Risk Assessment of the Economic Impacts of Climate Change on the Implementation of Mandatory Biodiesel Blending Programs: A Fuzzy Inoperability Input-Output Modelling (IIM) Approach

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Many countries have implemented biofuel programs designed to address pressing concerns such as climate change, energy security and rural development. However, recent works suggest that biofuel resources may be at risk due to climate-induced disruptions such as changes in precipitation levels, pest infestation, or increased frequency of extreme weather events. The incidence of such disruptions not only affects biofuel producers, but also energy-dependent economic sectors, resulting in “ripple effects” that further increase economic losses. A variant of the inoperability input-output model (IIM) is used to assess the economic effects of implementing mandatory biodiesel blending programs in the Philippines. This approach is an extension of input-output analysis that quantifies risk through the dimensionless inoperability metric, whose value ranges from 0 to 1 depending on the degree of failure. Using the IIM, we estimate the resulting crop losses using the storm damage and pest infestation scenarios at the proposed blending rate of 5% currently being considered in the Philippines. Uncertainties within the modelling framework are captured using fuzzy numbers. Different ranking strategies are then evaluated to determine sector vulnerability using inoperability levels and economic losses. The effect of uncertainties is also taken into account through fuzzy ranking of the sectors.

Keywords: Risk analysis; climate change; infestation; biodiesel; fuzzy inoperability input-output modelling

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1. Introduction

Anthropogenic climate change due to greenhouse gas emissions is widely regarded as the most serious environmental issue of the 21st Century [1]. In addition to the direct effects of climate change (e.g., sea level rise and shifts in weather patterns), it is also linked to other major issues such as biodiversity loss, ocean acidification, water stress, and land availability. Thus, climate change may have potentially complex impacts on human activity in the coming decades. The Intergovernmental Panel on Climate Change [2] has underscored the escalating risks associated with climate change and asserted that greenhouse gas mitigation can significantly reduce climate change risks; however, the implementation of such measures must be integrated with economic and demographic trends, such as the rapid energy demand growth in developing countries. As a result of a strong international scientific consensus on the gravity of the climate problem, there is plenty of research activity now focusing on both climate change mitigation and adaptation. Work on the former aspect is based mainly on the reduction of greenhouse gas emissions (e.g., through development of low-carbon energy); on the other hand, work on the latter is more diverse due to the involvement of complex socio-economic systems. In some cases, further complications arise when mitigation measures have interactions with adaptation measures.

The use of biofuels is one of the key strategies to reduce greenhouse gas emissions. As a result, many countries have mandated the blending of fuels such as biodiesel with diesel and bioethanol with gasoline. Much work has been done in the past years in exploring potential feedstocks and in improving the technology for biofuel production. A review of more recent academic publications shows that risks and uncertainties should also be integrated in the assessment process [3], especially when energy security is of interest. For example, the main feedstocks for the large scale production of biofuels are usually staple agricultural products. Thus, the sustainability of supply is potentially vulnerable to the effects of climate change [4]; for instance, supply disruptions may result from storms [5] or droughts [6]. With an increased reliance on agricultural feedstock, climate change induced disruptions such as extreme weather events (e.g., storms or droughts), forest fires or crop infestation will affect not only the agriculture sector but also other energy-dependent sectors, thus resulting in further economic losses outside of the agricultural sector. It is thus important to analyze the effect of climate change-induced disasters on an economy upon

the implementation of a biofuel policy. Furthermore, such analysis must include both direct and indirect effects in order to comprehensively reflect the risks arising from such policies. This will provide insights for the development of disaster risk management and recovery strategies as well as in the selection of the appropriate biofuel policy.

In the specific case of the Philippines, mandatory blending of biofuels has been legislated via Republic Act 9367: Biofuels Act of 2006. The legislation includes both bioethanol and biodiesel, and was primarily motivated to enhance energy security through reduction of energy imports. The total annual demand for diesel fuel is approximately 7×10^9 L/y, virtually all of which is derived from imported petroleum [7]; thus, the legislation was originally proposed to reduce the risks associated with dependence on foreign fuel supply. At the same time, secondary benefits arising from the use of biodiesel were also recognized – particularly the reduction of greenhouse gas emissions, and the stimulation of rural economies through new markets for crops. Coconut, a traditional staple crop for vegetable oil production in the country, is the main feedstock used for biodiesel production [8]. Total land area dedicated to coconut cultivation is 3.55 million hectares, or 36% of the total agricultural land of the Philippines; with current annual production of 15.3 million metric tons of coconuts with husk [9]. Recent attempts to introduce alternative oilseeds into the market, particularly *Jatropha curcas*, have failed due to unfavorable market dynamics [10]. A notable feature of the existing legislation is the provision to scale up blending rates subject to periodic review of feedstock supply and other economic considerations. Mandatory blending of biodiesel was initially set at 1%, and was subsequently increased to 2%. An additional increase to 5% blending rate is currently being considered in an effort to stimulate the coconut farming sector.

However, the onset of climate change can change the frequency of occurrence of extreme weather events that will affect the productivity of the agricultural sector, hence threatening the sustainability of biodiesel production in the Philippines. Statistical data reflect reduced, and sometimes even negative, levels of growth in agricultural production during years when the country suffers from extreme weather events, such as Typhoons Ketsana and Parma (2009), Nesat (2011), Bopha (2012) and Haiyan (2013) [9]. Stromberg et al. [5], for example, estimate an average of 2% loss in coconut plantation productivity in the

Philippines as a result of climate change-induced increased wind velocity associated with typhoons. It is now clear that biodiesel utilization increases vulnerability to disruptions in agricultural output, which in turn can result from climate change [5] or pest infestation [11, 12]. Thus, the potential benefits of increased biodiesel use must be balanced with various considerations, in order to achieve rational decision-making and policy development [13]. Assessment of benefits should thus be carried out along with analysis of risks. Because economic sectors are highly interdependent, the total consequences of disruptive events can be more severe than the direct effects alone. Hence, analysis must also account for indirect effects due to the extensive dependency of various economic activities on fuel supply.

Systematic risk analysis entails identifying possible adverse events, gauging their likelihood, and predicting likely consequences [14]. In the context of biofuel policy, such consequences may arise as “ripple effects” that emerge as a result of interdependencies among economic sectors that rely on energy and on transportation services. Input-output (I-O) analysis is one of the most established frameworks for modeling such interdependencies from an economic standpoint [15]. This methodology makes use of linear systems of equations to represent sectoral linkages. I-O modelling has traditionally been used for impact analysis of external changes, such as expansion of government projects. Technical coefficients derived from I-O tables are commonly criticized due to their time invariance, but it has been argued that these coefficients remain relatively stable over moderate time horizons [16]. This technique is extended to account for feedback effects from various agents of the economy and factors such as price changes and elasticities through computable general equilibrium modelling (CGE) [17]. In 2012, the use of inoperability input-output model (IIM) and CGE for assessing economic impact was lauded as one of the ten most important accomplishments in risk analysis from 1980-2010 [18]. While CGE has its advantages, it has been observed that results generated are often underestimated as a result of feedback relationships [19]. CGE, while also described to be “a more mature cousin or extension” of the I-O model [19], is known to be data-intensive. The sheer number of parameter estimates required by the CGE model and their associated uncertainties may potentially impact the validity of the results. Furthermore, long-run estimates resulting from CGE models increase its exposure to uncertainties with the possibility of further external shocks [20]. Zhou et al [21] provide a comparison of implementing both I-O and CGE, which

reveal the same vulnerability profiles, despite differences in numerical estimates. Thus, it has been argued that I-O models (and extensions thereof) give reliable results with low computational effort for disruptions whose overall magnitudes are small relative to the size of the entire economic system [16]. More recently, publications on I-O models have high visibility not only in the realm of economics, but also in other emerging fields such as disaster risk management, life-cycle analysis, energy, and environmental sustainability. Theoretical advancements and practical applications in the area of I-O analysis are documented in the textbook of Miller and Blair [22]. More recently, Haimes and Jiang [23] proposed the inoperability input-output model (IIM), which can predict how risks can propagate through interdependent systems using a dimensionless metric called inoperability. According to the definition they proposed, inoperability assumes a value of 0 for a system at its normal or baseline state, a value of 1 for a system in a state of complete failure, and fractional values to indicate intermediate levels of degraded functionality. Due to its dimensionless nature, inoperability may be computed using either physical or economic basis. Although the initial IIM concept focused on physical aspects of connectivity in infrastructure systems, the work of Santos and Haimes [24] introduced an approach for the application of the model to economic systems, while also allowing IIM parameters to be estimated from standard economic data. This formulation was derived from the effects of demand reduction in the aftermath of a disaster. Subsequent work then extended the approach for supply-side disruptions [25]; this approach has been utilized for the analysis of the effects of such disruptions as energy shortage and loss of pollination [26]. Anderson et al. [27] also demonstrated another application on modeling the effects of a short-term power outage in the US. In addition, there have been attempts to extend the conventional form of IIM to account for uncertainties inherent in prospective risk analysis of future events. Approaches based on probabilistic [28, 29], interval [30] or fuzzy [31] IIM have been reported in literature. In addition, decision-making and optimization models based on I-O or IIM have also been developed. Kananen et al. [32] proposed a multi-objective linear programming (MOLP) model for allocation of scarce resources in an I-O framework; one of the scenarios they assessed was an energy crisis in Finland. Then, Jiang and Haimes [33] then proposed an optimization model based on IIM, using different aggregation functions based on either economic loss or inoperability. A shock absorption index was recently proposed by Tan et al. [34] to quantify the ability of economic systems to tolerate disruptive events, using a linear

programming framework, while Yu et al. [35] proposed a multi-component vulnerability index to rank economic sectors vis-à-vis disaster scenarios. More recently, a hybrid approach based on I-O models and P-graph methodology was proposed by Aviso et al. [36] for the rational allocation of electricity in the event of a power shortage. Another work proposed a fuzzy linear programming approach to the economy-wide allocation of a scarce biomass crop [37].

Biofuels have become a commercially significant low-carbon option in many parts of the world; hence, there is clearly a need to address any climate-induced economic risks in bioenergy supply chains (for instance, as a result of extreme weather events or the propagation of invasive pests). **Note that a significant part of risk assessment should contain “reasoned imagination” which systematically anticipates and identify disruptive scenarios, including the rare ones whose magnitudes are inherently difficult to estimate [38].** The effects of adverse events on complex, highly interdependent economic systems can be elucidated through quantitative techniques such as IIM in order to formulate effective policies. This work describes the implementation of a fuzzy IIM model to assess the economic risks associated with mandatory biodiesel blending in the Philippines, where environmental and energy security issues have stimulated attempts to introduce alternative fuels for motor vehicles [13]. The proposed model combines features of the fuzzy IIM work [31] with the supply-reduction framework [25, 26].

The rest of the paper is organized as follows. The formal problem statement and model structure are described in the methodology section. Then, the results of two specific disaster scenarios are considered as case studies. First, we assess the system vulnerability to extreme weather events brought about by climate change, using the scenarios reported in a recent paper [5]. Next, we consider a scenario of massive pest infestation of coconut plantations in the Philippines. The scenario is based on an extrapolation of current regional infestation of coconut trees by the coconut scale insect, which invaded the coconut growing areas in southern Luzon and has grown into an epidemic proportion, and now poses the risk of becoming more geographically widespread if the insect population is not controlled [11]. **In both cases, the potential extent of the perturbations is not known precisely, thus necessitating an explicit framework for incorporating the uncertainty into the model.** A brief section then discusses the main findings and

implications of the two case studies. Finally, the conclusion section discusses policy insights arising from the model outcomes, as well as prospects for future work.

2. Methodology

The implementation of a biofuel policy will modify the structure of an economic system by potentially increasing its reliance on the agricultural sector. The formal problem statement is given as follows:

- An economic system consists of M number of sectors such that each sector i produces one homogeneous output.
- The productivity of each economic sector i is defined by its total output x_i and final demand y_i
- The technical coefficients matrix $\mathbf{A}$ is an $m \times m$ matrix which defines the fixed proportions of inputs necessary to produce a unit output for each sector i .
- The implementation of a biofuel policy results in a unique matrix $\mathbf{A}$ which can be transformed into the interdependency matrix $\mathbf{A}^*$ using the total output vector, $\mathbf{x}$, and demand vector $\mathbf{y}$.
- A perturbation occurs such that the total output of an economic sector is reduced. The degree of reduction is defined as inoperability and ranges from 0 to 1, with 0 being completely operational and 1 indicating complete failure.
- Impact uncertainty is represented by the degree and plausibility of the perturbation in the form of triangular fuzzy numbers. A fuzzy number may be denoted by a triad such as $[\tilde{x}^L, \tilde{x}^M, \tilde{x}^U]$ where $\tilde{x}^L$ represents the lower bound, $\tilde{x}^M$ is the most plausible perturbation, and $\tilde{x}^U$ is the upper bound. The interval defined by $\tilde{x}^L$ and $\tilde{x}^U$ thus gives the range of all marginally plausible values of the fuzzy number.
- The objective of the fuzzy IIM framework is to calculate the degrees of inoperability and associated economic losses experienced by all other sectors resulting from the initial perturbation.

The basic IIM formulation [18, 19] is given by:

$$\mathbf{q} = \mathbf{A}^* \mathbf{q} + \mathbf{c}^* \quad (1)$$

Sector inoperability ($\mathbf{q}$) results from a reduction in production capacity or an initial perturbation ($\mathbf{c}^*$) caused by a reduction in final demand, due to a disruption such as a natural disaster. This disruption propagates throughout the economic system due to the interdependencies between the economic sectors ($\mathbf{A}^*$). Note that Santos and Haimes [24] developed a procedure to calibrate $\mathbf{A}^*$ from the technical coefficient matrix ($\mathbf{A}$) which are normally compiled as part of economic records for most countries.

In general, Eq. 1 can be solved via matrix inversion to yield:

$$\mathbf{q} = (\mathbf{I} - \mathbf{A}^*)^{-1} \mathbf{c}^* \quad (2)$$

Note that this equation bears a strong structural similarity to Leontief's I-O model. Eq. 2 thus allows total inoperability, $\mathbf{q}$, to be computed given a disruption $\mathbf{c}^*$, based on the system structure as defined by the inverse $(\mathbf{I} - \mathbf{A}^*)^{-1}$ in Santos and Haimes [24]. The latter matrix has amplification properties such that, in general, any $\mathbf{q} \geq \mathbf{c}^*$. In other words, total damage incurred in an economic system as a result of a disruption or disaster tends to be greater than the initial direct effects, as a result of economic interdependencies. Note that the original interpretation of Eq. 2 considers a disruptive demand reduction as the initial perturbation. Supply reduction effects, on the other hand, have been modeled using either “forced demand reduction” [27] or alternatively through mathematically manipulating Eq. 1 [25, 26]. On the other hand, equivalent solutions may be derived without matrix inversion by using numerical methods to directly solve Eq. 1. Ripple effects can also be decomposed further via a power series expansion. The reader may refer to established I-O literature [22] for a detailed discussion of such methodological aspects; the mathematical principles also apply to IIM.

In practice, prospective risk analysis is fraught with uncertainty inherent in predicting the future [38, 39]. In particular, the uncertainties may be highly subjective in nature for events that are extremely rare or have not yet been encountered. It is essential that such uncertainties are reflected in models, instead of being simply ignored or neglected. Fuzzy set theory is a well-established mathematical framework for quantifying uncertainties arising from vagueness and subjectivity, as opposed to randomness [40]; its application to optimization and decision analysis was recognized early in its development [41]. Fuzzy set theory has also been applied for expressing imprecise quantities through fuzzy numbers, which express a range of plausible values instead of an exact point estimate. Fuzzy numbers may thus be interpreted as nested, graded intervals, as shown in Figure 1. Note that, at any given degree of plausibility denoted by the quantity α , where $0 \leq \alpha \leq 1$, the fuzzy number is characterized by an interval with an upper and lower bound; this interval is known as an α -cut. In general, fuzzy numbers may be defined by various membership functions (or possibility distributions), although in practice, stylized triangular or trapezoidal distributions are often used. Triangular distributions are used in this work for simplicity; such quantities can be characterized by a lower bound, a mode and an upper bound, as discussed in the previous section. Hence, fuzzy arithmetic operations on them may be based on repeated calculations on the corresponding intervals [42]. The final result of the operations is a fuzzy number that can be generated by nesting or stacking the results of the individual arithmetic operations at various α -cuts. This procedure can thus generate fuzzy computations to an arbitrary degree of precision, at the expense of additional computing effort. Buckley [43] first proposed the use of fuzzy numbers in I-O models using α -cuts. His approach has also been extended for use in problem domains with similar structures as conventional I-O, such as life cycle assessment [44] and IIM [31]. The latter work makes use of a matrix inversion approach consistent with the demand reduction methodology developed by Santos and Haines [24]. In this work, a supply reduction approach [26] is directly employed by embedding fuzzy arithmetic calculations in Eq. 1.

A brief outline of fuzzy arithmetic is as follows; the reader may refer to Kaufmann and Gupta [42] for a more detailed treatment of the subject matter. As shown in Figure 1, a fuzzy number can be decomposed into a set of intervals at different α -cuts. Each interval thus represents the range of plausible values for any given fuzzy quantity, for a specified degree of plausibility. Arithmetic operations on interval numbers

also provide a means to propagate uncertainties through a mathematical model. In this context, the problem is to use IIM (Eq. 2) to determine the fuzzy inoperability level ($\mathbf{q}$) given a fuzzy perturbation input ($\mathbf{c}^*$), thus extending the applicability of IIM to problems where the magnitude of disruption is not known precisely. Note that this approach may be seen as an extension of the interval IIM method of Barker and Rocco [30], but differs from the fuzzy IIM approach of Setola et al. [31] which focuses on uncertainties in the coefficients of $\mathbf{A}^*$.

Next, given two interval quantities $A = [a^L, a^U]$ and $B = [b^L, b^U]$, the following arithmetic operations hold:

$$A + B = [(a^L + b^L), (a^U + b^U)] \quad (3)$$

$$A - B = [(a^L - b^U), (a^U - b^L)] \quad (4)$$

$$A \times B = [\min(a^L b^L, a^U b^L, a^L b^U, a^U b^U), \max(a^L b^L, a^U b^L, a^L b^U, a^U b^U)] \quad (5)$$

$$A \div B = \left[\min\left(\frac{a^L}{b^L}, \frac{a^U}{b^L}, \frac{a^L}{b^U}, \frac{a^U}{b^U}\right), \max\left(\frac{a^L}{b^L}, \frac{a^U}{b^L}, \frac{a^L}{b^U}, \frac{a^U}{b^U}\right) \right] \quad (6)$$

Note that, in Eq. 6, the operation becomes undefined if b^L is negative and b^U is positive, since such values result in the inclusion of zero in the denominator. Fuzzy arithmetic is then accomplished by performing interval operations for various α -cut levels. Finally, the fuzzy result is determined by combining the different α -cuts that result from the individual interval calculations. Such calculations, although repetitive, can easily be automated with software (e.g., commercial spreadsheet applications). In this paper, the commercial software LINGO 14.0 [45] is used to solve the resulting linear equations in the two case studies that follow.

Fuzzy numbers thus contains two levels of information: the magnitude of the quantity, and the degree of uncertainty associated with this magnitude. The uncertainty has an effect on ranking fuzzy numbers [46]. At any given α -cut, two fuzzy numbers are not significantly different from each other if the corresponding intervals overlap, as shown in Figure 2a. On the other hand, if no overlap exists as shown in Figure 2b, then the two fuzzy numbers are significantly different. This approach can thus account for

the degree to which one fuzzy number outranks another, taking into consideration the ambiguities reflected in their fuzzy distributions. This fuzzy IIM methodology is applied to two case studies, whose results are described in the succeeding sections.

3. Results (Case Study 1)

This case study considers the impact caused by typhoons when the proposed 5% coconut biodiesel blend is implemented. The impact is measured in terms of inoperability levels and economic losses of economic sectors. This is done using the IIM framework as given in Eq. 1. The estimates are obtained using the national I-O tables of the Philippines in the year 2000 [47]. However, this I-O table utilized information which predates the biofuel act and may not accurately represent the interdependent relationship of economic sectors particularly that between the sector on coconut production and transportation. The I-O table is thus modified to increase the contribution of coconut oil in diesel production and to decrease the corresponding amount of diesel obtained from exports [48]. The updated I-O table is then aggregated into 16 sectors and utilized to generate the interdependency matrix ($\mathbf{A}^*$). The description of each sector is given in Table 1. We also note that such level of industry sector aggregation could potentially offset aberrant fluctuations in inter-industry flows that may have occurred in periods pursuant to year 2000.

A scenario assessing the damage caused by increased wind speed due to typhoons is considered using a fuzzy percentage direct damage of (1.50, 2.00, 2.50) in the coconut sector [5] to account for impact uncertainties. The middle value in the triangular fuzzy number indicates that the most plausible degree of loss that will occur is 2%, but that due to the inherent uncertainty in predicting future disruptions, levels of loss in the range of 1.5 – 2.5% may plausibly occur. On the other hand, the upper and lower bounds represent the most pessimistic and most optimistic estimates, respectively. The loss in coconut productivity will correspond to element q_1 in the inoperability vector, $\mathbf{q}$. The resulting inoperability of the other economic sectors because of this reduction in productivity can easily be obtained using Equation 1, under the assumption that all other sectors except that for coconut and copra making in the farm (Sector 1) do not experience any perturbation.

The resulting non-zero fuzzy inoperabilities of the economic sectors are presented in Figure 3a to Figure 3o, where the horizontal axis represents the inoperability in logarithmic scale while the vertical axis represents the plausibility. Figure 3a corresponds to economic sector on coconut farming including copra making in the farm (Sector 1) while Figure 3b corresponds to the sector on agriculture, fishery and forestry excluding coconut farming and copra making (Sector 2). Figures 3c to 3o similarly corresponds to Sectors 3 to 15. Sector 16 which corresponds to government services is no longer depicted since it remains completely operable (inoperability is equal to zero) even with the reduction in productivity in the sector of coconut farming including copra making in the farm (Sector 1). The results are obtained by making use of the direct fuzzy inoperability loss of $q_1 = (1.50, 2.00, 2.50)$ in the coconut farming including copra making in the farm sector. By minimizing the total inoperability of all sectors, the resulting inoperabilities for other economic sectors are then obtained using Equation 2. Furthermore, the results show that the sector of coconut farming including copra making in the farm (Sector 1) has the highest inoperability followed by the mining and quarrying sector (Sector 3) and the sector on agriculture, fishery and forestry except coconut farming and copra making in the farm (Sector 2) respectively. Regarding the magnitudes of the inoperability values, we note that the “failure rate” metric as used heavily in quality literature requires a threshold value of 3.4 parts per million (or 0.0000034) in order for a system to be considered six-sigma compliant [49]. Furthermore, while the inoperability values may initially be perceived as “negligible” in this case study, the magnitude of monetary losses and subsequent ripple effects can be quite significant and debilitating to the economy. Hence, the effect of the decrease in productivity of the sector on coconut farming including copra making in the farm (Sector 1) can be evaluated in terms of economic losses. Figures 4a through 4o show the fuzzy economic losses that result from the fuzzy reduction in feedstock where the x-axis reflects economic losses in million Philippine pesos (PhP)[†] in logarithmic scale and the y-axis in degree of plausibility. The economic loss for each economic sector is obtained by taking the product of the inoperability and the baseline capacity of the corresponding economic sector. The sector on coconut farming including copra making in the farm (Sector 1) bears the highest level of economic loss ranging from PhP 407 million to PhP 680 million within the plausible degrees of perturbation, with the most plausible scenario losing up to PhP 544

[†] The current exchange rate is approximately PhP45 $\cong$ US\$1

million. The sector for all other manufacturing sectors (Sector 8) is ranked second experiencing a loss between PhP 39 million to PhP 64 million with a loss of PhP 51 million being the most plausible. The sector on agriculture, fishery and forestry except coconut farming and copra making in the farm (Sector 2) ranks third with an economic loss ranging between PhP 19 million to PhP 32 million with a loss of PhP 25 million being the most plausible.

Ranking the sectors with respect to inoperability and economic loss reveals that there are differences in the ranking. The rank of the sectors with respect to inoperability and economic loss is shown in Figure 5, where each point represents a sector, the horizontal axis corresponds to the rank of the sector in terms of inoperability while the vertical axis corresponds to its rank in terms of economic loss. Sectors that lie along the 45° line, such as the sector on coconut farming including copra making in the farm (Sector 1), agriculture, fishery and forestry except coconut farming and copra making in the farm (Sector 2) and government services (Sector 16), have the same rank in terms of inoperability and economic loss. Furthermore, a lower ordinal rank implies higher sector criticality; hence a sector that is closer to the origin of the plot will tend to receive a higher priority. Nevertheless, this is not generally a trivial task since the inoperability and economic loss ranks of the sectors tend to be different. Figure 5, for example, reveals that all other manufacturing sectors (Sector 8) have a rank of 2 in terms of economic loss and a rank of 6 in terms of inoperability. Furthermore, the mining and quarrying sector (Sector 3) is ranked as the 2nd most critical sector in terms of inoperability, while on the contrary; it received a moderate rank of 8 in terms of economic loss. These observations clearly show that sector prioritization is a multi-criteria decision analysis problem that requires expert elicitation and sensitivity analysis methods to identify the appropriate preference structure across the objectives (i.e., minimization of economic loss versus minimization of inoperability).

Furthermore, taking into consideration the uncertainty in the perturbation and evaluating at α -cut of 0.50, a pairwise comparison of the fuzzy inoperabilities between economic sectors is performed to determine whether one sector completely outranks another. This was done by evaluating the lower and upper inoperability experienced by each sector at α -cut of 0.50. If the lower bound of the inoperability of a

sector falls within the lower and upper bound of another within the given α -cut, then it can be said that the difference in vulnerability ranking between these two sectors is not significant. The resulting pairwise comparison matrix is shown in Figure 6 wherein the sectors have been organized from top to bottom and from left to right in decreasing inoperability. The cells which are shaded in black represent the comparison of sectors with itself while cells shaded in gray indicate the existence of overlaps in inoperability between the row and the column sectors. As can be seen, the uncertainties can cause an overlap in the overall scores, in which case it becomes impossible to definitively assert that one sector outranks another at the given α -cut. Conversely, the absence of overlap means that there is a clear difference in rank of respective sectors [39]. For example, the sectors on transportation, communication and storage (Sector 11), all other manufacturing sectors (Sector 8) and the manufacture of asphalt, lubricants and miscellaneous products of petroleum and coal (Sector 7) do not definitely outrank each other for ranks 5, 6 and 7. The same interpretation can be made for all other sectors with shaded cells. However, it is definite that the sectors on coconut farming including copra making in the farm (Sector 1), mining and quarrying (Sector 3), agriculture, fishery and forestry except coconut farming and copra making in the farm (Sector 2) and petroleum refineries including LPG (Sector 6) are ranked 1st, 2nd, 3rd and 4th respectively in terms of inoperability and that government services (Sector 16) is ranked last since it has the lowest inoperability. Similarly, taking into consideration the fuzzy economic losses at an α -cut of 0.50, pair-wise comparison of sector ranking is shown in Figure 7.

4. Results (Case Study 2)

The coconut scale insect (*Aspidiotus rigidus*) invasion in the coconut-growing areas of the Philippines, particularly in Southern Luzon, is a major threat to the local coconut industry. The initial cases of coconut scale insect infestation was observed in 2009, however, official reports to the Philippine Coconut Authority were only made in March 2010 and by that time the damage had spread to nearby provinces. In 2013, the insect damage affected 50 – 70% of the coconut farms in Batangas, and 10-20% of farms in Laguna, Cavite and Quezon [11, 50]. There is a growing concern on the possible spread of this insect pest to other coconut-growing islands in Visayas and Mindanao, as well as, its potential capacity to attack other crop species. The current host range of *A. rigidus* includes coconut, *Cocos nucifera*, ornamental plants

in the family *Araceae*, banana, *Musa sp.*, and mangosteen, *Garcinia mangostana*, which are major crop exports of the country. The pest outbreak in the Philippines was probably due to accidental introduction of infested plant parts [50] most likely from Indonesia as suggested by the record of world distribution. The absence of natural enemies resulted in the rapid pest outbreak in Southern Luzon. By early April 2014, an insect parasitoid, *Comperiella sp.* was found directly associated with *A. rigidus*. The parasitoid *Comperiella sp.* is a tiny wasp under the insect order *Hymenoptera* family *Encyrtidae* known to parasitize or feed on the body of diaspine scale insects where the coconut scale insect belongs. *Comperiella sp.* was first noticed in Calauan, Laguna [11] and in just 5 months the parasitoid quickly spread in Southern Luzon with level of parasitization ranging from 70 – 90%. This finding suggests that *A. rigidus* population can potentially be controlled by this parasitoid alone.

Case Study 2 considers the loss in the productivity of Sector 1 due to the effect of coconut pest infestation. The fuzzy inoperability for the coconut sector is (5.00, 19.00, 37.00), which are based on percentage loss of output reported in Batangas in the years 2010 – 2013, immediately after the introduction of the coconut scale insect, relative to the average production level of preceding years. This fuzzy number once again indicates that the most plausible level of loss is 19%, while the range of values from 5 – 37% may be considered as marginally plausible.

The resulting non-zero fuzzy inoperabilities for the economic sectors are shown in Figure 8a to Figure 8o with the horizontal axis representing inoperability in logarithmic scale and the vertical axis representing plausibility. Similar to Figure 3a, Figure 8a represents the inoperability for the sector on coconut farming including copra making in the farm (Sector 1) while Figure 8b corresponds to the agriculture, fishery and forestry excluding coconut farming and copra making sector (Sector 2). Figures 8c to 8o similarly correspond to Sectors 3 to 15 respectively. The sector for government services (Sector 16) does not experience any inoperability resulting from the reduction in productivity of the sector on coconut farming including copra making in the farm (Sector 1) and is thus no longer shown in Figure 8. The inoperabilities are obtained by using Equation 2 while minimizing the total inoperability of the system when the direct fuzzy inoperability of the coconut farming including copra making in the farm sector (Sector 1) is $q_1 =$

(5.00, 19.00, 37.00). Based on the results, the highest inoperability is experienced by the sector on coconut farming including copra making in the farm (Sector 1), followed by the mining and quarrying sector (Sector 3) and the sector on agriculture, fishery and forestry except coconut farming and copra making in the farm (Sector 2) accordingly.

The resulting fuzzy economic losses on the other hand are illustrated in Figure 9a to Figure 9o where the horizontal axis represents economic losses in million pesos (PhP) in logarithmic scale and the vertical axis in degree of plausibility. These are obtained by taking the product of the inoperability and the baseline productivity of each economic sector. The decrease in productivity due to insect infestation is reflected in the resulting economic losses in all sectors with the highest economic loss in the sector of coconut farming including copra making in the farm (Sector 1) ranging from PhP 1.36 billion to PhP 10 billion within the plausible levels of perturbation, with the most plausible scenario estimated to lose up to PhP 5.17 billion. This can be attributed to the continuous decrease in the production of coconut from 2009 to 2013 particularly from Batangas coconut farms. The sector which ranks second is that of the manufacturing sector (Sector 8) with a potential economic loss ranging from PhP 127 million to PhP 940 million with the most plausible perturbation scenario resulting in an economic loss of PhP 484 million. The ranking of the sectors with respect to inoperability and economic loss is the same as that of Case study 1.

Again, integrating the uncertainty in the perturbation, the fuzzy inoperabilities experienced by the sectors at an α -cut of 0.50 are compared. Figure 10 shows the pairwise comparison of fuzzy inoperabilities between economic sectors while Figure 11 shows the pair-wise comparison of the economic losses. The economic sectors have been organized from top to bottom and from left to right in decreasing criticality. It can be seen that because of the large uncertainty in the perturbation, more sector rankings overlap. In Figure 10 for example, up to 9 economic sectors overlap in inoperability which happens in ranks 5 and 6 while up to 7 sectors overlap in ranks 6, 7 and 8 in terms of economic loss as shown in Figure 10.

5. Discussion

The two case studies shown illustrate how climate-induced disruptions such as extreme weather events or pest infestation can pose significant risks to biomass supply chains. In both cases, the initial direct effects of such impacts on agricultural activities have already been recognized in the Philippines, but the full extent of their economic impacts has not yet been fully appreciated. Furthermore, the risks are compounded by ripple effects that propagate through economic systems as a result of sector interdependencies. Fuzzy IIM can provide a rigorous approach for the analysis of such risks, while accounting for uncertainties that are inherent in estimating the magnitude of future events. The analysis of the Philippine case in this work illustrates that such collateral risks need to be taken into account in order to balance the benefits of biofuel mandates with the possible negative effects of supply disruptions. Planning for such disruptions is hence an essential aspect of climate change adaptation strategies for the Philippines in particular, and for many other countries in general. In other words, as previously noted [4], while implementation of low-carbon energy options (such as biofuels) is necessary to mitigate climate change on a global scale, it is also necessary to ensure that such measures are themselves sufficiently resilient in the face of climatic impacts. Such principles should apply to renewable energy in general. For instance, a recent paper considers the case of electricity shortage caused by reduced hydroelectric power supply as a consequence of drought; an I-O based optimization framework was thus proposed to rationalize allocation of electricity [36]. Another recent work [37] considers how palm oil can be allocated in an economic system when seasonal haze caused by forest fires reduces photosynthetic activity, and hence, crop yield.

In the case of biofuels, various options to improve the resilience of supply chains may be used (e.g., feedstock diversification, geographic dispersion of energy farms, and provision for importation in the event of crisis). Feedstock diversification is a particularly interesting strategy. The Philippine biodiesel mandate is based on the use of coconut, a ubiquitous traditional crop, as the main feedstock. This feature initially had the advantage of providing stimulus for rural development, while ensuring start-up biodiesel producers a reasonably reliable supply of feedstock. Attempts to introduce alternatives such as *Jatropha curcas* have met with failure [10]. Although the use of a single dominant feedstock may offer distinct

advantages, such as economies of scale, they may prove to be much more vulnerable than diversified supply chains. The fuzzy IIM methodology demonstrated here can be used to assess the effectiveness of such alternative measures relative to anticipated disruptions. It provides a risk management perspective which is critical for developing effective biofuel policies, because the typical recovery time for an agricultural system may take months, even if the disruption itself is relatively short-lived [5].

6. Conclusions

A fuzzy inoperability input-output model (IIM) has been developed based on a supply-reduction framework, and applied to the analysis of economic risks associated with 5% biodiesel blending in the Philippines, with respect to extreme weather events due to climate change and to large-scale infestation by the coconut scale insect. Both scenarios represent highly plausible climate change impacts which are already starting to manifest in the Philippines, and whose severity may escalate in the coming years. It is thus essential for policy analysis that the economic risks of such disruptions be systematically assessed via fuzzy IIM.

Results show that fuzzy IIM can provide insight on which economic sectors will be most affected by a particular disaster in terms of economic loss or inoperability. The ranking of economic sectors based on these two vulnerability measurements are not necessarily the same. Furthermore, due to the uncertainties in the perturbation resulting from disasters, some economic sectors do not fully outrank another when these uncertainties are considered. These insights have to be considered when identifying the key sectors in the development of disaster management strategies. A notable conclusion that can be gleaned from this paper is that the resulting disparity in the sector ranking due to the two vulnerability measures can be integrated to yield a single ranking by providing weight assignments to the prioritization measures (i.e., economic loss versus inoperability). This offers a rich opportunity to utilize preference elicitation methods (such as the analytic hierarchy process) in quantifying the weight assignments to the prioritization measures. A case in point, Resurreccion and Santos [51] developed a dynamic cross-prioritization plot (DCPP) to demonstrate how expert-elicited preferences could significantly alter the recovery timeline and the resulting total regional losses in the aftermath of disasters.

Furthermore, we observed in both case studies that the government services sector tends to be insensitive to disruptions in the coconut and copra industry. This result is due to the nature of the Philippine I-O data, which assumes that the government services sector's economic linkages with the rest of the sectors are practically negligible. Hence, this result implies that the analysis of other non-economic criteria (such as government image, public confidence, and other socio-political dimensions) could be additionally performed to complement the current economic loss and inoperability consequence metrics used in the sector prioritization process. Other significant future work will focus on exploring the impact of simultaneous or probability-weighted disaster scenarios and identifying strategies for improving the resilience of an economic system. More nuanced risk analysis can be done using updated, higher-resolution I-O data. In addition, further insights can be gained from developing a dynamic variant of the model proposed here. Such dynamic models can show subtle effects not evident in the static model presented here; for example, the compounded damage caused by disasters occurring in succession may be assessed via such an approach. It is also possible to envision applications of this methodology to other scenarios that are relevant for biofuel policies in other countries and regions. Finally, given the inherent limitations of I-O based models, the development of a fuzzy CGE framework for predicting the effects of disruptions should be considered as an important research problem.

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698 Figure 1. Representation of a triangular fuzzy number

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703 Figure 2. Outranking between two triangular fuzzy numbers indicating (a) no significant difference; (b)
704 significant difference
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(a)

(b)

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Figure 3a – 3o. Fuzzy Inoperability of Economic Sectors for Case Study 1.

Figure 4a - 4o. Sector-wise Fuzzy Economic Losses for Case Study 1 (in Million Pesos)

Figure 5. Inoperability Rank vs. Economic Loss Rank of Each Sector at the Highest Plausible Perturbation

Figure 6. Pair-wise comparison of sector ranking based on inoperability at α -cut of 0.50 for Case Study 1

Figure 7. Pair-wise comparison of sector ranking based on economic loss at α -cut of 0.50 for Case Study 1

Figure 8a – 8o. Fuzzy Inoperability of Economic Sectors for Case Study 2

Figure 9a – 9o. Sector-wise Fuzzy Economic Losses for Case Study 2 (in Million Pesos)

Figure 10. Pair-wise comparison of sector ranking based on inoperability at α -cut of 0.50 for Case Study 2

Figure 11. Pair-wise comparison of sector ranking based on economic loss at α -cut of 0.50 for Case Study 2

Table 1. Economic sectors for Case Study 1

Sector Code	Description
S1	Coconut farming including copra making in the farm
S2	Agriculture, fishery and forestry except coconut farming and copra making in the farm
S3	Mining and quarrying
S4	Production of crude coconut oil, copra cake and meal
S5	Manufacture of refined coconut oil and vegetable oil
S6	Petroleum refineries including LPG
S7	Manufacture of asphalt, lubricants and miscellaneous products of petroleum and coal
S8	All other manufacturing sectors
S9	Construction
S10	Electricity, gas and water
S11	Transportation, communication and storage
S12	Trade
S13	Finance
S14	Real estate and ownership of dwellings
S15	Private services
S16	Government services