the damage than Sector 1 in fractional terms. This solution corresponds to an optimal value of λ = 0.23, which means that the damage control goals set for the all sectors in the economy are met to at least 23% degree of satisfaction. The resulting GDP loss is 203.8 units. For comparison purposes, corresponding results using the weighted sum model (Eq. 15) are also shown, using both equal weights (Scenario A) and weights proportional to baseline final demand (Scenario B). For both weighted sum scenarios, all the final demand loss occurs in Sector 2 (i.e., priority is given to the use of Sector 2 outputs as input for Sector 1, at the expense of use as final product); this reduction corresponds to 194.2 units of GDP loss overall (by comparison, if all the final demand loss occurs in Sector 1, the GDP reduction will be 280.6 units; this result occurs when the ratio of the weight factors of the sectors fall below a value of about 1:7). This counterintuitive result may be explained as follows. Note that, from Table 1, only 20 units of resource are utilized by Sector 1, while 80 units are used up by Sector 2. Thus, the 10% resource loss, amounting to 10 units, would clearly account for a larger fraction of the usage of Sector 1, than of Sector 2. As a result, greater relative losses would be incurred if the loss is absorbed by Sector 1. Note that the compensatory nature of the weighted sum approach allows heavy losses to be incurred by one sector, for as long as avoid ed losses in the other sector result in a better aggregate objective function value. On the other hand, the max-min aggregation used in the fuzzy model ensures that the degrees of satisfaction of sector-wise fuzzy goals are met equitably, via the global modulating variable λ (Zimmermann, 1978).

Table 4
Optimal Values of Fractional Loss of Final Demand in Case 1

	Fuzzy Model	**Weighted Sum Model (Scenario A)**	**Weighted Sum Model (Scenario B)**
Sector 1	0.088	0	0
Sector 2	0.102	0.114	0.114

Sample Case Study 2

This case study demonstrates the use of the model for allocating land resources that are degraded as a result of climate change. It has been noted that climate change is a serious long-term threat to agricultural production in many parts of the world, and particularly the tropics, through changes in precipitation, infestation risk, and soil conditions (Dar & Gowda, 2013). Such changes in climate may make crop shifting imperative, as the suitability of agricultural land to current crops declines (Phalan et al., 2013). The net effect for any given agricultural sector is a loss of land availability. We consider the case of Malaysia, where the oil palm sector accounts for about 36% of total agricultural output, according to the 2005 input-output data. The total economic output of this sector is about Ringgit 21.8 billion (the approximate exchange rate is US$1:Ringgit 3), with much of the output being processed further into vegetable oil and other products (Department of Statistics Malaysia, n.d.). Oil palm plantations also account for 4.92 million hectares out of the 7.87 million hectares of total agricultural land in the country (Malaysian Palm Oil Board, n.d.). Because of the high water footprint of oil palm (Gerbens-Leenes, Hoekstra, & van der Meer, 2009; Phalan et al., 2013), prolonged changes in precipitation level can potentially render current plantation lands unsuitable for continued cultivation in the future. In this case study, a hypothetical but plausible scenario of 10% loss of land resource is considered. This may be a useful illustration of the 2014 El Niño case where Malaysian oil palm production was reduced by 10% (Lim, 2014). The input-output data has been aggregated into 12 sectors following the procedure outlined in Miller and Blair (2009). Table 5 shows the coefficients of matrices **A** and **B** for this case study; the final row corresponds to agricultural land resource and comprises **B**. Also, the upper and lower limits for fractional final demand degradation are given in Table 6. In this example, the values used are hypothetical and serve only to demonstrate the methodology itself. In practice, such limits may be determined based on policy decisions on tolerable losses (taking into account the socio-economic context of the problem).

Solving Eq. 16 gives the optimal level of fractional final demand losses of the 12 sectors, as shown in the first data column of Table 7. Note that final demand loss for non-palm agriculture is 15.8%, while the corresponding loss for oil palm is 23.6%. The loss for all other sectors in the economy is 7.9%, leading to an overall GDP loss of 8.0% relative to the baseline of Ringgit 874 billion. This solution corresponds to an optimal value of $\lambda = 0.21$. It can be seen that the losses are equitably distributed, since the model structure ensures that their values fall within the *a priori* bounds given in Table 6.

By comparison, the weighted sum model gives highly skewed results, as shown in the next two data columns of Table 7. Again, Scenario A corresponds to equal weights being assigned to all sectors, while Scenario B assigns weights in proportion to contribution to baseline GDP. Scenario A results in 14.3% losses in final manufacturing demand, with no losses occurring elsewhere in the system; the corresponding GDP loss is 8.7%. Unlike Case 1, this example shows markedly different results between Scenarios A and B. When the sectors are weighted in proportion to their contribution to the GDP, the optimum outcome results in all losses being concentrated only in agriculture, with 29.2% drop in final demand for the non-palm sector, and 100% drop for oil palm. This scenario also yields the least level of loss in GDP, at 0.7%. In other words, in Scenario A, priority is given towards diverting agricultural output to meet final demand, at the expense of using the produce as an input for manufacturing. On the other hand, in Scenario B, priority is given to using agricultural output to supply the requirements of other sectors, at the expense of final demand. Note the extreme case observed for the oil palm sector, where the final demand drops to zero; the result is not completely implausible,

Table 5
Coefficients of A and B Case 2

	Agriculture, Fishery and Forestry excluding Palm Oil	Palm Oil	Mining and Quarrying	Manufacturing	Electricity, Gas and Water	Construction	Trade	Transportation, Communication and Storage	Finance	Real Estate and Ownership of Dwellings	Private Services	Government Services
Agriculture, Fishery and Forestry excluding Palm Oil	0.114	0.013	0.002	0.019	0.000	0.001	0.014	0.000	0.001	0.000	0.000	0.003
Palm Oil	0.001	0.091	0.001	0.020	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.001
Mining and Quarrying	0.003	0.002	0.005	0.042	0.018	0.032	0.004	0.001	0.002	0.000	0.001	0.003
Manufacturing	0.144	0.108	0.100	0.324	0.223	0.305	0.100	0.106	0.030	0.028	0.063	0.101
Electricity, Gas and Water	0.004	0.010	0.002	0.009	0.186	0.004	0.008	0.010	0.007	0.013	0.031	0.020
Construction	0.000	0.000	0.007	0.000	0.043	0.001	0.004	0.022	0.000	0.010	0.001	0.086
Trade	0.024	0.025	0.044	0.047	0.010	0.027	0.043	0.012	0.025	0.139	0.011	0.037
Transportation, Communication and Storage	0.014	0.015	0.013	0.021	0.013	0.043	0.044	0.262	0.070	0.017	0.047	0.051
Finance	0.003	0.031	0.000	0.009	0.004	0.032	0.022	0.108	0.300	0.021	0.023	0.005
Real Estate and Ownership of Dwellings	0.000	0.000	0.001	0.000	0.001	0.007	0.014	0.023	0.013	0.081	0.044	0.030
Private Services	0.001	0.006	0.006	0.003	0.015	0.026	0.039	0.023	0.029	0.017	0.188	0.037
Government Services	0.000	0.000	0.001	0.000	0.004	0.005	0.004	0.015	0.004	0.007	0.009	0.064
Agricultural Land	0.077	0.226	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 6
Limits for Fractional Loss of Final Demand in Case 2

	u_j^{min}	u_j^{max}
Agriculture, Fishery and Forestry excluding Palm Oil	0	0.2
Palm Oil	0	0.3
Mining and Quarrying	0	0.1
Manufacturing	0	0.1
Electricity, Gas and Water	0	0.1
Construction	0	0.1
Trade	0	0.1
Transportation, Communication and Storage	0	0.1
Finance	0	0.1
Real Estate and Ownership of Dwellings	0	0.1
Private Services	0	0.1
Government Services	0	0.1

Table 7
Optimal Values of Fractional Loss of Final Demand in Case 2

	Fuzzy Model	Weighted Sum Model (Scenario A)	Weighted Sum Model (Scenario B)
Agriculture, Fishery and Forestry excluding Palm Oil	0.158	0	0.292
Palm Oil	0.236	0	1.000
Mining and Quarrying	0.079	0	0
Manufacturing	0.079	0	0
Electricity, Gas and Water	0.079	0	0
Construction	0.079	0	0
Trade	0.079	0	0
Transportation, Communication and Storage	0.079	0	0
Finance	0.079	0	0
Real Estate and Ownership of Dwellings	0.079	0	0
Private Services	0.079	0	0
Government Services	0.079	0	0

since much of the output of this sector (92.5% at the baseline state of the economy) is used as an input for the production of vegetable oils, oleochemicals, and other downstream products. Similarly, a zero final demand for the oil palm sector does not necessarily translate to zero level of output for the same sector since output is a sum of intermediate demand and final demand. Prioritizing intermediate demand will result to a reduced level of loss, which means that government regulation will play an important role in achieving minimal losses.

CONCLUSIONS

We have developed a fuzzy linear programming model for optimal allocation of inoperability losses arising from disaster-induced loss of natural resource inputs. Given an exogenously defined fractional loss of resource input, and linear fuzzy membership functions for acceptable losses in final economic demand for each sector of the economy, the model uses max-min aggregation to determine an optimal solution, which achieves the best partial satisfaction of the fuzzy goals. Two case studies were then used to illustrate the model: a simple two-sector illustrative example, and a more realistic case to explore the impact of climate change on the agricultural sector of Malaysia and its associated ripple effects. Future work on this model should explore multi-regional and dynamic extensions. Furthermore, its use in many developing countries will be hampered by lack of accurate or up-to-date input-output data, which suggests the need for better procedures for calibrating the model parameters. Future efforts can also be devoted in engaging policymakers for determining the limits of fractional losses based on the perceived criticality of each sector. Furthermore, we also propose the inclusion of sensitivity analysis to investigate the extent to which optimal solutions could be affected by changes in model parameter and coefficient values. Finally, we envision future work focusing primarily on the application of the method developed in this paper.

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