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A model for multi-criterion disaster vulnerability assessment of economic systems: implications for Vietnam's bioethanol policy

Nguyen Thi Hoa[1] · Le Quang Dien[2] · Michael Angelo B. Promentilla[1,3] · Krista Danielle S. Yu[4] · Kathleen B. Aviso[1,3]

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Abstract Implementing new strategies to mitigate the impacts of climate change may influence an economy's vulnerability to natural disasters. It is thus important to develop mechanisms for evaluating the impact of these changes prior to their implementation. Recent works have demonstrated the effectiveness of inoperability input–output models in assessing the impact of natural disasters on interconnected economic systems. This study develops a multi-criteria framework that measures the vulnerability of economic sectors by considering plausible disaster scenarios and the resulting "ripple effects" of such disruptions. The approach proposed here uses three metrics: average propagation length, economic loss, and inoperability. The model then uses the analytic hierarchy process to measure the importance of each component in a hierarchical framework to derive a composite vulnerability index. The method is used to assess the implications of implementing the mandatory bioethanol blending program in Vietnam, using cassava and sugarcane as bioethanol feedstocks. The disaster scenarios assessed include the incidence of typhoons, floods, and pest infestation. Results show that the cassava, sugarcane, and other manufacturing sectors are the key economic sectors which are most affected by these disasters. Furthermore, sensitivity analysis on different bioethanol blend rates indicates that a 5 % bioethanol blend policy does not significantly affect Vietnam's economy, while raising the blend to 10 % bioethanol or more may considerably change the country's economic structure and disaster vulnerability.

Keywords Inoperability input–output model · Analytic hierarchy process · Disaster vulnerability assessment · Bioethanol blend

Introduction

The impact of human activities on the environment has led to serious global concerns such as climate change. Rising carbon dioxide (CO_2) emissions from the continued use of fossil fuels remains a major contributor. Hence, the question of how clean, low-carbon energy can be used on a larger scale is now of great research interest (Bandyopadhyay 2014). Deployment of renewable energy systems, for example, has become an essential strategy for achieving sustainable development, and in particular the shift towards alternative motor vehicle fuels such as bioethanol and biodiesel has been encouraged to mitigate CO_2 emissions. Biofuels have lower net carbon emissions compared to fossil fuels since they have absorbed atmospheric CO_2 during the photosynthetic process of biomass growth (Balat and Balat 2009). Furthermore, the production and use of biofuels may provide additional benefits, such as improving national energy security and decreasing dependence on imported fuels (Demirbas 2009). As a result, many countries have implemented policies which encourage, or even mandate, the partial replacement of

✉ Kathleen B. Aviso
kathleen.aviso@dlsu.edu.ph

[1] Chemical Engineering Department, De La Salle University, Manila, Philippines

[2] Department of Pulp and Paper Industry, School of Engineering, Hanoi University of Science and Technology, Hanoi, Vietnam

[3] Center for Engineering and Sustainable Development Research, De La Salle University, Manila, Philippines

[4] School of Economics, De La Salle University, Manila, Philippines

gasoline with bioethanol and diesel with biodiesel at various blend rates (Balat and Balat 2009). However, the sustainability of such biofuel programs will depend not only on technical feasibility but also on socio-economic (Nasterlack et al. 2014), environmental (Kazamia and Smith 2014), ethical (Ng et al. 2010), and even political (Demirbas 2011) factors. Escobar et al. (2009) gives an analysis of the interactions of these factors, while Ng et al. (2010) provides a review on the recent trends and future directions in the biofuel industry. The use of chemical fertilizers and herbicides, which is a major contributor to environmental emissions (Brondani et al. 2015) is necessary for the sustainability of biofuels (Razon 2015). Biofuel supply chains may also be vulnerable to risks such as pest infestation and storm damage (Aviso et al. 2015). With the onset of climate change expected to bring more adverse weather events, it is thus essential to evaluate how an increased reliance on agricultural feedstock for biofuel production can adversely affect an economy. Favorable climatic conditions are a key prerequisite for ensuring long-term viability of biofuel programs (Kojima and Johnson 2006). Caution should thus be exercised when evaluating strategies for climate change mitigation to minimize unintended consequences (Ingwersen et al. 2014) and rebound effects (Bandyopadhyay 2015). Furthermore, it has been suggested that such risks need to be accounted for in planning energy systems (Tan 2011). Bare (2014) proposed a sustainability assessment framework for renewable biofuels, while financial analysis was conducted by Cucchiella et al. (2014) to provide information on investment and policy decisions in renewable systems. Gurram et al. (2016) also indicated the importance of analyzing the chemical composition of feedstocks that may be affected as a result of climate change. If a more holistic impact assessment is desired, input–output (IO) analysis (Leontief 1936) provides a framework for accounting both direct and indirect impacts particularly in interdependent systems. The IO framework was initially developed for forecasting the performance of an economy. However, extensions of this model have been made to account for the environmental impacts of economic transactions (Leontief 1970), which has led to the emergence of IO-based life cycle assessment (Hendrickson et al. 2006). This framework has also been used recently for evaluating enterprise-level sustainability (Jia et al. 2015). Furthermore, it has been extended to the inoperability input–output model (IIM) to show the propagation of failure through interdependent structures (Haimes and Jiang 2001). IIM was later applied to economic systems (Santos and Haimes 2004) and has since been used for analyzing the impact of extreme events such as pandemic outbreaks (Santos et al. 2009), malicious attacks (Crowther and Haimes 2005), the September 11, 2001 terrorism (Santos and Haimes 2004), and hurricane disruptions (Akhtar et al. 2013), among others.

Extreme events expose economies to risk and vulnerability. In this work, we adapt Timmerman's (1981) definition of vulnerability as the reaction of a system to a disruption, and several criteria must be considered to evaluate the vulnerability of an economy to disasters (Armas 2012; Zarafshani et al. 2012). Economic, physical, and environmental factors have been considered for vulnerability assessment and several techniques have been used to simultaneously evaluate the multiple criteria. Tonmoy and El-Zein (2012), for example, used the outranking method ELECTRE III for evaluating the vulnerability of Sydney to heat stress, while Armas (2012) used a multi-criteria vulnerability analysis approach for analyzing earthquake hazards. The most widely used approach is to take the weighted sum of criteria scores to give a single index, in such cases, the challenge is in identifying the appropriate scheme for aggregation. Nouri et al. (2011), for example, utilized the analytic hierarchy process (AHP) for vulnerability assessment of education centers, while Cheng and Tao (2010) used AHP to generate the weights for a drought vulnerability index. Zarafshani et al. (2012) elicited the relative importance of economic, socio-cultural, psychological, technical, and infrastructural factors to farmers to assess the drought vulnerability of Western Iran. Ahsan and Warner (2014) used the Likert scale for obtaining the relative weights of the socio-economic vulnerability index of the coastal areas of Bangladesh, while Yu et al. (2014) proposed a vulnerability index for post-disaster sector prioritization with economic impact, sector size, and average propagation length (APL) as its components. In addition, Yu et al. (2014) utilized various scenarios of component weighting, and implemented Monte Carlo simulation to evaluate the sensitivity of the index to variations in the component weights.

Economic vulnerability is strongly influenced by economic structure, which in turn is influenced by international or national policies. However, it has been recognized that policy changes may require the restructuring of an economy (Zimmer et al. 2015), which will thus influence the vulnerability of economic sectors to disruptions. Analysis of the impact of biofuel policies has thus been conducted for evaluating the effects on the income of farmers in the EU (Deppermann et al. 2016), GHG emission and energy security (Sarica and Tyner 2013), and livestock production (Miljkovic et al. 2012) in the US to name a few. In addition, Kumar et al. (2013) emphasized that the impacts of biofuel policies on land use change, food prices, and farmer welfare in the ASEAN should further be studied.

In this work, we evaluate the impact of biofuel policies on the vulnerability of an economy to disasters. Several vulnerability indices have been designed to specifically account for the impact of disasters on economic systems. Examples include analysis of potential impact of sea level rise and total economic impact of natural disasters (Adrianto and Matsuda 2002); integration of shock indicators such as population size, trade, share of agriculture, and index of remoteness (Guillaumont 2009); and a multidimensional index that accounts for an economy's resilience (Bates et al. 2014). However, these indices provide overall scores for an economy. This study develops a vulnerability index based on the framework by Yu et al. (2014) for each sector, by integrating IO and AHP methodology for prioritizing economic sectors in consideration of plausible natural disasters. This approach is then used to assess the biofuel blending policy in Vietnam.

The rest of the paper is organized as follows. In "Methodology" section discusses the formal problem statement and presents the overview of the proposed vulnerability index. Case studies, which relate to the implementation of a bioethanol blending policy, are then utilized to demonstrate the capability of the proposed index. Sensitivity analysis is then conducted to show the change in the prioritization of sectors, should the biofuel blending policies change. Finally, conclusions and recommendations for future work are discussed.

Methodology

This work focuses on economic vulnerability resulting from structural changes in the economy and thus the vulnerability index proposed here capitalizes on the insights from IO analysis. Similar to that of Yu et al. (2014), the three main components of the proposed index are economic loss, inoperability, and propagation length. However, in this work, AHP is utilized to integrate the components of the vulnerability index with identified climate change-induced disasters.

The formal problem statement can thus be stated as follows:

- Given an economy with M number of sectors, an $m \times m$ technical coefficient matrix $\mathbf{A}$ can be obtained to describe the interactions between the economic sectors.
- Given N number of plausible disasters, the vulnerability of economic sectors is affected by the nature of the sector interdependencies and are evaluated based on P number of components such as economic loss, inoperability, and propagation length.
- Relative importance weights (w_{rk}) for the index components, k, with respect to natural disaster, r, and the relative weight of disasters (d_r) with respect to overall vulnerability are elicited from domain experts and stakeholders
- The overall vulnerability index is a weighted aggregate of component scores

The goal is to rank the economic sectors based on their vulnerability index scores in consideration of plausible disasters. The vulnerability index scores can potentially change when implemented policies require changes in an economy's technical coefficient matrix.

Input–output preliminaries

The IO framework is widely used in assessing interdependencies between various economic sectors. Its basic formulation is given by Eq. (1).

$$\mathbf{A}\mathbf{x} + \mathbf{y} = \mathbf{x}, \tag{1}$$

where $\mathbf{A}$ is the $m \times m$ technical coefficient matrix, $\mathbf{x}$ is the output vector, and $\mathbf{y}$ is the final demand vector (Miller and Blair 2009). The technical coefficient matrix ($\mathbf{A}$) contains the elements a_{ij}, which indicate the amount of product from sector i needed to produce one unit of output from sector j. The coefficients, a_{ij}, describe the structure of an economy and are assumed fixed unless technological changes are introduced. The mathematical foundations of this equation can be found in standard input–output books such as that of Miller and Blair (2009).

The components of the vulnerability index are grounded on the economic structure as defined in Eq. (1).

Vulnerability index component 1: economic loss (EL)

The economic losses incurred reflect an economy's vulnerability towards a disruptive event. The individual economic sector contribution to the total loss indicates the vulnerability of the sector, which may not be the same as the whole. Some sectors may suffer minimal losses while others may contribute a huge share to the total economic loss. Given the same level of reduction in sector productivity, an economic sector with a higher level of output will bear higher economic losses. Economic loss is computed by taking the difference between the total output of the ideal system and the perturbed system.

The proposed vulnerability index implies that higher economic loss translates to higher vulnerability.

Vulnerability index component 2: inoperability

Haimes and Jiang (2001) developed the inoperability input–output model (IIM) to assess critical infrastructure systems, where they defined inoperability as "the inability of the system to perform its intended function". Santos and Haimes (2004) further developed the model to adapt widely available economic IO tables to calculate inoperability metrics. For each sector i, an inoperability metric, q_i, is defined as a continuous dimensionless variable with values ranging from 0 to 1, with 0 corresponding to the fully functional state of a system, 1 corresponding to total failure, and intermediate values indicating varying degrees of inoperability. The inoperability is associated with the system perturbation c_i* through Eq. 2.

$$\mathbf{A}^*\mathbf{q} + \mathbf{c}^* = \mathbf{q} \tag{2}$$

A comprehensive derivation of the IIM is found in Santos (2003). A high inoperability value also translates to high vulnerability within the context of the index.

Vulnerability index component 3: average propagation length (APL)

Aside from economic losses and inoperability, it is also important to account for the network of interconnections among various economic sectors. This study adapts the average propagation length (APL) methodology developed in Dietzenbacher et al. (2005) as a metric for economic distance and size of linkages. The APL is grounded in the IO framework and factors in the demand-pull effect of an exogenous change in final demand and cost-push effect of an exogenous change in primary cost; thus, providing a two-pronged approach to observing the interconnectivity between sectors. In the proposed vulnerability index, a higher APL value corresponds to higher sector vulnerability because it indicates that the economic sector is highly interconnected with other sectors, thus its failure will impact the economy to a greater extent. It is derived from the Ghosh inverse based on the supply-driven IO model (Ghosh 1958) and the Leontief inverse is based on the demand-side IO model. A detailed exposition of the APL can be found in Dietzenbacher et al. (2005).

Composite vulnerability index

The varying range of each component discussed may yield inconsistencies in terms of its contribution to the overall index. This is resolved by utilizing the normalized score, z_{ik}, of an economic sector i in vulnerability component k instead of using the absolute numerical values of EL_i, q_i, and APL_i obtained for each sector i. The composite vulnerability index (VI_{ir}) found in Eq. 3 is thus the weighted vulnerability score of each economic sector i with respect to disaster type r.

$$\mathrm{VI}_{ir} = \sum_{k=1}^{N} w_{rk} z_{ik} \quad \forall i \in M, \quad \forall r \in N \tag{3}$$

The overall vulnerability index (VI_i) on the other hand is the weighted aggregate of the disaster vulnerability index scores as shown in Eq. (4), where d_r is the relative weight of disaster r. This index not only takes into consideration the relative importance of disasters to an economy but also considers the relative importance of each vulnerability component factor. Equations (5) and (6) ensure that the weights do not exceed 1.0, while Eqs. (7) and (8) ensure that the sum of the importance weights will be equal to 1.0.

$$\mathrm{VI}_i = \sum_{r=1}^{N} d_r \mathrm{VI}_{ir} \quad \forall i \in M \tag{4}$$

$$0 \le d_r \le 1 \quad \forall r \in N \tag{5}$$

$$0 \le w_{rk} \le 1 \quad \forall r \in N, \quad \forall k \in P \tag{6}$$

$$\sum_{r=1}^{N} d_r = 1 \tag{7}$$

$$\sum_{r=1}^{N} \sum_{k=1}^{P} w_{rk} = 1 \tag{8}$$

Multi-Criteria vulnerability analysis with analytic hierarchy process (AHP)

The analytic hierarchy process (AHP) which was developed by Saaty (1980) is utilized to integrate all the components of the decision hierarchy into a single vulnerability index. AHP is one the most widely used multi-criteria decision analysis tool in environment and energy-related problems; and it is based on three basic tenets namely: 1) structuring complexity using hierarchy, 2) measuring priority weights with ratio scale, and 3) synthesizing by hierarchic composition (Tan 2011). In this study, the relative importance weights for the considered disasters (d_r) and the vulnerability index components (w_{rk}) are elicited from domain experts and stakeholders using pairwise comparison matrices as described in Saaty (1980).

The decision hierarchy is illustrated in Fig. 1 where the overall goal is to calculate the vulnerability index of each sector in consideration of the most probable disasters that occur in a country (2nd level), and the impact of these disasters on the economic sector as characterized by the three vulnerability components (3rd level). The bottom most level corresponds to the economic sectors considered.

Results and discussion

Case study: the bioethanol blending policy in Vietnam

The Vietnamese national government has affirmed the policy of biofuel energy (Decision No. 177), which seeks

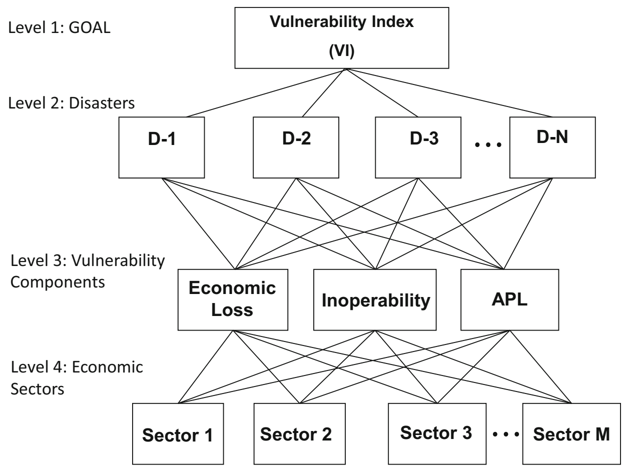

Fig. 1 Decision hierarchy for obtaining the overall vulnerability index of economic sectors

to increase the share of bioethanol and vegetable oil in the total projected gasoline and diesel oil demand, respectively, from 1 % in 2015 to 5 % in 2025 (Tuan et al. 2009). Under this policy, the replacement of gasoline by 5 % bioethanol blend (E5) and diesel oil by 5 % biodiesel blend (B5) should be used in the country. Cassava and sugar cane are the main feedstocks utilized for bioethanol production in Vietnam, while jatropha is used for biodiesel production. It is expected that the implementation of biofuel regulations will increase the demand for the growth of feedstock crops to meet the demand for biofuel. However, this increase in dependence on the agricultural sector can potentially pose challenges for Vietnam. The reason is that Vietnam is located in a region where extreme weather events such as flood and storms occur frequently (WEPA, n.d.). Every year, Vietnam suffers from various flood and storm catastrophes which result in severe aftermaths such as human and economic losses (Le et al. 2013). For instance, according to the statistical data from PreventWeb (2015), on average in the period from 1980 to 2010 there have been 2.52 storms, 1.94 floods, 0.29 pest infestations, and 0.16 droughts that occurred in Vietnam yearly. Thus, this case study considers the top three disasters: storms, floods, and pest infestation as the components of the second level in the decision hierarchy.

The IO table of Vietnam for the year 2011 compiled by Vietnam General Statistics Office (VGSO 2011) which is a 138 × 138, commodity by commodity matrix is utilized in this case study. The IO table was aggregated and disaggregated into 17 sectors such that sectors directly affected by the bioethanol blending policy implementation are isolated. Wolsky's method is used for the disaggregation of sectors (Wolsky 1984), while standard matrix calculations were applied for the aggregation of sectors (Miller and Blair 2009). The description of the 17 sectors used for the case study is shown in Table 1.

The relative weights for the disasters (d_r) and the vulnerability components (w_{rk}) are obtained through interviews with experts and stakeholders. In this study, 10 respondents consisting of experts from bioethanol production companies, the department of statistics of Vietnam and the Central Committee for Flood and Storm Control (CCFSC) were asked to answer a questionnaire. The relative weights were then obtained using the eigenvector method (Saaty 1980). The results are shown in Table 2.

In Table 2, it can be seen that the computed weights referring to the relative impact of flood in relation to the vulnerability of Vietnam's economy is the highest at 0.47, while that of storm is slightly lower at 0.40 and that of pest infestation results in the least impact of 0.12. The results are consistent with empirical data where the occurrence of typhoons generating storm surges often times result in floods in Vietnam (Mai et al. 2008). Meanwhile, the effect of pest infestation on Vietnam's economy is not as significant because historical incidence of diseases from pests has been relatively low. Furthermore, the relative weights of the sub-criteria (EL, q, and APL) are similar when considering the disaster on flood and storm, possibly because of the correlation between the two disaster events. Looking at the sub-criteria weights it can be seen that economic loss (EL) is the most important component in determining the vulnerability of sectors, while inoperability component is considered as the least important. On the other hand, the weights of sub-criteria under pest infestation are approximately evenly distributed.

The overall vulnerability index will also depend on the performance of the economic sectors in the three identified components, which in turn will vary based on the bioethanol blending policy to be implemented, as well as the perturbation introduced into the economic system. In the case study considered here, three scenarios are explored further: (1) the baseline case, (2) implementation of a 5 % bioethanol blend from a single feedstock crop, and (3) implementation of the 5 % bioethanol blend using equal contribution from two different feedstocks. In addition, these scenarios consider the perturbation resulting from the occurrence of three different disasters. The perturbations used in the different disaster scenarios for the two feedstocks considered are summarized in Table 3 and were based from the highest perturbation experienced in any year in Vietnam recorded between 1995 and 2009 by the Central Committee for Flood and Storm Control during floods and storms. Historical data on pest infestation show that up to 1.8 % of the sugarcane plantation area has been affected in the past (APPC, n.d.). However, a perturbation value of 5 % has been exogenously defined here for analyzing the impact of pest infestation, in anticipation of increasing incidence in the future. It should be noted however, that more pessimistic scenarios

Table 1 Nomenclature of the 17 economic sectors

Sector number	Economic sector
1	Sugarcane
2	Other agricultural products and services, fishery, and forestry
3	Mining and quarrying
4	Alcohol
5	All of other manufacturing sectors
6	Electricity, gas, and water
7	Construction
8	Trade
9	Transport using gasoline: bus transport, road passenger, and airport services
10	Other transport, communication, and storage
11	Finance (banks, non-banks, insurance)
12	Real estate and the ownership of dwellings
13	Public services
14	Private services
15	Cassava
16	Other crops except sugarcane and paddy and cassava
17	Motor gasoline

Table 2 Relative weights for disaster scenarios (d_r) and sub-criteria (w_{rk})

Criteria	Flood (d_1)			Storm (d_2)			Pest (d_3)		
Weight of disaster scenarios	0.4706			0.4050			0.1244		
Sub-criteria	EL	q	APL	EL	q	APL	EL	q	APL
	(w_{11})	(w_{12})	(w_{13})	(w_{21})	(w_{22})	(w_{23})	(w_{31})	(w_{32})	(w_{33})
Relative weights of sub-criteria	0.5532	0.1750	0.2718	0.5752	0.1456	0.2791	0.3284	0.3551	0.3164

Table 3 Perturbation experienced on sugarcane and cassava sector with respect to disasters

Disaster	Year	Sector	Perturbation (c^*)	Source
Flood	1996	Sugarcane	0.1379	CCFSC (2014)
	2008	Cassava	0.1271	CCFSC (2014)
Storm	1998	Sugarcane	0.1216	CCFSC (2014)
	2007	Cassava	0.0899	CCFSC (2014)
Pest infestation	–	Sugarcane	0.05	Exogenously defined
	–	Cassava	0.05	Exogenously defined

(higher values of perturbation) can be considered in future simulations.

Scenario 1: baseline case IO tables

From the aggregation and disaggregation of the original IO table, the matrix **A** can be derived and is shown in the Appendix. Then, the resulting inoperability and economic loss values resulting from the three disaster scenarios together with sector ranking using the baseline case IO table are shown in Table 4. For the inoperability component (q), the sectors which are most affected by the initial perturbation for the three disaster scenarios are the cassava and sugarcane sectors. All the other sectors suffer inoperabilities at lower levels. For economic loss, Sector 5 which represents all of the other manufacturing sectors, experiences the largest economic loss (it is ranked sixth in terms of inoperability) in all three disaster scenarios even when the perturbation occurred in the sugarcane and cassava sectors. This is because it is the largest economic sector. Meanwhile, the alcohol, construction, and public sectors experience the least economic loss because of their relatively small sector sizes.

Table 4 Inoperability and economic loss (in Millions of Vietnamese Dongs) for Scenario 1: Baseline case

Sector	Flood				Storm				Pest				APL	Rank
	q	Rank	EL	Rank	*q*	Rank	EL	Rank	*q*	Rank	EL	Rank		
Sugarcane	0.14050	1	2,451,178	3	0.12355	1	2,155,402	2	0.05098	1	889,410	3	0.04370	12
Other agricultural products and services, fishery and forestry	0.00133	5	1,247,537	4	0.00102	5	956,322	4	0.00051	5	477,584	4	0.10283	2
Mining and quarrying	0.00028	11	94,755	10	0.00021	11	72,854	10	0.00011	11	36,236	10	0.05013	11
Alcohol	0.00011	15	1712	17	0.00008	15	1312	17	0.00004	15	655	17	0.03085	15
All of other manufacturing sectors	0.00111	6	3,839,302	1	0.00085	6	2,942,223	1	0.00043	6	1,469,920	1	0.12211	1
Electricity, gas, and water	0.00091	7	158,686	8	0.00069	7	121,633	8	0.00035	7	60,750	8	0.06812	6
Construction	0.00002	16	13,206	15	0.00001	16	10,124	15	0.00001	16	5056	15	0.06170	8
Trade	0.00064	8	396,515	6	0.00049	8	303,939	6	0.00025	8	151,797	6	0.08355	3
Transport using gasoline	0.00052	10	26,173	14	0.00040	10	20,069	14	0.00020	10	10,019	14	0.05270	9
Other transports	0.00055	9	143,050	9	0.00042	9	109,655	9	0.00021	9	54,763	9	0.06941	5
Finance	0.00026	13	45,204	12	0.00020	13	34,650	12	0.00010	13	17,305	12	0.05270	9
Real estate	0.00026	12	35,068	13	0.00020	12	26,884	13	0.00010	12	13,425	13	0.02185	17
Public services	0.00001	17	3326	16	0.00001	17	2550	16	0.00000	17	1273	16	0.02956	16
Private services	0.00023	14	90,325	11	0.00017	14	69,252	11	0.00009	14	34,576	11	0.07455	4
Cassava	0.12957	2	2,564,935	2	0.09186	2	1,818,537	3	0.05092	2	1,008,064	2	0.03470	13
Other crops except sugarcane and paddy and cassava	0.01311	3	676,413	5	0.00978	3	504,927	5	0.00506	3	261,352	5	0.03342	14
Motor gasoline	0.00307	4	168,318	7	0.00237	4	130,221	7	0.00117	4	64,224	7	0.06812	6

Consequently, using Eq. (3) to integrate the APL component, the disaster vulnerability index scores (VI_{ir}) of sectors can be obtained and ranked. The VI_{ir} values of the top 10 most vulnerable sectors are shown in Table 5 wherein Rank 1 indicates that it has the highest VI_{ir} while Rank 10 has the lowest. In Table 5, it can be seen that for flood, all other manufacturing sectors (Sector 5) ranks first, followed by the sugarcane (Sector 1) and the cassava sector (Sector 15). However, when storms are considered, the sugarcane sector (Sector 1) ranks first followed by all of other manufacturing sectors (Sector 5). Meanwhile, the most vulnerable to pest infestation is the cassava sector (Sector 15), followed by the sugarcane sector (Sector 1). Since these three sectors (cassava, sugarcane, and all of other manufacturing sectors) have dominant VI values compared to the other sectors, they are identified as the key sectors of the country which must be prioritized for various risk management measures. The priority given to the sugarcane (Sector 1) and cassava (Sector 15) sectors primarily results from the direct perturbation, while that for all other manufacturing sectors (Sector 5) is due to its relatively large sector size and high degree of connectivity.

Equation (4) is used to find the overall VI of sectors computed by combining the effect of all disaster scenarios. The results are shown in the second to the last column of Table 5. Based on this result, the sugarcane sector (Sector 1) has the highest VI, followed by all of other manufacturing sectors (Sector 5). The cassava sector (Sector 15) ranks third. Thus, the combination of overall scores of the sectors also indicates that these sectors are still the key sectors of Vietnam. Sectors such as the electricity, gas, and water sector (Sector 6) and the other transport sector (Sector 10) consistently show mid-level prioritization ranking. These sectors have mid-level interactions with the other sectors as shown by their ranks in the APL component, and at the same time assume mid-level sector size. The real estate and ownership of dwellings sector is the least priority, which is mainly attributable to the very low level of interconnectivity with other sectors coupled with relatively low inoperability and sector size.

Scenario 2: implementation of the 5 % bioethanol blend relying only on one feedstock source

The biofuel program in Vietnam mandates the blending of 5 % bioethanol into gasoline. This policy will result in a change in the technical coefficients matrix (**A**) as inputs from the sugarcane or cassava sectors into the manufacturing sector will increase as these products become feedstocks for bioethanol production. The contribution of the gasoline sector to the transportation sector also decreases accordingly with the proportion of the bioethanol used for blending. This change in matrix **A** will affect the APL component in the proposed vulnerability index due to changes in inter-industry interactions and in effect affects inoperability as well. Inputs, outputs, and final demand of all other sectors are assumed to remain the same. The perturbation implemented is as indicated in Table 3 corresponding to a perturbation in the cassava sector of 0.13 in the incidence of flood, 0.09 for storm, and 0.05 for pest infestation.

The results of derivation from the updated IO table to reflect the 5 % bioethanol substitution produced from cassava indicate that the rank of sectors in terms of each component is not significantly different from that of Scenario 1. There is a slight difference in the rank of sectors between the two scenarios in terms of APL. The difference is due to the increase in the input of the alcohol sector (Sector 4) to the transportation using gasoline sector (Sector 9), resulting in the increase in priority of the

Table 5 VI of the top 10 most vulnerable sectors and their ranks due to different disaster scenarios and overall VI in Scenario 1: Baseline case

Sector		Flood		Storm		Pest		Overall VI	Rank
		VI_{i1}	Rank	VI_{i2}	Rank	VI_{i3}	Rank		
1	Sugarcane	0.2094	2	0.2232	1	0.2417	2	0.2190	1
2	Other agricultural products and services, fishery, and forestry	0.0865	4	0.0886	4	0.0686	4	0.0851	4
5	All of other manufacturing sectors	0.2115	1	0.2170	2	0.1460	3	0.2056	2
6	Electricity, gas, and water	0.0264	8	0.0270	8	0.0270	8	0.0267	8
8	Trade	0.0414	6	0.0425	6	0.0382	6	0.0415	6
10	Other transports	0.0258	9	0.0264	9	0.0266	9	0.0262	9
14	Private services	0.0246	10	0.0252	10	0.0264	10	0.0251	10
15	Cassava	0.2056	3	0.1800	3	0.2473	1	0.2004	3
16	Other crops except sugarcane and paddy and cassava	0.0482	5	0.0468	5	0.0457	5	0.0473	5
17	Motor gasoline	0.0281	7	0.0286	7	0.0299	7	0.0285	7

gasoline sector (from rank 15 to 13) in terms of APL. There was no difference in the rank of sectors in terms of economic loss and inoperability, but the numeral values of the two components between the two scenarios are slightly different. The results point out that the change in economic loss is largest during the event of flood, while it is the least during the incidence of pest infestation. The change occurs mainly in the sugarcane sector (Sector 1), all of other manufacturing (Sector 5) sectors, and cassava (Sector 15) sectors. The results also indicate that the key sectors in this scenario are the same as that of Scenario 1. The stability of key sector ranking in terms of the three components yields consistent results in identifying the key sectors when considering different disaster scenarios.

When AHP is used to evaluate the final ranking, the relative weights of criteria and sub-criteria are kept constant in all scenarios. Based on the weights listed in Table 2 and the value of economic loss, inoperability, and APL computed from Scenario 2, the priority ranking of the sectors can easily be determined as shown in Table 6.

When comparing Scenarios 1 and 2 we can see that the results are similar, and the only noticeable change is the reversal in rank between the electricity, gas, and water sector (Sector 6) and the other transport sector (Sector 10). However, to know whether a further increase in bioethanol blend contribution will affect the prioritization of sectors or not, it is necessary to conduct a sensitivity analysis of different bioethanol blend policies. Changes in the blending requirements will influence the technical coefficient matrix **A**.

Sensitivity analysis

Sensitivity analysis is implemented by assessing different bioethanol blending rates particularly 0, 10, 20, 50, and 100 % bioethanol substitutions. These different bioethanol blending strategies are considered with the assumption that the feedstock is obtained from sugarcane and cassava at equal proportions. The computation of vulnerability index components and ranks of sectors for these substitution ratios is implemented using the same steps as those in Scenario 2. However, focus is given on the overall VI of the sectors.

The results of using different bioethanol blend rates indicate that key sectors still remain the same as that of Scenario 1. Figure 2 shows how the VI of the top 5 most vulnerable sectors vary with respect to the degree of bioethanol substitution. It can be seen that the VI of the sugarcane sector (Sector 1) increases with the increase in bioethanol substitution while the VI of all other manufacturing sectors decreases (Sector 5). The VI of the cassava sector (Sector 15) on the other hand remains relatively the same. It should be noted however, that in the AHP framework, the sum of the vulnerability indices of the economic sectors will always be equal to 1. This means that a great increase in the VI of one sector will result in the decrease of the VI of other economic sectors. Furthermore, the VI of the economic sectors should be interpreted relative to and not independently of each other. As shown in Fig. 2, there is a steep increase in the VI of the sugarcane sector (Sector 1), indicating that it is the most sensitive to changes in the bioethanol blend. This can be attributed to an increase in sector size by virtue of the increase in demand for sugarcane to serve as bioethanol feedstock, and due to changes in the APL component of the sugarcane sector. The rank reversal between the cassava sector (Sector 15) and all other manufacturing sectors (Sector 5) at the bioethanol substitution rate of 10 %, shows that the vulnerability of the cassava sector (Sector 15) becomes more significant relative to Sector 5. Even if it seems that the VI of the cassava sector remains relatively constant and relatively less sensitive than the sugarcane sector (Sector 1), its performance should be evaluated in comparison to the changes experienced by other sectors. Maintaining a consistent VI indicates that its vulnerability remains

Table 6 VI of top 10 most vulnerable sectors and their ranks due to different disaster scenarios and overall VI in Scenario 2

Sector		Flood		Storm		Pest		Overall score	Rank
		VI	Rank	VI	Rank	VI	Rank		
1	Sugarcane	0.2099	1	0.2208	1	0.2411	2	0.2182	1
2	Other agricultural products	0.0858	4	0.0881	4	0.0682	4	0.0846	4
5	All of other manufacturing sectors	0.2099	2	0.2157	2	0.1450	3	0.2042	2
6	Electricity, gas, and water	0.0252	9	0.0258	9	0.0257	10	0.0255	9
8	Trade	0.0412	6	0.0423	6	0.0380	6	0.0412	6
10	Other transports	0.0257	8	0.0263	8	0.0265	8	0.0261	8
14	Private services	0.0245	10	0.0251	10	0.0263	9	0.0250	10
15	Cassava	0.2072	3	0.1838	3	0.2485	1	0.2028	3
16	Other crops	0.0485	5	0.0473	5	0.0463	5	0.0477	5
17	Motor gasoline	0.0280	7	0.0285	7	0.0299	7	0.0285	7

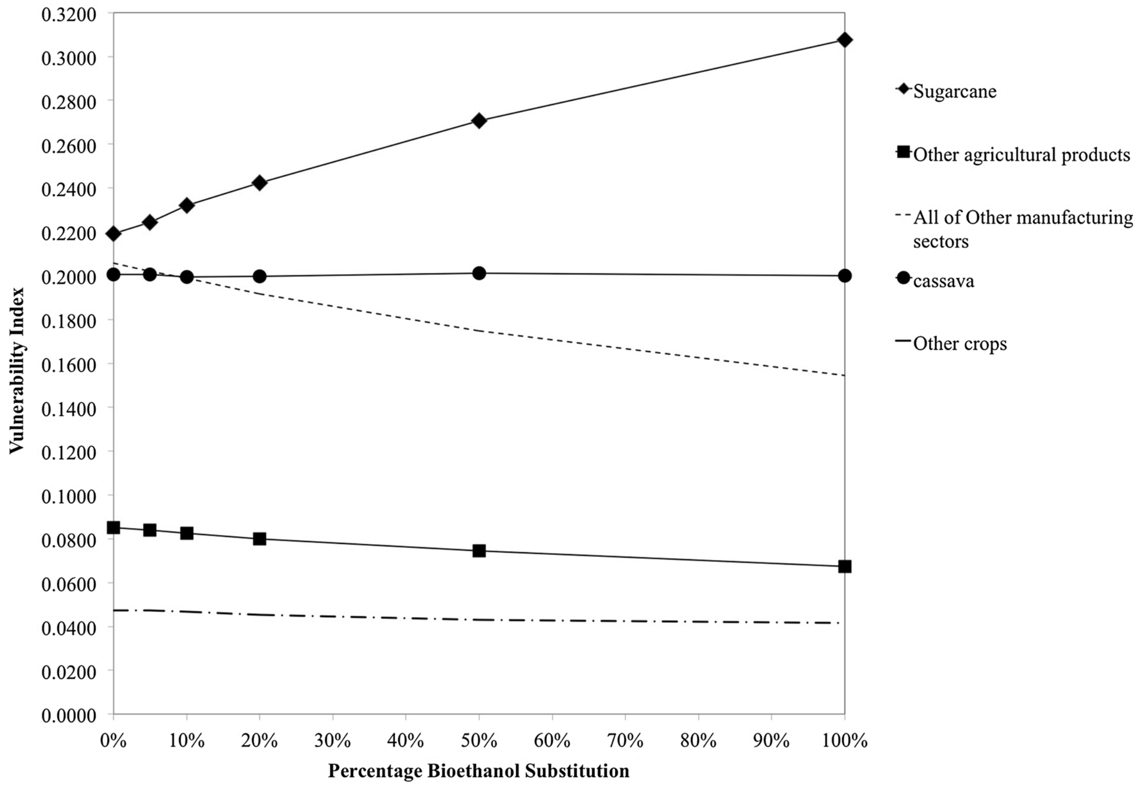

Fig. 2 Overall VI of sectors as a function of increasing percentage of bioethanol substitution

significant even with the changes in the parameters of the scenarios considered. For the cassava sector, this is due to the increase in its sector size in order to meet the demand for bioethanol feedstock. The demand from Sector 5 on the other hand remains unchanged.

Conclusions and future work

An IO-based AHP model has been developed for evaluating the vulnerability of economic sectors to climate-induced disasters upon the implementation of changes in bioethanol blend policies in Vietnam. Three vulnerability criteria, namely, economic loss, inoperability, and APL, are applied in consideration of different disasters. The integration of AHP in the model further enhances the analysis by capturing the priority weights of the stakeholders, in order to determine the relative vulnerability indices of the economic sectors. This feature thus provides insights on where recovery efforts should focus. A comprehensive evaluation of the vulnerability index components and the elicited weight factors can provide insights towards developing strategies for disaster risk mitigation and recovery.

The scenarios considered in this work show that the vulnerability of the economic sectors is affected by changes in the economic structure as well as sector size resulting from variations in the bioethanol blend requirement. It has been shown that the key sectors identified are the sugarcane sector (Sector 1), all other manufacturing sectors (Sector 5), and the cassava sector (Sector 15). An increase in the percentage of bioethanol in gasoline (using equal contributions of sugarcane and cassava feedstocks) results in a steep increase in the vulnerability index of the sugarcane sector. This indicates that the sugarcane sector is highly sensitive to the degree of bioethanol substitution; thus policy makers should reconsider the use of sugarcane as bioethanol feedstock. Possible strategies include reducing the amount of bioethanol substitution, increasing the proportion of cassava as bioethanol feedstock, or exploring other potential feedstock. Thus, future research could focus on looking into more disaster scenarios, considering other crops for bioethanol production and integrating the effect of volatility in prices of the feedstock. In addition, the framework can be extended to dynamic IIM while integrating additional components (e.g., social impacts) into the vulnerability index.

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Appendix

See Table 7.

Table 7 Technical coefficient matrix (**A**) for Scenario 1: Baseline case

Sector number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	0.0037	0.0013	0.0000	0.0004	0.0039	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0068	0.0026	0.0000
2	0.1020	0.1158	0.0000	0.1077	0.0834	0.0002	0.0007	0.0147	0.0000	0.0002	0.0000	0.0008	0.0016	0.0789	0.1840	0.0706	0.0000
3	0.0005	0.0008	0.0425	0.0024	0.0110	0.0757	0.0174	0.0009	0.0006	0.0005	0.0000	0.0002	0.0001	0.0040	0.0009	0.0003	0.1832
4	0.0000	0.0008	0.0000	0.0006	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0060	0.0000	0.0000	0.0000
5	0.1296	0.2259	0.1271	0.4087	0.6148	0.0942	0.4699	0.0777	0.1287	0.2043	0.0129	0.0297	0.1243	0.1886	0.2406	0.0924	0.4944
6	0.0042	0.0079	0.0090	0.0186	0.0202	0.1511	0.0058	0.0201	0.0027	0.0136	0.0046	0.0397	0.0190	0.0282	0.0076	0.0029	0.0028
7	0.0002	0.0008	0.0051	0.0003	0.0012	0.0060	0.0436	0.0030	0.0008	0.0172	0.0002	0.0040	0.0137	0.0030	0.0004	0.0001	0.0001
8	0.0226	0.0280	0.0172	0.0302	0.0446	0.0170	0.0300	0.0165	0.0523	0.0305	0.0018	0.0044	0.0152	0.0241	0.0407	0.0156	0.0023
9	0.0014	0.0008	0.0244	0.0011	0.0015	0.0016	0.0017	0.0053	0.0154	0.0265	0.0017	0.0005	0.0038	0.0028	0.0024	0.0009	0.0006
10	0.0053	0.0055	0.0151	0.0409	0.0166	0.0071	0.0143	0.0278	0.0276	0.0925	0.0068	0.0278	0.0197	0.0354	0.0095	0.0036	0.0037
11	0.0002	0.0006	0.0020	0.0011	0.0027	0.0182	0.0033	0.0045	0.0098	0.0051	0.5749	0.0011	0.0041	0.0034	0.0004	0.0001	0.0012
12	0.0020	0.0008	0.0008	0.0037	0.0014	0.0001	0.0016	0.0159	0.0080	0.0244	0.0011	0.0463	0.0254	0.0152	0.0037	0.0014	0.0012
13	0.0001	0.0001	0.0016	0.0008	0.0004	0.0009	0.0006	0.0007	0.0005	0.0013	0.0002	0.0004	0.0336	0.0017	0.0002	0.0001	0.0001
14	0.0016	0.0038	0.0129	0.0525	0.0116	0.0354	0.0165	0.0191	0.0250	0.0241	0.0177	0.0116	0.0483	0.0709	0.0029	0.0011	0.0147
15	0.0069	0.0096	0.0000	0.0017	0.0024	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0023	0.0015	0.0090	0.0000
16	0.0541	0.0178	0.0000	0.0154	0.0063	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0003	0.0095	0.1933	0.0008	0.0000
17	0.0127	0.0241	0.0435	0.0122	0.0043	0.0198	0.0121	0.0187	0.3342	0.0091	0.0035	0.0097	0.0119	0.0101	0.0160	0.0061	0.1143

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