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A Fuzzy Data Envelopment Analysis Framework for Dealing with Uncertainty Impacts of Input–Output Life Cycle Assessment Models on Eco-efficiency Assessment

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Abstract

The uncertainty in the results of input-output-based life cycle assessment models makes the sustainability performance assessment and ranking a challenging task. Therefore, introducing a new approach, fuzzy data envelopment analysis, is critical; since such a method could make it possible to integrate the uncertainty in the results of the life cycle assessment models into the decision-making for sustainability benchmarking and ranking. In this paper, a fuzzy data envelopment analysis model was coupled with an input-output-based life cycle assessment approach to perform the sustainability performance assessment of the 33 food manufacturing sectors in the United States. Seven environmental impact categories were considered the inputs and the total production amounts were identified as the output category, where each food manufacturing sector was considered a decision-making unit. To apply the proposed approach, the life cycle assessment results were formulated as fuzzy crisp valued-intervals and integrated with fuzzy data envelopment analysis model, thus, sustainability performance indices were quantified. Results indicated that majority (31 out of 33) of the food manufacturing sectors were not found to be efficient, where the overall sustainability performance scores ranged between 0.21 and 1.00 (efficient), and the average sustainability performance was found to be 0.66. To validate the current study's findings, a comparative analysis with the results of a previous work was also performed. The major contribution of the proposed framework is that the effects of uncertainty associated with input-output-based life cycle assessment approaches can be successfully tackled with the proposed Fuzzy DEA framework which can have a great area of application in research and business organizations that use with eco-efficiency as a sustainability performance metric.

Key Words: Life Cycle Assessment; Input-Output Analysis; Sustainability Performance Index; Fuzzy Data Envelopment Analysis; U.S. Food Manufacturing; Sensitivity Analysis.

1. Introduction

Sustainable food production and agriculture are integral elements of sustainable development efforts due to steeply rising worldwide socio-economic and environmental problems as a result of profit-only-minded economic growth and unsustainable food consumption (Park et al., 2016). Like any manufacturing process, food manufacturing also utilizes natural resources such as water, energy and has various environmental impacts such as atmospheric pollution, hazardous waste generation and toxic releases (Egilmez et al., 2013; Kucukvar and Samadi, 2015). Among the entire socio-economic and environmental footprint of our activities, manufacturing activities are one of the major drivers, which account for significant portion of the total environmental impacts. For instance, food manufacturing is responsible for 33.6% of nation's water withdrawals and approximately 20% of energy and carbon footprint in the U.S. is around 20% each (Blackhurst et al., 2010; Egilmez et al., 2013). Additionally, for the hazardous waste and toxic release inventories, 5% to 8% share is recently estimated (Egilmez et al., 2013).

While studying sustainability assessment of manufacturing systems, it is important to determine the scope of assessment considering the entire life cycle. With regard to sustainability assessment of food manufacturing, there are a plenty of studies that addressed the problem from life cycle perspective, including canned food (Iribarren et al., 2010) and (Hospido et al., 2006), meat (Calderón et al., 2010), non-wood fibre production (González-García et al., 2010), school lunches (Saarinen et al., 2012), tomato distribution systems (Roy et al., 2008), cane sugar (Ramjeawon, 2004), etc.

The typical outcomes of LCA studies usually provide crucial insights about the overall impacts of environmental indicators such as energy, carbon, water footprint due to its comprehensive system boundary. A typical LCA consists of goal scope definition, life cycle inventory, impact assessment, and interpretation. Life cycle inventory consists of quantified impacts in specific social, economic, and/or environmental impact category such as GHG emissions. While such indicator-based life cycle inventory provides practical understanding about the environmental impacts, it is also important to compare sustainability performance of products, processes or industrial sectors to prioritize the policy focus to the certain areas where higher environmental impacts stress the society and the planet compared to economic and societal benefits.

In typical LCA studies, environmental impact categories bring different units of measurement such as energy footprint (joule), carbon footprint (CO_2-equivalent); benchmarking sustainability performance task becomes a challenging issue while comparing such systems considering all aspects of environmental pressure. In this regard, literature is abundant with studies that merge various environmental pressures by utilizing subjective weightings or assigning equal weights to all impact categories considered in their sustainability framework (Amekudzi et al., 2009). However, there is still neither a consensus nor a

satisfactory method to guide the assignment of weightings in literature (Ding, 2008). Therefore, a theoretical framework which does not require *a priori* (a pre-determined weighting) can better serve in determining a single sustainability performance score. In this context, Data Envelopment Analysis (DEA), a mathematical programming-based sustainability performance benchmarking method, has been a robust option, since it does not require any subjective weighting in evaluating the sustainability performance of different products, processes or systems comparatively (Egilmez et al., 2015)

While utilizing conventional DEA approaches for sustainability performance benchmarking has been a robust approach in literature, discussions still exist in the literature about the uncertainty associated with the result of the life cycle impact assessment methods. Especially, when working with the large-scale systems such as industrial sectors, process-based analysis involves the limited number of processes and inclusion or exclusion of processes is decided on the basis of subjective choices which create a system boundary problem (Kucukvar et al., 2014). Earlier studies on the direct plus indirect sustainability impact analysis of economic sectors also showed that process-based life-cycle inventories (LCI) suffer from significant truncation errors which can be an order of 50% or higher (Lenzen, 2000). Economic input-output based life-cycle models provide a top-down analysis that uses sectoral monetary transaction matrixes considering complex interactions between the sectors of nations' economy (Hendrickson et al., 2005; Suh & Nakamura, 2007). However, working with such large-scale systems (country, city, sector, etc.) creates uncertainty in the life cycle inventory (LCI) results. Input-output analysis has several sources of uncertainties due to the high level of aggregation in industry or commodity classifications, import assumption, data age, the incompleteness of the sectoral environmental statistics, etc. (Foran et al., 2005; Wiedmann & Lenzen, 2009). Therefore, the novelty of current research is to account for such uncertainties in the LCI for a valid sectoral sustainability performance indexing, thus ranking, towards realizing sustainable development goals and assisting with policy-making initiatives to government and private organizations. In this context, a fuzzy DEA model is constructed as a robust sustainability performance assessment framework to deal with uncertainties as a result of big scale life cycle models since it captures the inherent uncertainty associated with the LCA results by introducing fuzzy crisp efficiency assessment (Guo & Tanaka, 2001).

1.1. On the importance of dealing with uncertainty and Fuzzy Set Theory

Life cycle assessment researchers and practitioners in industry and academia utilize such models to quantify various indicator categories from environmental and ecological sustainability assessment domains as environmental pressures, resource consumption, societal and economic aspects. The current literature and applications are heavily dominated by deterministic models where the LCA model generates a deterministic life cycle inventory. Unfortunately, such a deterministic approach does not

provide depth in terms capture the uncertainty and variability in LCA (Lloyd & Ries, 2008). In this regard, LCA approaches can be supported with decision support frameworks and sustainability benchmarking can be performed to include the inherent uncertainty associated with the life cycle inventory. The literature consists of several works, which are predominantly grouped on three methods: stochastic modeling, scenario-based modeling and fuzzy set theory (Lloyd & Ries, 2008). In this context, Lloyd and Ries' (2008) recent literature survey about the quantitative approaches (16 works based on stochastic modeling, seven works based on scenario-based modeling, four works based on fuzzy set theory, and three works based on other approaches) used to deal with uncertainty associated with LCA models is a sufficient resource. Examples of fuzzy set theory-based methods include Weckenmann & Bushi, (2004) and Weckenmann et al. (2001).

Among the three approaches, Tan et al. (2002) argues that using fuzzy set theory-based approach is more appropriate compared to stochastic models due to the statistical characteristics of the LCI data, especially the ambiguity exists in LCI datasets which makes the statistical fitting tests fail to provide appropriate probabilistic distributions to be used in stochastic models. On the other hand, scenario-based modeling is more appropriate in cases where LCI data is not sufficient or large enough. Among the quantitative approaches, the research has not reached to a consensus on a specific approach. Rather, it is important to note that each of the quantitative decision support approaches has advantages depending on the specific problem addressed. Stochastic models can provide significant insights to problems where extensive LCI data exists which can be statistically modeled and replicated with a Monte Carlo sampling. It is interesting to see that only one of the 16 stochastic modelling-based studies used statistical fitting test prior to modeling and rest of the works defined stochastic modeling parameters arbitrarily, which caused researchers argue such approaches (Lloyd & Ries, 2008).

On the other hand, lack of LCI in some phases of life cycle could be a case of scenario-based modeling where survey or expert opinions are additionally consulted along with the LCI data. However, fuzzy set theory is in this regard a more appropriate approach which can be used in either situation. Furthermore, the aforementioned approaches were used for estimating uncertainty propagation. Current study takes one more step forward by not only model the uncertainty propagation with fuzzy set theory but also integrate the propagated LCI data into a linear programming-based mathematical optimization model to evaluate the sustainability performance while taking the uncertainty into account. The integrated methods are termed as "Fuzzy DEA" in the literature, which is explained in the following section.

1.2. Fuzzy DEA

Conventional DEA models (CCR (Cooper-Charnes-Rhodes) developed by Charnes et al., 1978 and BCC (Banker-Charnes-Cooper) developed by Banker et al., (1974)) have a great application potential on

problem domains, where inputs and outputs are known and deterministic. However, the observed values in real-world problems can be often imprecise or vague where uncertainty associated with collected data or estimated outcomes could be of importance. In this regard, fuzzy DEA approach is the integration of DEA and fuzzy set theory used as a prominent tool for handling imprecision or vagueness associated with real-world problems" (Emrouznejad. et al., 2014). The recent literature survey groups the fuzzy DEA methods into four: 1) the tolerance approach, 2) the fuzzy ranking approach, 3) the possibility approach and 4) the alpha level-based approach (Emrouznejad et al., 2014).

Based on the classification of Emrouznejad et al. (2014), in the tolerance approach, the uncertainty is incorporated into the DEA models by defining tolerance levels on constraint violations. For instance, Sengupta used tolerance approach in two of the studies: (1992a, 1992b). On the other hand, the fuzzy ranking approach quantifies the fuzzy efficiency scores of the DMUs using fuzzy linear programs which require ranking the fuzzy set. In the previous similar works, Azadeh et. al. (2013) introduced an adaptive network based fuzzy inference system based on fuzzy DEA algorithm for improvement of long-term natural gas (NG) consumption forecasting and analysis. Soleimani-damaneh (2008) presented the approach of fuzzy upper bounds for the objective function in fuzzy DEA model. Furthermore, the possibility approach is based on assumption that the fuzzy variable is considered as a random variable, which is associated with a probability distribution (e.g. (Nedeljković & Drenovac, 2012; Wen et al., 2010). And, in the α-cut level approach, the most popular fuzzy DEA method, the main idea is to turn the fuzzy variables into crisp values using α-cut sets, which are basically used to define the membership functions of the input and output values of DMUs. Since the alpha level-based approach is the most robust approach in terms of applicability to wide range efficiency assessment problems, this study preferred to use the alpha level-based method.

In the alpha level-based fuzzy DEA method, after the fuzzy membership functions are defined, the efficiency scores are calculated as fuzzy intervals by employing a pair of parametric programs. Sengupta (1992a) introduced a fuzzy set theoretic measure based on DEA. Also, his work had three different fuzzy statistic types, namely: fuzzy regression, fuzzy mathematical programming, and fuzzy entropy. Later, Guo and Tanaka (2001) proposed fuzzy DEA approach, which utilizes the basic CCR model to handle efficiency problem based on the fuzzy input and output data. Thus, a generalized version of a *fuzzy*-DEA model is structured by taking into account the relationship between regression analysis and DEA. Kao and Liu (2000) developed an algorithm to measure DMUs' efficiencies with fuzzy data where fuzzy observations are transformed into crisp variables using α-cut approach. In another work, Saati et al. (2002) introduced a fuzzy DEA model based on triangular fuzzy number-based membership functions. Furthermore, Lee et al., (2013) used a hybrid application of fuzzy triangular number, analytical hierarchy process, and DEA to

quantify the relative efficiency scores of energy technologies. In terms of other application areas, a fuzzy DEA is used for wide range areas in including sustainable supply chain management, irrigation, energy and resource management. Problem domains include sustainable supplier selection problem (Azadi et al., 2015), irrigation (Srinivasa Raju & Nagesh Kumar, 2013), sustainable agriculture (Houshyar et al., 2012). In fuzzy DEA literature, several applications of the methods based on the α-cut approach and interval efficiency have been also presented, such as Entani et.al. (2002), Hosseinzadeh et al., (2009) and Azadeh & Alem (2010). In a recent work, Angiz et al. (2012) introduced a local α–cut level approach to measure the efficiency of DMUs with fuzzy data which is then used to improve a multi-objective linear programming. Similar to the previous literature, this study also utilizes α–cut level-based Fuzzy DEA approach to assess the sustainability performance of 33 U.S. food manufacturing sectors. Emrouznejad, T. et al. (2014) have recently published book chapter that provides comprehensive review of fuzzy DEA works provided in a recent state of art survey.

1.3. Joint Application of LCA and DEA

Combined application of LCA and DEA has been utilized by many researchers on various environmental and ecological sustainability assessment problems due to the need for sustainability benchmarking along with the life cycle impact assessment. For instance, in a recent work, sustainability performance index (SPI) of household electric appliances was quantified by using a hierarchical LCA and DEA approach, where the retail price was considered as a measure of the product's economic value and the LCA results were used as the assessment of its environmental impact (Barba-Gutiérrez et al., 2008). Environmental performance across product types and household types were evaluated with DEA where weighted environmental effect indices were used to form an overall environmental performance score (Wier et al., 2005). Similarly, more examples of LCA+DEA methods also exist in areas including operational efficiency of mussel cultivation in rafts (Lozano et al., 2009), grape production (Vázquez-Rowe et al., 2012), integration of labor as social indicator (Iribarren & Vazquez-Rowe, 2013), fisheries (Avadí, Vázquez-Rowe, & Fréon, 2015), consumption at different spatial levels: nation, city, and household (Munksgaard et al, 2008), building materials (Tatari and Kucukvar, 2012) and U.S. manufacturing sectors' sustainability performance (Egilmez et al., 2013), food manufacturing sectors' sustainability evaluation (Egilmez et al., 2014), input-output LCA-based analysis of transportation and manufacturing nexus in the U.S. (Egilmez & Park, 2014). Recently, a critical review article that covers integrated LCA and DEA applications is provided by Vazquez-Rowe and Iribarren (2015).

1.4. Motivation and Organization of the Research

The basic aim of this research is to develop a hierarchical LCA + Fuzzy DEA method to compare sustainability performance of the U.S. food manufacturing sectors while taking into account the impacts

of *uncertainty* on *eco-efficiency assessment*. The results of Economic Input-Output LCA (EIO-LCA) performed for 33 U.S. food manufacturing sectors (by Egilmez et al., 2014) were integrated into a Fuzzy DEA model. The integrated use of LCA and Fuzzy DEA will enable sustainability performance assessment researchers and business sustainability analysts to capture the uncertainty impacts of LCA results better due to the synergetic use of fuzzy crisp value intervals with the life cycle inventory results. The fuzzy crisp efficiency scores will represent the SPI scores. In the hierarchical methods (See Fig. 1), first, the composite efficiency scores will be determined and efficient/inefficient sectors will be classified and ranked based on overall SPI scores. Later, a sensitivity analysis of environmental impact categories will be performed to understand the underlying effect of each impact category. The rest of the paper is organized as follows. Section 2 describes the mathematical structure of the EIO-LCA model, data collection, and Fuzzy DEA approach. Section 3 provides the results. A validation and comparison procedure is provided in section 4. Finally, conclusions and future work are given in section 5.

2. Methods

2.1. Joint EIO-LCA and Fuzzy DEA Approach

In this study, a two-step hierarchical approach is employed. The methodology basically consists of a joint application of the EIO-LCA and Fuzzy DEA. In the first step, basically environmental impacts of food manufacturing industries are quantified and related life cycle inventory is prepared. In the second step, considering potential uncertainties in the results of the first step, a Fuzzy DEA-based sustainability performance evaluation is performed. In this regard, it is important to note that the performance metric used, “SPI”, is defined as the ratio of total production output to the overall environmental impact. In this context, utilizing Fuzzy DEA is the best way to deal with such multiple inputs with different units of measurement, scale differences, and uncertainties due to its robust applicability nature of dealing with multiple inputs and outputs (Angiz et al., 2012). A typical DEA model basically measures the efficiency (called SPI for the particular problem studied) by utilizing the normalized input(s) and the normalized output(s) as a single efficiency score via rigorous mathematical programming where the subjective weighting is not required (Tatari & Kucukvar, 2012).

The LCA stage of the hierarchical framework consists of two steps. First, the scope and goals of life cycle study are determined. For instance, the scope of current study includes the cradle-to-gate phases of life cycle impact assessment of 33 major food manufacturing in the U.S. Moreover, the basic goal of LCA is to evaluate the 33 sectors’ environmental pressures in terms of including three environmental impact domains as carbon footprint (tCO_2-eqv), water footprint (kgal) and energy footprint (Tj), and four land footprint categories including fishery (gha), grazing (gha), forest land (gha) and cropland (gha) based on

total economic output of each sector. Following is the specific definitions of the LCA indicators used in this study:

In this regard, the basic description of the selected indicators is as follows:

- Energy footprint is obtained by summing the energy content of different fossil fuels and electricity from non-fossil sources. Using input-output tables of the U.S. economy, the consumption amount of major fuels for each industrial sector is determined (CMU, 2002; Joshi, 1999). The unit of measurement is tera-joules (Tj).
- The total emitted carbon dioxide, nitrogen oxides, and methane from fossil fuel combustion is defined as the carbon footprint (CMU, 2002). The unit of measurement is metric tons of CO_2 equivalents (t CO_2-eqv).
- The total amount of water used by the sectors and related supply chain sectors is considered as the water footprint (Blackhurst et al., 2010; CMU, 2002). The unit of measurement is kilo-gallons (kgal).
- Cropland is described as "the most bio-productive of all the land use types and includes areas used to produce food and fiber for human consumption, feed for livestock, crops, and rubber" (GFN, 2010). The data source is Global Footprint Network (GFN) which provides various land footprint indicators according to the production quantities of 164 different crop categories. The unit of measurement is global hectare (GHA), which is defined as "the productivity weighted area used to report both the bio-capacity of the earth and the demand on bio-capacity" (GFN, 2010).
- Similar to cropland, the grazing footprint is determined by comparing "the amount of livestock feed available in a country with the amount of feed required for the livestock produced in that year, with the remainder of feed demand assumed to come from grazing land" (GFN, 2010).
- In terms of forestland footprint, it is quantified base on the amount of lumber, pulp, timber products and wood consumed per year (GFN, 2010). In the EIO-LCA model, the total ecological footprint of forest use is allocated to the U.S. forestry nurseries, forest products, and timber tracks sector.
- Fishery footprint is defined as fishing grounds' land footprint which is calculated based on the previous primary production required to support the fish caught (GFN, 2010). In terms of the industrial sector, the total ecological footprint of fishing ground is estimated based on the economic activity within the fishing sectors. The summary of the sustainability performance indicators is provided in Table 1.

Table 1. Summary of the Sustainability Performance Indicators

Indicator	Unit of Measurement	Data Sources
Energy Footprint	Tera-joule (Tj)	(Joshi, 1999; CMU, 2002)
Carbon Footprint	Metric tons of CO_2 equivalents (t CO2-eqv).	(CMU, 2002)
Water Footprint	Kilo-gallons (kgal)	(Blackhurst et al. 2010; CMU, 2002)
Cropland	Global hectare (gha)	(GFN, 2010)
Grazing	Global hectare (gha)	(GFN, 2010)
Forestland	Global hectare (gha)	(GFN, 2010)
Fishery	Global hectare (gha)	(GFN, 2010)

Once goals and scopes are defined, life cycle inventory is acquired by using the economic transactions of each manufacturing sector within the U.S. economy (see Egilmez et al., 2014 for more detailed information about LCI). In this context, life cycle inventory (LCI) is typically termed as quantification of the environmental and/or socio-economic impacts based on the scope and goal definition. According to the available methods, LCI can be quantified with 6 distinctive ways including process- based, product-based, input-output-based, and 3 different hybrid LCI methods (see Suh & Huppes, 2005 for more detailed information). Since an input-output based LCA was performed for the U.S. food manufacturing sectors, input-output based LCI is utilized in this study.

Later, the results of LCA study are normalized and transformed into fuzzy values so as to address the uncertainty during the benchmarking stage. The normalization procedure is utilized to avoid the potential scale effects of inputs as a result of different units of measurement (Tj, kgal, etc.). In addition to seven environmental and land footprint indicators utilized as inputs, the output is considered as the total amount of food products produced by each food sector. After integrating the fuzzified life cycle inventory results into the Fuzzy DEA models, SPI scores and rankings were derived. And in the final part potential policy implications are discussed. To illustrate, Fig. 1 presents the hierarchical framework of the proposed EIO-LCA + Fuzzy DEA method.

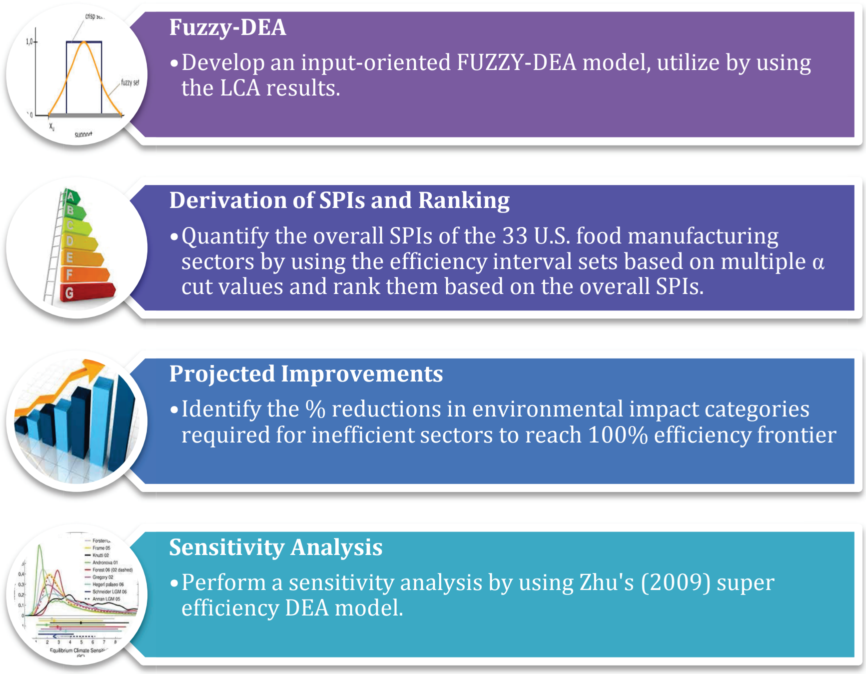


Fig. 1. Hierarchical framework of the proposed EIO-LCA + Fuzzy DEA method

2.2. Mathematical Framework of EIO-LCA

The EIO-LCA is a well-established environmental and ecological sustainability assessment approach based on the earlier works of Nobel prized economist *Wassily Leontief* (Weber & Matthews, 2008). The EIO-LCA model basically performs the environmental impact assessment via using input-output tables of an economy, environmental impact multipliers and the theory of linear algebra (Kucukvar & Tatari, 2013). The application areas of the EIO-LCA models are quite extensive which include various environmental, economic and social topics of interest due to EIO-LCA models' robustness and practical applicability. Some of the areas are built environment, energy technologies, transportation, manufacturing systems, international trade and household consumption (Kucukvar and Tatari, 2011; Onat et al., 2015; Wiedmann et al., 2011).

This paper utilizes an industry-by-industry EIO-LCA model developed by Kucukvar and Tatari (2013) where the total sustainability impact is formulated as follows:

$$\mathbf{r} = \mathbf{E_{dir}}\,[(\mathbf{I}-\mathbf{DB})^{-1}]\,\mathbf{f} \qquad (1)$$

In Eq. 1, $\mathbf{r}$ is the total sustainability impacts vector per unit of final demand, and $\mathbf{E_{dir}}$ is the diagonal matrix, which makes up the direct environmental impact values per dollar of output, $\mathbf{I}$ is the identity matrix, and $\mathbf{f}$ is the total final demand vector for manufacturing industries. Besides, $\mathbf{B}$ represents the input requirements for products per unit of output, and $\mathbf{D}$ is the market-share matrix. Also, the term $[(\mathbf{I}-\mathbf{DB})^{-1}]$

represents the total requirement matrix, which is also known as the Leontief inverse and **DB** is the direct requirement matrix, which is denoted as **A** matrix in the Leontief's model (Leontief, 1970). For more explanation about the integration of the industry-by-industry EIO-LCA model, see Kucukvar and Tatari (2013).

2.3. Mathematical Framework of Fuzzy DEA Model

In this section, the basic definitions and properties of fuzzy numbers are provided. Then, Kao and Liu's (2000) Fuzzy DEA model is described. A fuzzy set, *A,* in the universe of non-empty sets, *X,* is characterized by $\mu_{\tilde{A}}(x)$ and $0 \leq \mu_{\tilde{A}}(x) \leq 1$ for every *x∈X*. $\mu_{\tilde{A}}(x)$ *i*s called membership degree of *x∈X* in A. A fuzzy set $\widetilde{A}$ in the universe of X is characterized by $\mu_{\tilde{A}}(x)$. Then, support set of $\widetilde{A}$ is showed $S(\widetilde{A})$ and defined as $S(\widetilde{A}) = \{x \in X | \mu_{\tilde{A}}(x) > 0\}$. The α-cut set of a fuzzy set $\widetilde{A}$ is defined as: $A_\alpha = \{x \in S(\widetilde{A}) | \mu_{\tilde{A}}(x) \geq \alpha\}$. The definition of α-cut sets as intervals are given as follows:

$$A_\alpha = \left[(A)_\alpha^L, (A)_\alpha^U\right] = \left[\min_A \{x \in A | \mu_{\tilde{A}}(x) \geq \alpha\}, \max_A \{x \in A | \mu_{\tilde{A}}(x) \geq \alpha\}\right]. \tag{2}$$

Considering triangular fuzzy number *A=(a,b,c)*, it's α-cut set can be derived as follows:

$$A_\alpha = \left[(A)_\alpha^L, (A)_\alpha^U\right] = \left[(b-a)\alpha + a, c - (c-b)\alpha\right]. \tag{3}$$

It should be noted that α-cut sets function as useful link between fuzzy sets and crisp variables. Therefore, they have an important role to solve many problems that have fuzzy variables so that those variables are represented by crisp variables that allows using interval properties.

The notations used in parallel with the Kao-Liu Fuzzy DEA model (2000) are explained as follows. Here, i^{th} DMU's j^{th} input is represented X_{ij} where $j=1,2,\ldots,s$; $i=1,2,\ldots,n$ and i^{th} DMU's k^{th} output is represented Y_{ik} *where* $k=1,2,\ldots,t$. A small non-Archimedian number is symbolized with ε. The weight of j^{th} input is v_j *and* the weight of k^{th} output is v_j . E_r represents r^{th} DMU's relative efficiency which consists of lower and upper-efficiency scores based on α-cut sets. In this context, X_{ij} and Y_{ik}, input and output values are aimed to represent the uncertainty. Therefore, X_{ij} and Y_{ik} are defined as convex fuzzy numbers. The associated fuzzy membership functions are represented with $\mu_{X_{ij}}$ and $\mu_{Y_{ik}}$, respectively.

The definitions of X_{ij} and Y_{ik} can be defined as follows; $\left(X_{ij}\right)_{\alpha} = \left[\left(X_{ij}\right)_{\alpha}^{L}, \left(X_{ij}\right)_{\alpha}^{U}\right]$ and $\left(Y_{ik}\right)_{\alpha} = \left[\left(Y_{ik}\right)_{\alpha}^{L}, \left(Y_{ik}\right)_{\alpha}^{U}\right]$. Thus, the fuzzy membership function of $\widetilde{E}_r$ is shown in Eq. 4, which was based on Zadeh's extension principle (Zadeh, 1978):

$$\mu_{\widetilde{E}_r}(z) = \underset{x,y}{Sup}\min\left\{\mu_{X_{ij}}(x_{ij}), \mu_{Y_{ik}}(y_{ik}), \forall i, j, k \middle| z = E_r(x, y)\right\} \tag{4}$$

The lower and upper bounds of $\widetilde{E}_r$ at different α levels are derived so that the membership functions of $\mu_{\widetilde{E}_r}(z)$ are established. According to Eq. 6, $\mu_{\widetilde{E}_r}(z)$ is equal to the minimum value of $\mu_{X_{ij}}(x_{ij})$ and $\mu_{Y_{ik}}(y_{ik})$, $\forall i, j, k.$ Therefore, at least one $\mu_{X_{ij}}(x_{ij})$ or $\mu_{Y_{ik}}(y_{ik})$, that is equal to α, is needed, and $\mu_{X_{ij}}(x_{ij}) \geq \alpha$, $\mu_{Y_{ik}}(y_{ik}) \geq \alpha$, such that $\mu_{\widetilde{E}_r}(z) = \alpha$, $\forall i, j, k.$ In addition, the nested structure based on α-cuts is represented as follows: $\left[\left(X_{ij}\right)_{\alpha_2}^{L}, \left(X_{ij}\right)_{\alpha_2}^{U}\right] \subseteq \left[\left(X_{ij}\right)_{\alpha_1}^{L}, \left(X_{ij}\right)_{\alpha_1}^{U}\right]$ $\left[\left(Y_{ik}\right)_{\alpha_2}^{L}, \left(Y_{ik}\right)_{\alpha_2}^{U}\right] \subseteq \left[\left(Y_{ik}\right)_{\alpha_1}^{L}, \left(Y_{ik}\right)_{\alpha_1}^{U}\right]$, for $0 < \alpha_1 \leq \alpha_2 \leq 1$. Therefore, $\left\{x_{ij} \in S(\widetilde{X}_{ij}) \middle| \mu_{\widetilde{X}_{ij}}(x_{ij}) \geq \alpha\right\}$, $\left\{x_{ij} \in S(\widetilde{X}_{ij}) \middle| \mu_{\widetilde{X}_{ij}}(x_{ij}) = \alpha\right\}$, $\left\{x_{ij} \in S(\widetilde{Y}_{ik}) \middle| \mu_{\widetilde{Y}_{ik}}(y_{ik}) \geq \alpha\right\}$, and $\left\{x_{ij} \in S(\widetilde{Y}_{ik}) \middle| \mu_{\widetilde{Y}_{ik}}(y_{ik}) = \alpha\right\}$ have same maximum and minimum elements, respectively. To calculate the lower bound (E_r^L) and upper bound (E_r^U) of the efficiency scores for a specific α-level, Kao and Liu (2000) introduced the following mathematical framework;

$$\left(E_r\right)_{\alpha}^{U} = \max_{\substack{\left(X_{ij}\right)_{\alpha}^{L} \leq x_{ij} \leq \left(X_{ij}\right)_{\alpha}^{U} \\ \left(Y_{ik}\right)_{\alpha}^{L} \leq y_{ik} \leq \left(Y_{ik}\right)_{\alpha}^{U} \\ \forall i, j, k}} = \begin{cases} E_r = \max \sum_{k=1}^{t} u_k y_{rk} + u_0 \\ s.t. \quad \sum_{j=1}^{s} v_j x_{rj} = 1 \\ \qquad \sum_{k=1}^{t} u_k y_{ik} - \sum_{j=1}^{s} v_j x_{ij} + u_0 \leq 0, \ \forall j \\ \qquad u_k, v_j \geq 0, \ \forall k, j \end{cases} \tag{5}$$

$$
\left(E_r\right)_\alpha^L = \min_{\substack{\left(X_{ij}\right)_\alpha^L \le x_{ij} \le \left(X_{ij}\right)_\alpha^U \\ \left(Y_{ik}\right)_\alpha^L \le y_{ik} \le \left(Y_{ik}\right)_\alpha^U \\ \forall i,j,k}} = \begin{cases} E_r = \max \sum_{k=1}^{t} u_k y_{rk} + u_0 \\ s.t. \quad \sum_{j=1}^{s} v_j x_{rj} = 1 \\ \quad \sum_{k=1}^{t} u_k y_{ik} - \sum_{j=1}^{s} v_j x_{ij} + u_0 \le 0, \ \forall j \\ \quad u_k, v_j \ge 0, \ \forall k, j \end{cases} \tag{6}
$$

For a specific α-cut level, the smallest efficiency score for r^{th} DMU is calculated by adjusting its fuzzy inputs as the upper bounds and the fuzzy outputs at the lower bounds. Meanwhile; the fuzzy inputs of all other DMUs at their corresponding lowest level and the fuzzy outputs at their highest level are kept the same (Liu, 2008). Since different efficiency scores are calculated based on different α-cut levels, there is a need to calculate a composite efficiency score for each DMU. Thus, the composite efficiency scores of DMUs are utilized for ranking and comparing them.

Eq. 5-6 give us two level mathematical model is transformed to the classical one-level model by considering as follows. When the outputs and inputs of every DMU change in intervals, to find the highest relative efficiency of a DMU compared with other DMUs, one will set the output level of this DMU and the input levels of all other DMUs to their highest values and set the input level of this DMU and the output levels of all other DMUs to their lowest values (Eq.5). On the contrary, to find the smallest relative efficiency of a DMU, one will set the output level of this DMU and the input levels of all other DMUs to their lowest values and set the input level of this DMU and the output levels of all other DMUs to their highest values (Eq.5) (Kao-Liu 2000).

With regards to finding composite efficiency scores, various methods have been introduced in the literature (Chen & Klein, 1997; Guo & Tanaka, 2001; Hatami-Marbini et.al. 2011). Some of these methods use membership functions of fuzzy numbers to capture uncertainty. However, fuzzy membership function-based methods cannot be used in this study, since the EIO-LCA results are defined as fuzzy crisp values (which has lower and upper bounds, in other words based on intervals). Therefore, as one of the most commonly used methods, Chen and Klein's (1997) ranking method, which doesn't need the exact membership functions of the fuzzy numbers, is utilized in this study (e.g. Azadeh et.al. 2010; Chen et. al. 2013; Mugera, 2013). The formulation of the method is notated as follows.

$$
I\left(\tilde{E}_r\right) = \frac{\sum_{i=0}^{n}\left(\left(Er\right)_{\alpha_i}^{U} - c\right)}{\left[\sum_{i=0}^{n}\left(\left(Er\right)_{\alpha_i}^{U} - c\right) - \sum_{i=0}^{n}\left(\left(Er\right)_{\alpha_i}^{L} - d\right)\right]}, \quad n \to \infty \tag{7}
$$

where $c = \min_{i,j}\left\{(E_r)^L_{\alpha_i}\right\}$, $d = \max_{i,j}\left\{(E_r)^U_{\alpha_i}\right\}$ and n is the number of α-cuts. $\sum_{i=0}^{n}\left((E_r)^U_{\alpha_i} - c\right)$ is a positive value and $\sum_{i=0}^{n}\left((E_r)^L_{\alpha_i} - d\right)$ is a negative value. Therefore, the denominator calculates the total area as n approaches ∞. $I(\widetilde{E}_r)$ is the ranking index of r^{th} DMU. Descending order of the $I(\widetilde{E}_r)$ determines the place of DMUs in the list. Theoretically, infinite α-cut partitions can be generated. However, Chen and Klein (1997) suggested that 3 to 4 α-cut intervals are enough to determine the differences. Therefore, based on the EIO-LCA results of 33 manufacturing sectors, three α-cut sets are determined and calculated their fuzzy efficiency scores considering 10%, 20% and 30% upper and lower bounds of the EIO-LCA results. In terms of returns to scale property, variable returns to scale (VRS) was selected since the production capability of inputs was assumed to have non-constant returns to scale, which enabled the model to account for the possible scale diseconomies between food manufacturing sectors that are different in size of the inputs. The flowchart of the Fuzzy DEA approach that describes the fuzzy DEA method and experimentation is also provided in Fig. 2.

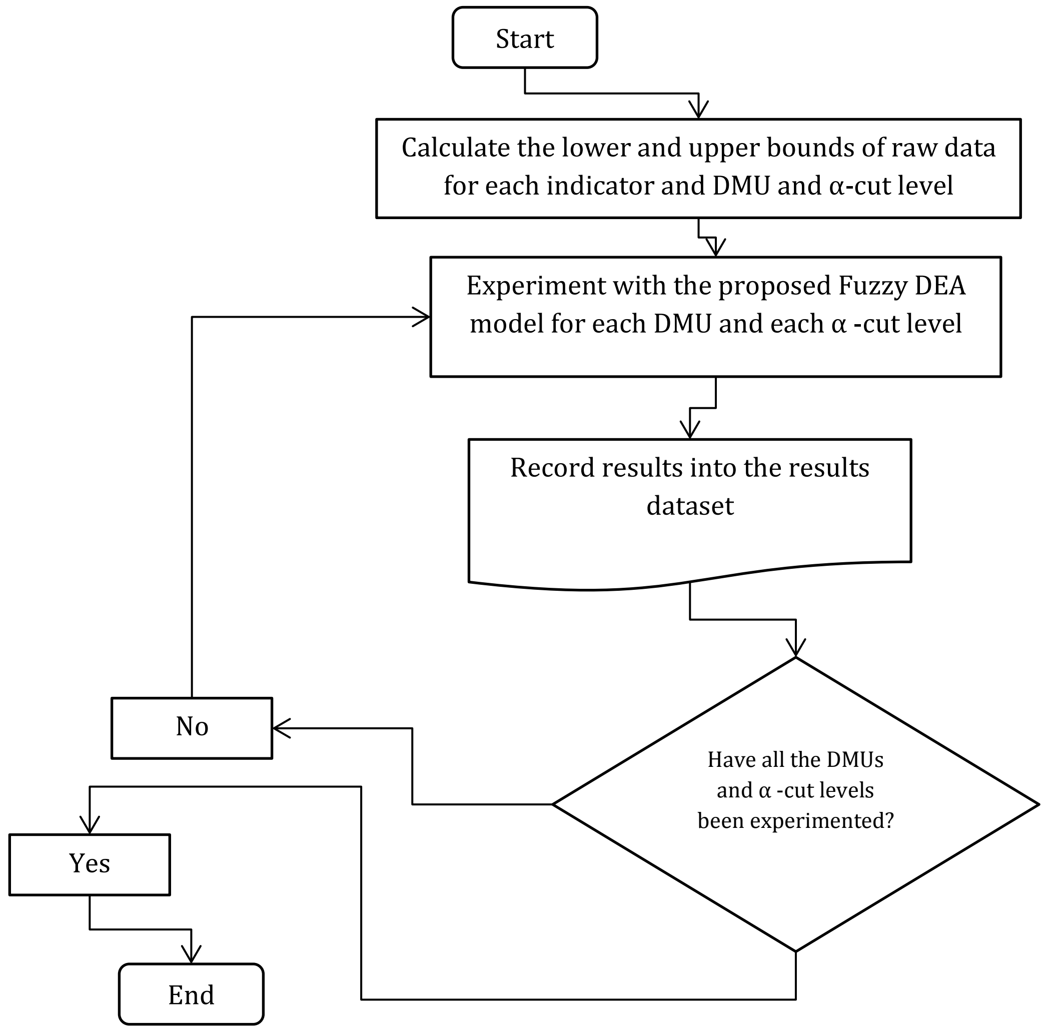


Fig. 2. Flowchart of the Fuzzy DEA Approach

2.4. Sensitivity Analysis

Charnes et al.(1992), Rousseau and Semple (1995) and Charnes et al. (1996) introduced sensitivity analysis employing super efficiency DEA models. These studies assumed synchronous proportional variation in all inputs and outputs for the specific DMU under consideration. At the same time, data for the rest of DMUs is assumed to be fixed. In this paper, super efficiency sensitivity algorithm developed by Zhu (2001) is utilized. This approach takes into account simultaneously data perturbations in all the DMUs. In the left hand side of the constraints, test DMU *l* is not included. However, it is included in the measure specific input-oriented VRS super-efficiency model, which is utilized to analyze the VRS sensitivity of input *i*, as given below:

Let $\boldsymbol{I}$ and $\boldsymbol{O}$ denote, respectively, the input and output subsets. The mathematical framework that is notated in Eq. 8-13 is used to calculate the maximum increase rate of inputs linked with $\boldsymbol{I}$ and the maximum decrease rate of outputs linked with $\boldsymbol{O}$, respectively, required for DMU_0 to reach the efficiency frontier of DMU_j $(j \neq 0)$ when other inputs and outputs are kept at their current levels.

$$\theta^{o^*} = min\theta_{\mathbf{I}}^{o} \quad (8)$$

$$s.t. \sum_{j=1, j\neq o}^{n} \lambda_j x_{ij} \leq \theta_{\mathbf{I}}^{o} + x_{io}, \quad i \in \mathbf{I} \quad (9)$$

$$\sum_{j=1, j\neq o}^{n} \lambda_j x_{ij} \leq x_{io}, \quad i \notin \mathbf{I} \quad (10)$$

$$\sum_{j=1, j\neq o}^{n} \lambda_j y_{rj} \geq \theta_{\mathbf{I}}^{o} - y_{ro}, \quad r \in \boldsymbol{O} \quad (11)$$

$$\sum_{j=1, j\neq o}^{n} \lambda_j y_{rj} \geq y_{ro}, \quad r \notin \mathbf{O} \quad (12)$$

$$\theta_{\mathbf{I}}^{o}, \lambda_j \ (j \neq o) \geq 0 \ and \ \sum_{j\neq o} \lambda_j = 1 \quad (13)$$

2.5. Explanation of Sustainability Indicators and Collection of Data

The aforementioned EIO model was used for calculating environmental impacts of the 33 food manufacturing sectors. The direct and indirect impacts are quantified based on the seven indicators such as carbon, energy and water footprints and land footprint categories as fishery, grazing, forest land, and cropland. A comprehensive EIO study on environmental footprint analysis of the 277 U.S. manufacturing sectors showed that food manufacturing sectors are found to have the largest water withdrawals, energy use and GHG emissions compared to other sectors (Egilmez et al. 2013). Therefore, these impact categories are involved within the scope. The ecological footprint indicators, which have already been used as a metric for environmental sustainability in previous studies, are also considered as a part of the environmental dimension, (Galli et al., 2012). Especially, cropland, fishery land, forestland and grazing land are dominantly utilized by the U.S. agriculture sectors to support the nation's increasing food consumption (Egilmez et al. 2014). The CO_2 uptake land, which represents the largest ecological footprint category of the U.S., accounts for a hectare of forest needed to absorb human-induced CO_2 emissions (GFN, 2010). Since current study calculated the carbon footprint of each food manufacturing sector (including the amount of CO_2 emissions), the CO_2 uptake land is excluded from the scope in order to prevent a double-counting issue.

3. Results and Discussion

In this section, the results are provided in parallel with the sub-sections of the methods section. Firstly, the EIO-LCA results are summarized. Secondly, SPI results and overall rankings are given. Thirdly, the

ranges of SPIs associated with the uncertainty of the EIO-LCA results are provided. Fourthly, sensitivity analysis results are given.

3.1. Results of Life Cycle Assessment

LCA inventory provides quantitative extend about 33 food manufacturing sectors' environmental impact assessment results. The descriptive statistics of LCI is provided in Table 2.

Table 2. Descriptive Statistics of LCI

Indicator	N	Minimum	Maximum	Mean	Std. Dev.
Energy FP	33	1.87E+04	1.28E+06	2.29E+05	2.30E+05
Water FP	33	1.56E+08	8.86E+09	1.74E+09	1.89E+09
Carbon FP	33	1.68E+06	3.36E+08	2.89E+07	5.72E+07
Fishery	33	4.47E+02	5.91E+06	2.50E+05	1.03E+06
Grazing	33	1.27E+03	4.83E+07	1.63E+06	8.38E+06
Forestry	33	5.63E+03	2.94E+05	7.36E+04	6.03E+04
Cropland	33	6.50E+05	6.08E+07	1.12E+07	1.24E+07
Output	33	1.46E+03	8.22E+04	1.57E+04	1.54E+04

Since the LCA inventory data has a large amount of information, graphical illustration is preferred to make the visual interpretation easier. Therefore, the results of the life cycle assessment are illustrated in Fig. 3a and 3b. As shown in Fig. 3a, energy footprint ranged between 1.8E+04 Tj and 2.3 E+06 Tj, where the average energy footprint was 1.28E+06 Tj. The top driver sector is Animal (except poultry) slaughtering, rendering, and processing with 17% share and rest of the sectors' shares are found to be between 0.2% and 8%. Similar results are also observed for water footprint. Animal (except poultry) slaughtering, rendering, and processing sector's share is significantly greater with 15.4% share and it is followed by other animal food (10.1%) and poultry processing (8.6%). For the carbon footprint category, animal (except poultry) slaughtering, rendering, and processing sector had significant share with over 35%. The water footprint ranged between 1.6E+06 and 3.4E+08 k-gals with an average of 2.9E+07. It can be seen that carbon, water and energy footprint shares indicated close impact shares among different food manufacturing sectors.

In terms of land footprint, four categories as fishery, grazing, forestland and cropland are represented (See Fig. 3b). As expected, fishery is driven by seafood product preparation and packaging sector with an over 70% share. On the other hand, vast majority of grazing land footprint is caused by animal (except poultry) slaughtering, rendering, and processing sector (90% share). In terms of forest land footprint, relatively fairly distributed shares are observed that range between 0.2% (tortilla manufacturing) and

12.1% (Soft drink and ice manufacturing). In cropland footprint category, top three sectors are found to be animal (except poultry) slaughtering, rendering, and processing (16.5%), soybean and other oilseed processing (11.4%) and other animal food manufacturing (7.5%).

3.2. SPI Results and Rankings

Fuzzy DEA approach reveals significant insights about the sustainability performance ranking of U.S. manufacturing sectors due to its robust applicability to deal with uncertainty in inputs and/or outputs. The performance metric, SPI, basically enable us understand to what extend the manufacturing sectors put environmental pressure on the earth as a result of the manufacturing or production activities. The total production (K-ton) is considered as the output and the selected environmental impact categories are considered as negative indicators. Therefore, the greater SPI score a sector has the more sustainable manufacturing processes compared to sectors with lower SPI scores. This section provides the SPI analysis results (see Table 3). As shown in Table 3, there are a total of 6 SPI scores derived from the lower and upper bounds associated with the α cuts of 10%, 20% and 30%. By using Eq. 9, the overall SPI scores were calculated from the SPI sets and a composite sustainability performance metric was obtained for each food manufacturing sector. Then, associated rankings were determined and provided as well.

The sustainability performance evaluation results indicate that the SPI scores ranged between 0.21 and 1.00. Among the sectors, only 2 food manufacturing sectors are identified as efficient whereas the remaining 31 sectors' sustainability performance are not efficient, which indicates that majority of the food industry's environmental impact is still more severe compared to its benefit to nation's economy. It is important to note that when the uncertainty is acquired within the benchmarking model (Fuzzy DEA), more than 90% of total U.S. food manufacturing sectors are identified as inefficient and require significant improvements in their life cycles. Additionally, the average SPI of 33 food manufacturing sectors is found to be 0.66. Poultry processing is identified as the most environmentally burdening sector with an overall SPI of 0.21. It is important to note that there is a parallelism between the EIO-LCA and DEA results in terms of life cycle impacts and SPI scores. The sectors with the significant environmental impacts are measured with least SPI scores. For instance, animal (except poultry) slaughtering, rendering and processing is the major driver of carbon, energy and water footprint, grazing and cropland categories and it's SPI is found to be 0.53. Moreover, descriptive statistics of the SPI results are also performed and related histogram and descriptive statistics are provided in Fig. 4.

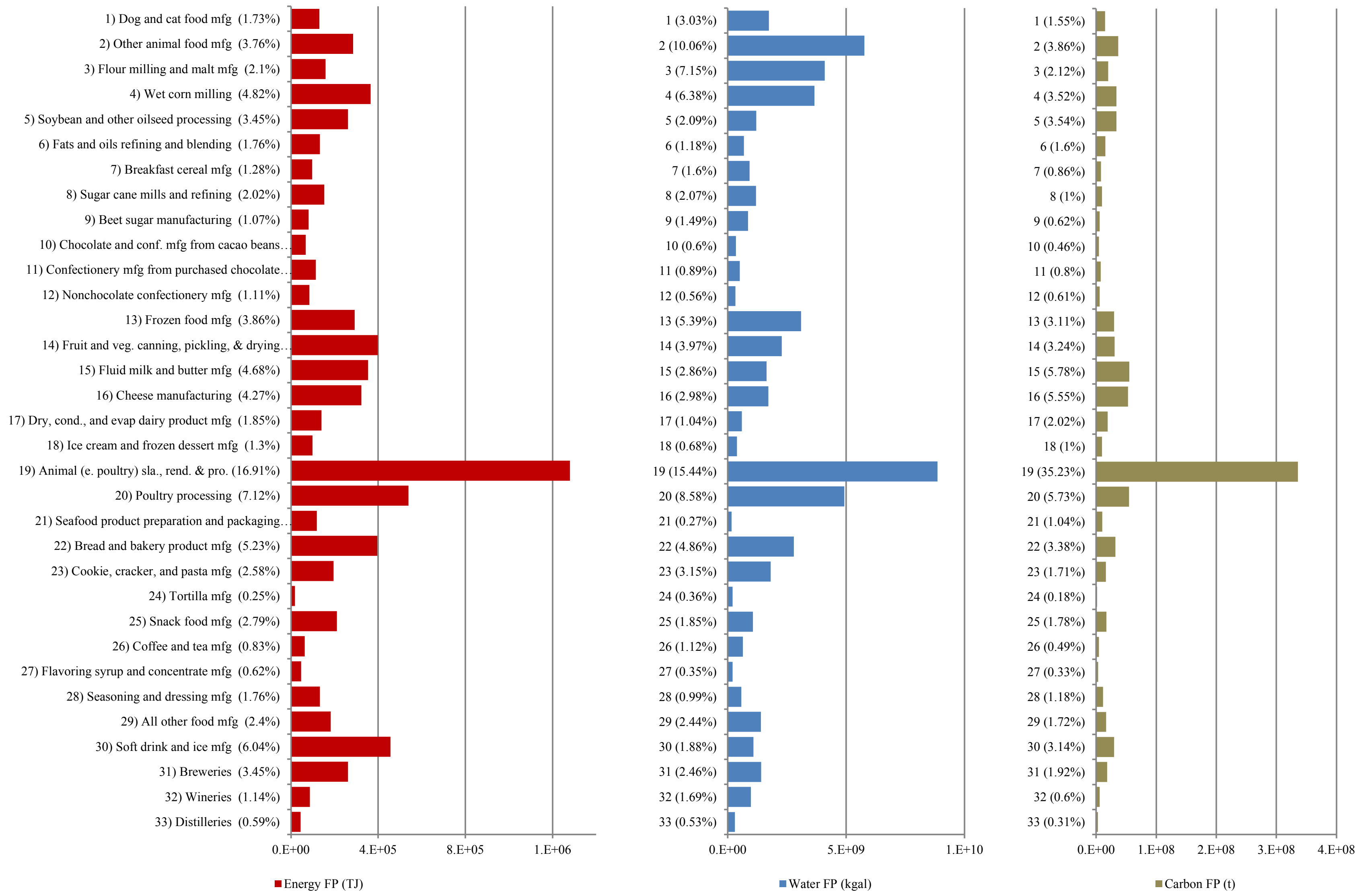


Fig. 3a. Results of Life Cycle Assessment

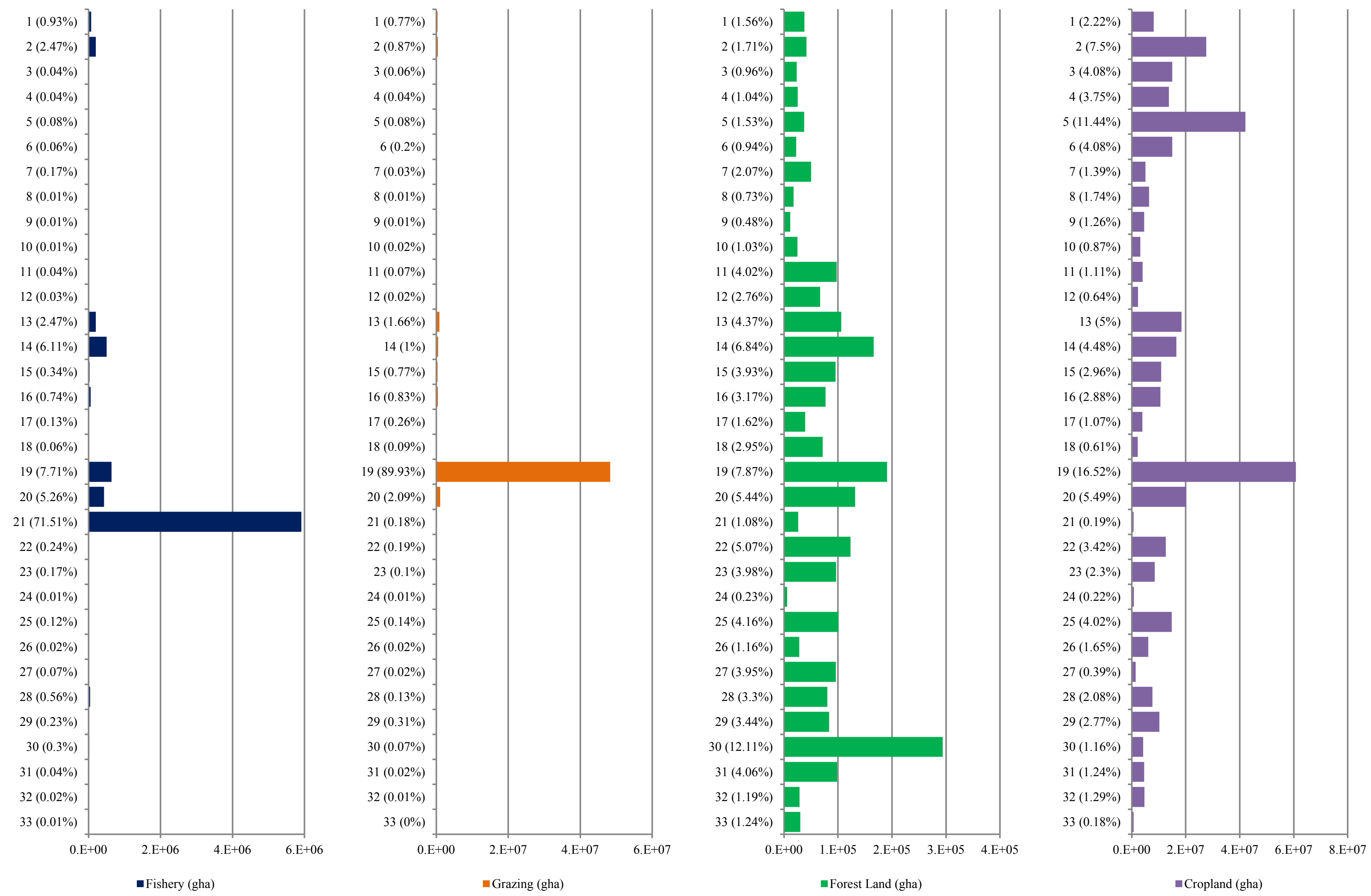
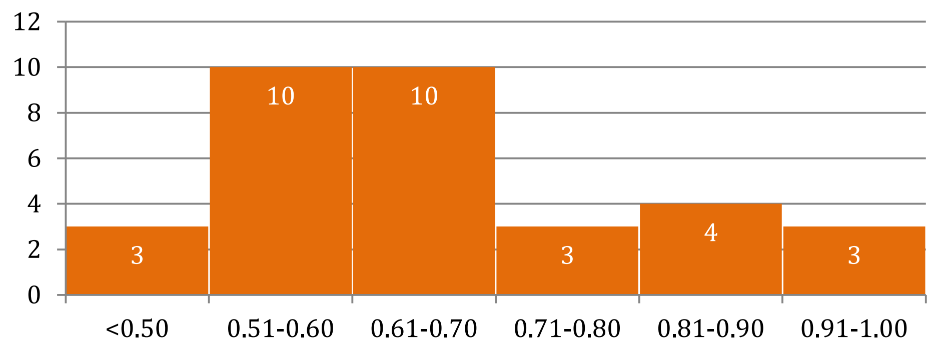


Fig. 3b. Results of Life Cycle Assessment



Data Summary	
Number of Data Points	33
Min Data Value	0.21
Max Data Value	1
Sample Mean	0.66
Sample Std. Dev.	0.17
Histogram Summary	
Histogram Range	0.13 to 1
Number of Intervals	5

Fig. 4. Histogram of food manufacturing sectors by overall SPI scores

Table 3. The lower & upper bounds of SPI sets

ID	Food Manufacturing Sector	SPI-1 (LB)	SPI-1 (UB)	SPI-2 (LB)	SPI-2 (UB)	SPI-3 (LB)	SPI-3 (UB)	Overall SPI	Rank
24	Tortilla manufacturing	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1
33	Distilleries	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1
17	Dry, condensed, and evaporated dairy product manufacturing	1.00	1.00	1.00	1.00	0.89	1.00	0.96	2
27	Flavoring syrup and concentrate manufacturing	1.00	1.00	0.94	1.00	0.70	1.00	0.89	3
21	Seafood product preparation and packaging	1.00	1.00	0.88	1.00	0.71	1.00	0.87	4
30	Soft drink and ice manufacturing	1.00	1.00	1.00	1.00	0.57	1.00	0.87	4
2	Other animal food manufacturing	1.00	1.00	1.00	1.00	0.47	1.00	0.84	5
31	Breweries	1.00	1.00	0.84	1.00	0.43	1.00	0.80	6
1	Dog and cat food manufacturing	0.91	1.00	0.91	1.00	0.41	1.00	0.79	7
9	Beet sugar manufacturing	0.89	1.00	0.72	1.00	0.34	1.00	0.73	8
8	Sugar cane mills and refining	0.72	1.00	0.50	1.00	0.34	1.00	0.67	9
32	Wineries	0.73	1.00	0.50	1.00	0.34	1.00	0.67	9
12	Nonchocolate confectionery manufacturing	0.63	1.00	0.48	1.00	0.37	1.00	0.65	10
5	Soybean and other oilseed processing	0.65	1.00	0.44	1.00	0.29	1.00	0.64	11
10	Chocolate and confectionery manufacturing from cacao beans	0.58	1.00	0.45	1.00	0.35	1.00	0.64	11
14	Fruit and vegetable canning, pickling, and drying	0.81	1.00	0.37	1.00	0.23	1.00	0.64	11
26	Coffee and tea manufacturing	0.60	1.00	0.41	1.00	0.28	1.00	0.63	12
4	Wet corn milling	0.55	1.00	0.38	1.00	0.26	1.00	0.61	13
18	Ice cream and frozen dessert manufacturing	0.52	0.94	0.40	1.00	0.30	1.00	0.61	13
22	Bread and bakery product manufacturing	0.56	1.00	0.36	1.00	0.23	1.00	0.61	13
11	Confectionery manufacturing from purchased chocolate	0.48	0.97	0.35	1.00	0.26	1.00	0.60	14
29	All other food manufacturing	0.52	1.00	0.35	1.00	0.23	1.00	0.60	14
3	Flour milling and malt manufacturing	0.48	1.00	0.33	1.00	0.23	1.00	0.59	15
7	Breakfast cereal manufacturing	0.40	1.00	0.27	1.00	0.19	1.00	0.57	16
28	Seasoning and dressing manufacturing	0.40	0.80	0.30	1.00	0.23	1.00	0.56	17
6	Fats and oils refining and blending	0.39	0.77	0.28	1.00	0.20	1.00	0.55	18
23	Cookie, cracker, and pasta manufacturing	0.33	0.82	0.21	1.00	0.14	1.00	0.54	19
15	Fluid milk and butter manufacturing	0.23	1.00	0.16	1.00	0.12	1.00	0.53	20
19	Animal (except poultry) slaughtering, rendering, and processing	0.25	1.00	0.13	1.00	0.09	1.00	0.53	20
25	Snack food manufacturing	0.32	0.78	0.21	1.00	0.15	1.00	0.53	20
13	Frozen food manufacturing	0.24	0.51	0.16	0.77	0.11	1.00	0.46	21
16	Cheese manufacturing	0.20	0.40	0.14	0.59	0.10	0.87	0.40	22
20	Poultry processing	0.09	0.19	0.07	0.28	0.05	0.42	0.21	23
	U.S. Average	0.62	0.91	0.50	0.96	0.35	0.98	0.66	-

The fitting distribution of SPI scores was found to be Gamma with 7% square error (See Fig. 4). According to the histogram given in Fig. 4, three sectors (frozen food, poultry and cheese manufacturing) were found to have SPIs lower than 0.50. In addition, 60% of the sectors have SPI score between 0.51 and 0.70. Only three sectors had SPI score that was greater than 0.90: tortilla manufacturing (1.00), distilleries (1.00) and dry, condensed, and evaporated dairy product manufacturing (0.96). The final rankings and overall SPI scores are also illustrated in Fig. 5.

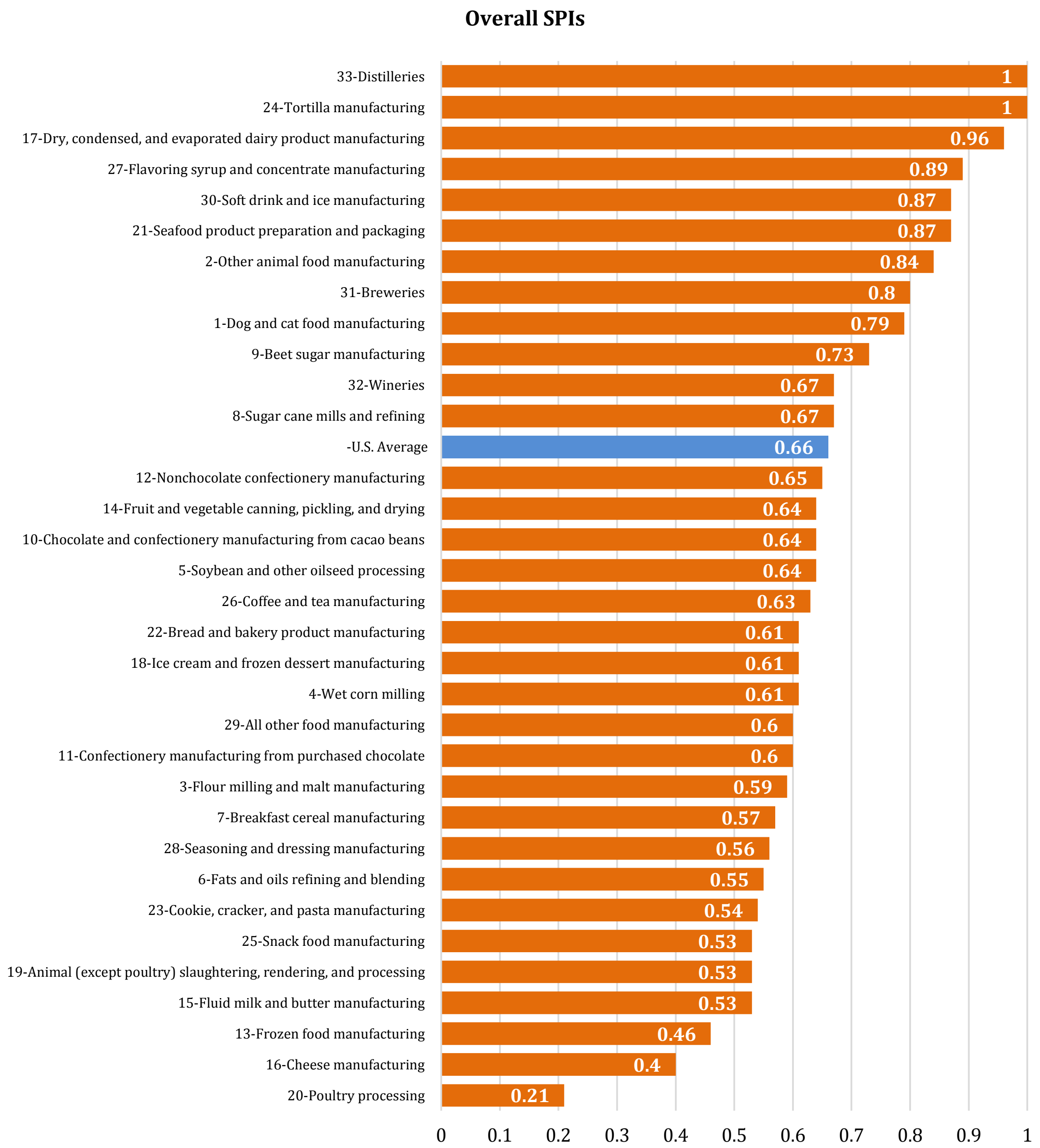


Fig. 5. Overall (Difuzzified) SPIs and Rankings

3.3. Ranges of the SPIs

To illustrate how the uncertainty of the LCA results could be affecting the SPI scores, three bar graphs were provided in Fig. 6 based on the three alpha cut intervals. In the first bar graph, the SPI ranges can be observed as the shortest for the majority of the food manufacturing sectors and even for some sectors, SPI range is zero due to the corresponding sector's SPI score is found to be as 1 (e.g. 31). These results are of importance due to the fact that the ranges between SPI scores are provided, which were found to be quite large. Therefore, such robust methods that can incorporate the uncertainties as intervals in sustainability performance assessment studies are necessary for accurate and reliable assessments.

As more variation is reflected in fuzzy intervals associated with the life cycle inventory, significantly increased ranges of SPI scores can be observed in the third graph in Fig. 6. These three bar graphs indicate that integrating fuzzy DEA with EIO-LCA is critical and important, due to the increasing ranges observed in larger alpha-cut intervals. The eco-efficiency ranges (the orange bars) are quite large for the majority of food manufacturing industries. This reveals the fact that eco-efficiency concept can be misleading if the uncertainty effects of LCA studies are not taken into consideration. This is also true for business sustainability analytics, where eco-efficiency measurements are widely used for sustainability performance assessment of corporates, business and government organizations. If the stakeholders work with the average (deterministic) LCA results, the eco-efficiency in other words sustainability performance assessment could mislead the decision-making processes and outcomes. The uncertainty in LCA projects' findings is a real cumbersome issue, which needs to be integrated into quantitative frameworks (such as fuzzy-DEA in this study) of research or business activities. Therefore, the proposed integrated EIO-LCA and fuzzy DEA approach can be identified as a more robust method to quantify sustainability performance on a broader scale. Since the current study utilized a composite SPI methods, it can be concluded that the current study's results are more realistic and comprehensive.

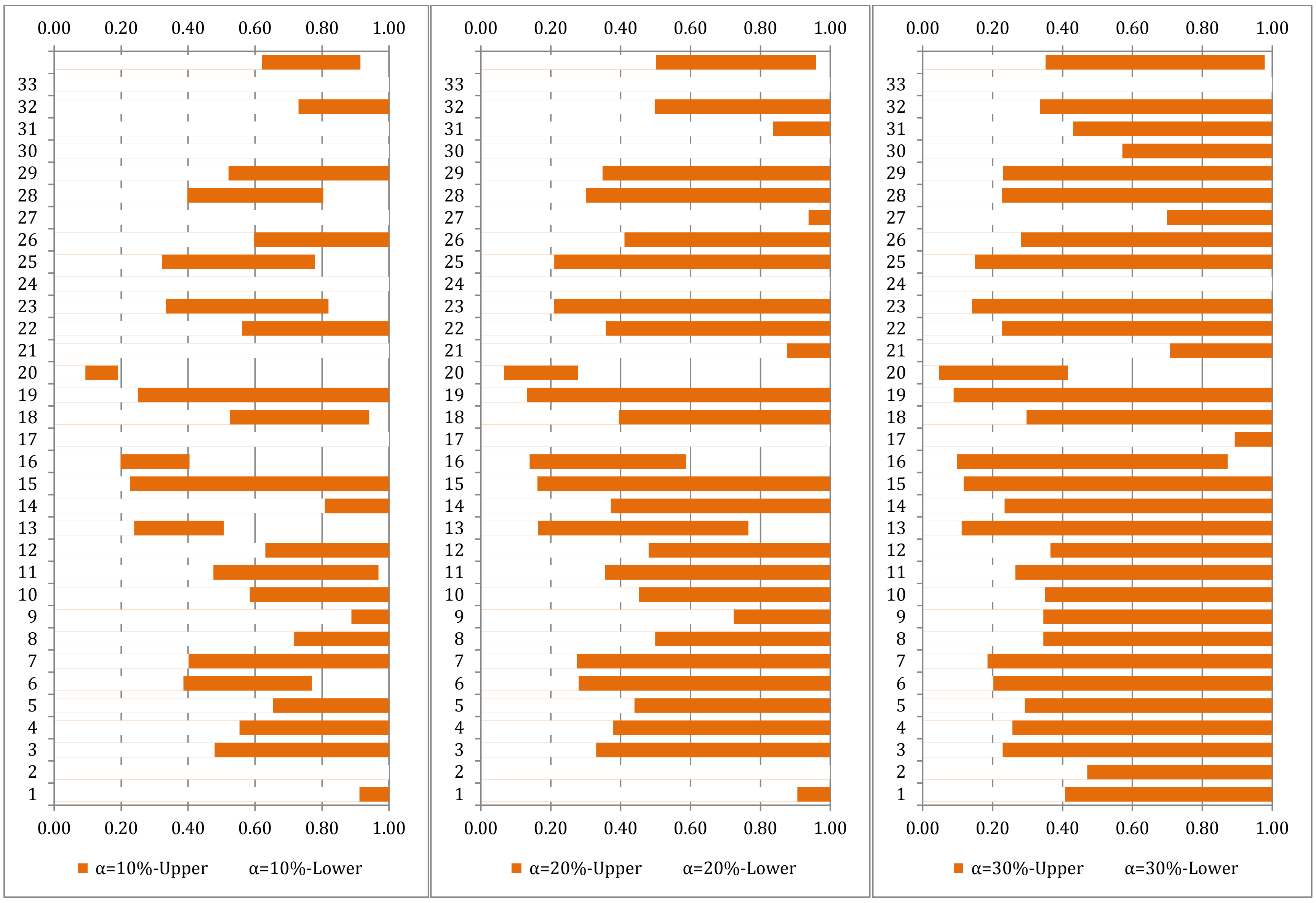


Fig. 6. Fuzzy SPI Ranges (Vertical axis: Sector ID, Horizontal axis: SPI score, Top bar: U.S.

3.4. Sensitivity Analysis

In addition to determining the difuzzified SPI scores and ranks, it is also important to assess the sensitivity of environmental impact indicators to the sustainability performance. In this regard, sensitivity analysis reveals an overall understanding about the level of change in the SPI, which is explained by the variation in specific environmental impact indicator. Zhu's (2001) super-efficiency DEA model is utilized to quantify the sensitivity of impact categories on the SPI score. The results are illustrated in Fig. 7. The sensitivity values range between 20% and 50% where forestry was found to be the most sensitive and cropland footprint was identified as the least sensitive. In this regard, higher rate of sensitivity means that even a smaller reduction in highly sensitive impact category will result in a relatively more significant impact on the SPI score. Sensitivity analysis for eco-efficiency scores can provide critical insights for prioritizing policy-making areas. Even though eco-efficiency concept itself is *still* a controversial topic and sustainability performance metric, governments and stakeholders at the global scale do not tend/want to put the policy-making focus on the environment only. Economic impact domain has always been the central topic while discussing environmental sustainability problems since the Kyoto protocol (Shah, 2015). The sensitivity results indicate that forestry impact category is the most critical area that causes the inefficiencies in food manufacturing sectors' sustainability performance, to a degree of 49.2% variation impact on eco-efficiency scores. While cropland is found to have 20.1% sensitivity, this is still a critical level of variation for eco-efficiency scores. These results are obtained due to the problematic relationship or lack of communication between sustainable food manufacturing policy-making and natural resource protection at the national level.

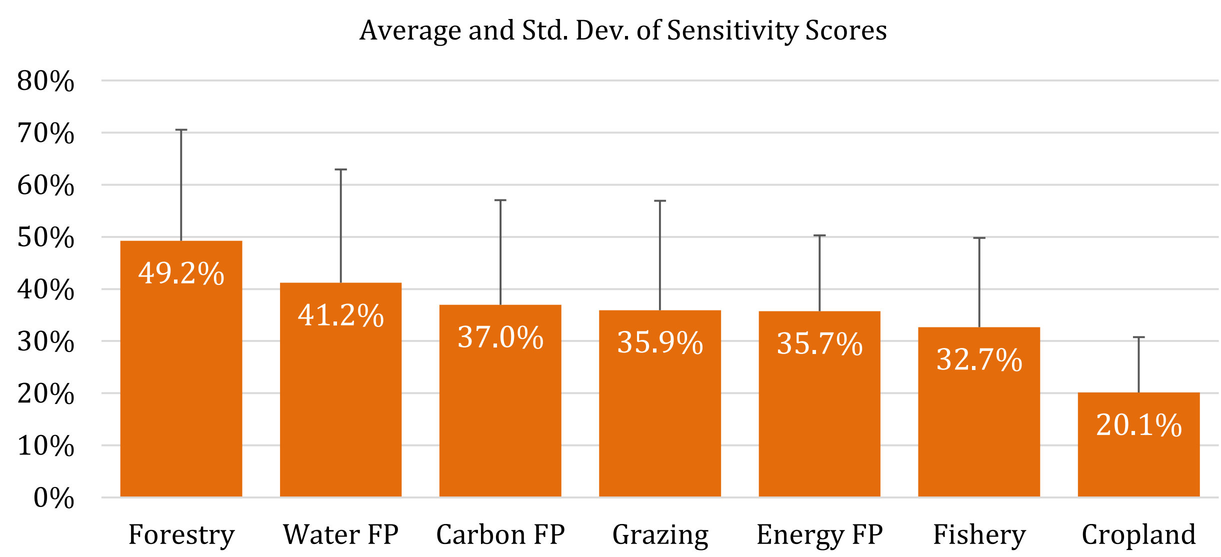


Fig. 7. Results of sensitivity analysis

4. Validation

In addition to the quantitative sustainability performance assessment, it is important to compare the results of the proposed Fuzzy DEA approach with a previous benchmark study from the literature for validation purpose. In the previous work, Egilmez et al. (2014) focused on quantifying sustainability performance of 33 major U.S. food manufacturing sectors' by tracing direct plus indirect (supply chain) environmental impacts and economic outputs which were quantified with the EIO-LCA. Then, sustainability performances were evaluated based on eco-efficiency scores. This study is taken as the benchmark work because the problem focus was the same, except, the sustainability performance assessment was performed by considering the EIO-LCA results as *deterministic* and the inherent uncertainty associated with EIO-LCA results *was not* considered.

In this study, the newly proposed Fuzzy-DEA framework is utilized to deal with the uncertainty in LCI results. Each of the 33 food manufacturing sectors' environmental impacts was quantified. The comparison with the previous work was made with bivariate correlation analysis and linear difference calculation. Firstly, the basic descriptive statistics of the two studies were provided in Table 4. It can be seen that the standard deviation of the sustainability performance scores was found to be 52% more in the previous study (0.26) compared to the current study (17%). In addition to the descriptive statistics, the linear differences between the sustainability scores obtained from both works are calculated and the comparison with Egilmez et al. (2014) is shown in Table 5.

Table 4. Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Current Study	.6603	34	.17087	.02930
	Egilmez et al. (2014)	.7650	34	.25628	.04395

Table 5. Comparison with Egilmez et al. (2014)

DMU	Food Manufacturing Sector	Current	Egilmez et al.	Differenc
1	Dog and cat food manufacturing	0.79	1.00	-0.21
2	Other animal food manufacturing	0.84	1.00	-0.16
3	Flour milling and malt manufacturing	0.59	0.69	-0.10
4	Wet corn milling	0.61	0.81	-0.20
5	Soybean and other oilseed processing	0.64	1.00	-0.36
6	Fats and oils refining and blending	0.55	0.54	0.01
7	Breakfast cereal manufacturing	0.57	0.59	-0.02
8	Sugar cane mills and refining	0.67	1.00	-0.33
9	Beet sugar manufacturing	0.73	1.00	-0.27
10	Chocolate and confectionery manufacturing from cacao	0.64	0.76	-0.12
11	Confectionery manufacturing from purchased chocolate	0.60	0.64	-0.04
12	Nonchocolate confectionery manufacturing	0.65	0.83	-0.18
13	Frozen food manufacturing	0.46	0.35	0.11
14	Fruit and vegetable canning, pickling, and drying	0.64	1.00	-0.36

15	Fluid milk and butter manufacturing	0.53	0.33	0.20
16	Cheese manufacturing	0.40	0.28	0.12
17	Dry, condensed, and evaporated dairy product	0.96	1.00	-0.04
18	Ice cream and frozen dessert manufacturing	0.61	0.70	-0.09
19	Animal (except poultry) slaughtering, rendering, and	0.53	0.47	0.06
20	Poultry processing	0.21	0.13	0.08
21	Seafood product preparation and packaging	0.87	1.00	-0.13
22	Bread and bakery product manufacturing	0.61	0.89	-0.28
23	Cookie, cracker, and pasta manufacturing	0.54	0.53	0.01
24	Tortilla manufacturing	1.00	1.00	0.00
25	Snack food manufacturing	0.53	0.50	0.03
26	Coffee and tea manufacturing	0.63	0.87	-0.24
27	Flavoring syrup and concentrate manufacturing	0.89	1.00	-0.11
28	Seasoning and dressing manufacturing	0.56	0.56	0.00
29	All other food manufacturing	0.60	0.78	-0.18
30	Soft drink and ice manufacturing	0.87	1.00	-0.13
31	Breweries	0.80	1.00	-0.20
32	Wineries	0.67	1.00	-0.33
33	Distilleries	1.00	1.00	0.00
	U.S. Average	**0.66**	**0.76**	**-0.10**
	Standard Deviation	**0.17**	**0.26**	**0.15**

The difference results varied between 0 and 0.36, which was found to be significant. This means that if the uncertainty associated with EIO-LCA results was not considered, the sustainability performance scores can vary up to 36%, which also supports the findings of Lenzen (2000). Besides, the U.S. average results also provided 10% gap. The proposed Fuzzy DEA method can deal with potential uncertainty issues exist in the EIO-LCA results and provide more reliable results in terms of less standard deviation with strong correlation with the previous methods that do not consider uncertainty.

Additionally, a paired sample t-test is performed to see if there is statistically significant difference between the means of the two dataset given in Table 5. The results are shown in Table 6, and 7. In Table 4, mean and standard deviation statistics are provided, which indicate that current study provided a lower mean and lower standard deviation compared to the previous study. It is critical to reiterate that previous work (Egilmez et al., 2014) does not consider uncertainty, which resulted in overestimation of eco-efficiency scores and higher standard deviation. Correlation analysis results between the current study's eco-efficiency results and the benchmark study are provided in Table 6. The correlation is positive, strong and significant, which indicates that current study's findings are not different than previous study in terms of eco-efficiency trends. However, according to the paired-sample test results given in Table 7, the mean of the differences between two paired samples differs from 0, and the difference is statistically significant since sigma value is less than the test statistic (0.05). This indicates that current study is not totally different than the previous work since there is correlation between the eco-efficiency results. On the other hand, considering the previous work is being a deterministic approach, the proposed fuzzy-DEA method is more robust and reliable due to its capability of taking the uncertainty into consideration.

Table 6. Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	Current Study & Egilmez et al. (2014)	34	.842	.000

Table 7. Paired Samples Test

			Paired Differences					t	df	Sig. (2-tailed)
			Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
						Lower	Upper			
Pair 1	Current Study Egilmez et al. (2014)		-.10471	.14536	.02493	-.15542	-.05399	-4.200	33	.000

5. Conclusions and future work

In this paper, sustainability performance assessment of the 33 U.S. food manufacturing sectors was performed by using an integrated EIO-LCA and Fuzzy DEA approach. Seven environmental impact categories were considered as the inputs and the total production amounts were considered as the output category, where each food manufacturing sector was identified as decision-making unit. In input-output LCA research, one of the major challenges that researchers and practitioners have been facing is the inherent uncertainty in the LCA results. The fundamental impact of such uncertainty is that result interpretation phase in input-output-based LCA studies becomes a subjective and sometimes a challenging task, especially when the LCI results are aimed to be used for sustainability performance assessment purposes. In this context, considering the uncertainty in the results of EIO-LCA studies, this study introduces the Fuzzy DEA concept to sustainability performance assessment literature as a critical contribution since a set of SPIs are combined into a single SPI score with fuzzy theory-based DEA models. Unlike the other DEA-based sustainability benchmarking methods, Fuzzy DEA approach enables us derive an overall SPI score based on the multiple SPI scores obtained from the minimum and maximum threshold values of life cycle inventory, which is extremely important due to the fact that EIO-LCA models are criticized with the uncertainty of life cycle inventory associated with the assumptions made.

It is believed that the proposed integrated EIO-LCA + Fuzzy DEA method contributes significantly to the body of knowledge on the sustainability performance analysis, where input-output models are mainly utilized for life cycle impact assessment. The proposed integrated framework reveals significant insights about the current sustainability performance of U.S. food manufacturing sectors, which can be beneficial for stakeholders, government agencies towards developing sound policies for sustainable development. On the other hand, combining the life cycle results with Fuzzy DEA concept provides first multiple SPIs, which are then combined into an overall SPI score; second enables to make an overall comparison across the food manufacturing sectors; third reveals the sensitivity of impact categories to the SPI scores.

Current newly introduced integrated EIO-LCA + Fuzzy DEA concept can be utilized for other sustainability performance benchmarking problems such as other industrial sectors (e.g. construction, service, etc.), products, consumption categories, etc. The authors also plan to focus on food waste as the future research direction, which is another crucial area that needs attention for sustainable development by reducing food waste. Finally, utilizing network DEA models for the sustainability performance assessment of supply chains is another extension that the authors are planning to focus in recent future.

Supplementary Data

Supplementary files that includes LCI data and detailed results can be accessed through the following link:

https://drive.google.com/folderview?id=0B7oO7uor7BuxdU5WUVB0WVNLV1E&usp=sharing

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