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Sustainability assessment and modeling based on supervised machine learning techniques: The case for food consumption

Galal M. Abdella [a], Murat Kucukvar [a, *], Nuri Cihat Onat [b], Hussein M. Al-Yafay [c], Muhammet Enis Bulak [d]

[a] Department of Mechanical and Industrial Engineering, College of Engineering, Qatar University, Doha, Qatar
[b] Qatar Transportation and Traffic Safety Center, College of Engineering, Qatar University, Doha, Qatar
[c] Engineering Management Program, College of Engineering, Qatar University, Doha, Qatar
[d] Department of Industrial Engineering, Faculty of Engineering and Natural Sciences, Uskudar University, Istanbul, Turkey

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ABSTRACT

Sustainability of food consumption requires the understanding of multi-dimensional environmental, economic and social impacts using a holistic and integrated sustainability assessment and modeling framework. This article presents a novel method on the assessment and modeling of sustainability impacts of food consumption. First, sustainability impacts of food consumption categories are quantified using high sector resolution input-output tables of U.S. economy. Later, an integrated sustainability modeling framework based on two supervised machine-learning techniques such as k-means clustering and logistics regression is presented. The proposed framework involves five steps: (1) economic input-output life cycle sustainability assessment, (2) non-dimensional normalization, (3) sustainability performance evaluation, (4) centroid-based clustering analysis, and (5) sustainability impact modeling. The findings show that the supply chains of food production sectors are accounted for major environmental impacts with higher than 80% of portions for total carbon footprints. Animal slaughtering, rendering, and processing is found as the most dominant sector in most of the environmental impact categories. The logistic model results revealed an overall model accuracy equal to 91.67%. Furthermore, among all the environmental sustainability indicators, it has found that CO and SO_2 are the most significant contributors. The results also show that 13.7% of the food and beverage sectors are clustered as high, in which the bread and bakery product manufacturing is the central sector. The large value of the variance (5.24) is attributed to the large total weighted impact value of the animal (except poultry) slaughtering, rendering, and processing cluster.

1. Introduction

1.1. Background

The strategic decision-making for sustainable industrial growth should acknowledge the necessity of achieving Sustainable Development Goals of the United Nations (UN General Assembly, 2015). Food security is one of the grand challenges of sustainability, listed among the Sustainable Development Goals (SDG 2) (UN, 2015). The United Nations Educational, Scientific and Cultural Organization (UNESCO) also contributes significantly to SDGs through education, technology and innovation-based integrated solutions to achieving environmental goals such as improving the quality of water resources and supporting carbon mitigation and climate change adoption efforts (Sepehri and Sarrafzadeh, 2018, 2019). Achieving goals related to the food security and sustainability shall consider the complex food value chains taking into account extraction, processing, and end of life management (Wulfa et al., 2018).

While the food consumption and production is among the main drivers of the United States' national economy, SDG 12, known as Sustainable Production and Consumption, has attracted a great interest and policymakers are concerned with exploring policies related to the resource-efficient food production and minimization of consumption and waste to improve the sustainability of the food supply chains (Bennbaia et al., 2018).

* Corresponding author.
E-mail address: mkucukvar@qu.edu.qa (M. Kucukvar).

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Nomenclature

Symbol	Description
$\boldsymbol{B}$	Technical coefficient matrix
$\boldsymbol{U}$	Matrix of the product consumption by each industry
x_j	the overall output of j_{th} industries
$\boldsymbol{V}$	Make matrix
$\boldsymbol{D}$	An industry-based technology coefficient matrix
q_i	The total domestic and imported output of the i_{th} products
E_{dir}	Matrix of direct effects per one dollar of the output
f	A vector of final product demand
$\boldsymbol{Y}$	The overall indicator-matrix
$y_{ij}^{s"}$	The normalized value of the (i,j) element in $\boldsymbol{Y}$
$\mathrm{M}_{max,\,j}^{s}$	The maximum value under the j_{th} indicator and the s_{th} aspect
$\mathrm{M}_{min,\,j}^{s}$	The minimum value under the j_{th} indicator and the s_{th} aspect
a_0 , a_1	Normalizing constants
$\Vert . \Vert$	The Euclidian norm operator
TWI_i	The total weighted impact per unit of standard deviation
P_s	The s_{th} sustainability aspect
w_j	The weight assigned to the indicator j_{th}
$\mathrm{SUM}-\mathrm{I}_i$	The sum of the individual sustainability impact of the i_{th}industry
$\boldsymbol{A}$	The within sum-of-squares and cross products matrix
$\boldsymbol{T}$	The total inertia matrix
$\boldsymbol{Z}$	The between sum-of-squares and cross-products matrix
H	A subset of the K clusters
$\boldsymbol{I}$	The identity matrix
μ_k	The centroid of the cluster h_k
α_k	A constant (intercept)
β_{ik}	The i_{th} regression coefficient of the k_{th} cluster
Chi^2	Chi-square statistic

1.2. Life cycle assessment and input-output analysis

The supply chains of the food industry involves processing, production, and transport, which continues to grow in parallel to the rising world population (Kucukvar et al., 2016). The policy-makers are interested in analysing the complexity of food supply chains and its relation to sustainable development (Wognuma et al., 2011). Life cycle assessment (LCA) models are used to measure environmental impacts of food products (such as dairy products, fresh food categories, and beverages) from cradle-to-grave involving raw materials acquisition and processing, production, packaging, distributing, and end-of-life (Kucukvar and Samadi, 2015; Tasca et al., 2017). Some examples include organic food production (Tasca et al., 2017), fruit production (Cerutti et al., 2013), food sector (Cerutti et al., 2016), and food consumption categories (Creanna et al., 2019; Notarnicola et al., 2017). In conclusion, the results of LCA studies in food production showed that there is high sectoral complexity and interconnectivity in food production systems, and therefore there is a requirement for food tailored and integrated LCA methods, taking also into account the significant role of ecosystem goods and services (Karabulut et al., 2018).

To quantify the impact related to food production and consumption, environmental life cycle assessment (E-LCA), economic input-output life cycle assessment (EIO-LCA) and global multiregional input-output (MRIO) analysis are used as a method for estimating material acquisition and processing, transportation and end-of-life (Kucukvar et al., 2019 a, b). LCA is one of the most commonly used methods for assessing environmental impacts and resources utilized along with the life cycle, involving the purchasing, manufacturing, utilizing, and end-of-life stages of raw material (Onat et al., 2018, 2019a; Virtanen et al., 2011). LCA models are widely applied for process-specific impacts (Onat et al., 2014a, b; Shaikh et al., 2017). However, when analyzing the regional and global scale effects of sectors, EIO-LCA becomes one of the preferred methods to model all export and import activities and associated environmental impacts of food supply chains (Yu et al., 2016). EIO-LCA models merge economic transactions data of trade between sectors of the national economy with environmental accounts and quantify the environmental effects of direct and indirect suppliers ' goods or procedures at the economic scale (Kucukvar et al., 2018, 2015).

The EIO-LCA method is extensively utilized for carbon, water, and energy footprint analysis for food production and consumption. For example, Egilmez et al. (2014, 2016a) analyzed the direct and indirect environmental impacts of 33 food-manufacturing sectors in the USA. Park et al. (2015) conducted an in-depth analysis of ecological resource consumption, atmospheric emissions, land, and water footprints of 54 agricultural and food industries in the USA. The researchers developed supply-chain linked life cycle analysis using the ecologically-based Life Cycle Assessment (Eco-LCA) software developed by the Center for Resilience at Ohio State University. Jiang et al. (2018) developed a hybrid Economic Input-Output and Life Cycle Assessment (EIO-LCA) model to investigate the carbon footprint of Chinese 15 food products from 1979 to 2009. Pairotti et al. (2015) applied a combined application of process-based LCA and economic input-output LCA to estimate energy and carbon footprints of the European diet.

While single region input-output models are estimating regional environmental impacts (Kucukvar et al., 2014a, b), MRIO models use global trade data (Onat et al., 2017a, b), which is combined with environmental and socioeconomic accounts such as emissions, energy use, material consumption and economic value-added (Wiedmann and Lenzen, 2018). Using the global MRIO analysis, Kucukvar et al. (2019) analyzed the regional and global energy, water, carbon footprints, and economic value added to the world's largest food producers. Scherer and Pfister (2016) also investigated water-related resource consumption, emissions and ecological impacts of Swiss food consumption using a tailor-made multi-region input-output analysis. Yu et al. (2016) used a global multiregional input-output analysis to trace agricultural land use of China's future food consumption by 2030. Galli et al. (2017) developed an MRIO-based ecological footprint accounting model for Mediterranean countries' food sector. The results of the abovementioned studies showed that food production and consumption are considerable contributors to environmental pollution and resource depletion (Martinez and Levin, 2017). In conclusion, most of the reviewed studies focused mainly on the environmental sustainability of food production and consumption, and a full triple-bottom-line sustainability analysis of food consumption is still considered an important extension of these studies.

1.3. Decision-making methods in sustainability assessment

Social, economic, and environmental pillars are considered the three main pillars of sustainable development (Silvestre and Mihaela, 2019). These triple bottom lines of sustainability are usually conflicting with each other during the multi-objective decision making (Egilmez et al., 2016b), which should be properly addressed (Onat et al., 2016a, b). To address this issue, several sustainability indicators are used for creating composite metrics such as sustainability index (Mori and Christodoulou, 2012), eco-efficiency (Tatari and Kucukvar, 2011), resource efficiency (Huysman et al., 2015), and renewability ratio (Baral and Bakshi, 2010; Park et al., 2016).

Several parametric and nonparametric methods are also used to aid in multi-objective decision making for sustainability assessment. For example, Data Envelopment Analysis (DEA) (Tian et al., 2020), Principal Component Analysis (PCA) (Jiang et al., 2018), fuzzy Multi-Criteria Decision Making (MCDM) (Solangi et al., 2019), and Weighted Arithmetic Mean (WAM) (Ahmad and Wong, 2019; Gumus et al., 2016a, b) methods are usually applied in multi-criteria decision analysis of multiple sustainability metrics. Azapagic and Perdan (2005) analyzed 19 general MCDM techniques used in sustainability research. Cinelli et al. (2014) concentrated on five MCDM methods such as Multi-Attribute Utility Theory (MAUT), AHP, Elimination and Choice Translating Algorithm (ELECTRE), and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) and Dominance Based Rough Set Approach (DRSA). Wang et al. (2009) studied nine MCDM methods like weighted sum method (WSM), weighted product method (WPM), AHP, TOPSIS, Grey relation method, MCDA combined fuzzy methods, etc. Diaz-Balteiro et al. (2017) performed a critical review of MCDM methods in measuring and decision making for sustainability. Similar decision-making methods were also applied for developing composite scores for the sustainability performance assessment in food waste management (Cristóbal et al., 2016), transportation (Onat, 2015), manufacturing (Egilmez et al., 2013; Martín-Gamboa et al., 2017), cities (Egilmez et al., 2015), and supplier selection (Govindan et al., 2013).

1.4. Machine learning techniques

Sustainability assessment models have become an emerging subject of research due to their importance in providing business owners and stakeholders with a data-driven framework for overall sustainable development assessment. Ness et al. (2007) presented a wide range of approaches for sustainability performance assessment, some of which are well known and widely used in practice in both public and private sectors such as multiple indicators-based and composite indicators-based approaches. Despite their effectiveness and low-computational complexity, there are always tendencies in the literature to criticize these approaches for the extent of inclusion of the main sustainability aspects and the subjectivity of the selection of the key indicators and weighting (Mori and Christodoulou, 2012; Tajbakhsh and Hassini, 2018).

Though “machine-learning”, as a word, is not usually mentioned literally under the sustainability research context, machine learning techniques can be observed in some of the researches. For example, the Principal Component Analysis (PCA), Fuzzy Analytic Hierarchy Process (AHP), and fuzzy k-means clustering have always been the core of several of sustainability assessment methods. Implications of aforementioned methods can be observed in previous researches such as sustainable cities (Gagliardi et al., 2007), sustainable urban development (Tan and Lu, 2016), sustainable production (Jayawickrama et al., 2017), sustainable development (Turskis et al., 2019), electric vehicle technologies (Onat et al., 2019b) and companies (Beekaroo et al., 2019). Fig. 1 shows a typical classification of machine learning techniques as supervised and unsupervised learning. Using two of these machine learning techniques, this research introduces a systematic and tailor-made sustainability performance assessment based on a new composite sustainability index that is more comprehensive in the sense of considering the triple bottom line sustainability impacts and more robust to the uncertainty of the weight scores of the sustainability indicators.

1.5. Novelty and organization

This research presents the first sustainability assessment and modeling framework integrating the economic input-output life cycle assessment with two machine-learning techniques: logic regression and k-means clustering. Using the latest high-resolution economic input-output tables of the U.S. economy merged with several social, economic and environmental metrics, the supply-chain linked sustainability impacts of food consumption categories are quantified, and a detailed sustainability analysis is performed. After the sustainability impacts of each food consumption category are measures, k-means clustering and logistics regression are used as supervised machine-learning techniques to develop a novel sustainability modeling and assessment method that deals with multiple decision-making units (food consumption categories) and sustainability indicators. The proposed method performed the five-step analysis:

(1) Economic input-output life cycle assessment
(2) Non-dimensional normalization
(3) Sustainability performance evaluation
(4) Centroid-based clustering analysis
(5) Sustainability impact modeling

The rest of the paper is organized as follows. Section 2 presents the integrated method with economic input-output life cycle analysis, sustainability assessment indicators, and machine learning applications. Section 3 represents the results for sustainability impact based on total output, scope-based carbon footprint accounting, supply chain decomposition analysis, and sustainability modeling based on k-means clustering and logistics regression. Finally, in section 4, the findings are summarized, and a possible future study is pointed out.

2. Method

This section is dedicated to illustrate and explain the overall-framework followed in this work, including both the methods and tools. The U.S. food consumption categories are examined by analyzing each sector's sustainable assessment indicators, either direct and/or indirect sustainability impacts. The method presented in this paper is a broadened concept of machine learning applications under the sustainability research context. Two of the machine learning techniques are consequently applied in this research. These are the k-means clustering and the multinomial logistic regression. Fig. 2 summarizes the proposed sustainability assessment and modelling framework based on method, category, purpose, input and output data of each step.

2.1. Economic input-output life cycle assessment

The supply and use data obtained from the U.S. Bureau of Economic Analysis are combined with environmental and socioeconomic accounts to develop EIO-LCA model of the food consumption categories in the USA. In this paper, the raw data entered were influencing each other food manufacturing industries in different factors because of the complex relationship between sectors of the national economy. The matrix used for this study, represented by $\boldsymbol{U}$,

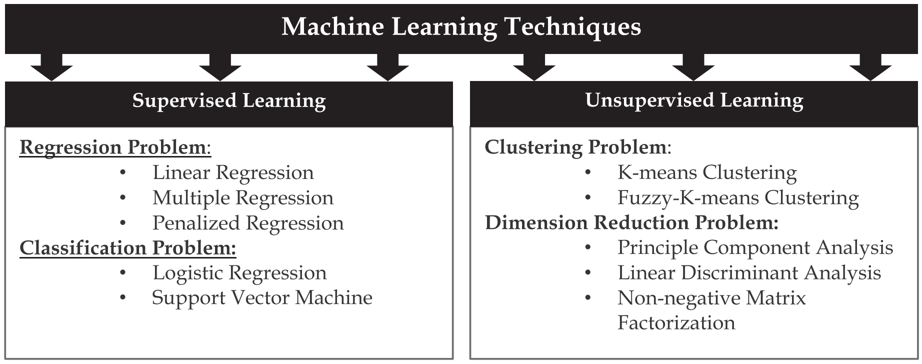

Fig. 1. Machine learning problems and techniques.

specifies the quantity of product consumption by each sector. Hence, u_{ij} specifies the purchased quantity of i_{th} products by the j_{th} sector. From the mentioned indicators, the technical coefficient matrix, $\boldsymbol{B}$, can be identified as equation (1) to calculate the essential quantity of products for making one $ output of different sectors (Miller, 2009).

$$\boldsymbol{B} = [b_{ij}] = \left[\frac{u_{ij}}{x_j}\right] \tag{1}$$

where x_j accounts the overall output of j_{th} industries taking into consideration the imports.

Let $\boldsymbol{V}$ represents the number of productions processed by each sector and called as the Make matrix v_{ij} indicates a Make matrix component where i_{th} is the product value made by the j_{th} manufacturing factory. Then, the industry-based technology coefficient matrix, $\boldsymbol{D}$, can be identified as equation (2) to calculate the market-share matrix with the following formula (Miller, 2009):

$$\boldsymbol{D} = [d_{ij}] = \left[\frac{v_{ij}}{q_i}\right] \tag{2}$$

where q_i indicates the total output (domestic and imported) of i_{th} products processed by a sector. Thus, d_{ij} represents the amount of overall output of i_{th} product processed by industries. Using $\boldsymbol{B}$ and $\boldsymbol{D}$ matrices, k vector can be defined and calculated using equation (3) below (Miller, 2009):

$$k = \left[\boldsymbol{D}\ (\boldsymbol{I} - \boldsymbol{BD})^{-1}\right]\mathrm{f} \tag{3}$$

where k defines as the vector of overall industry output, and f is a vector of final product demand. The term $[\boldsymbol{D}\ (\boldsymbol{I\text{-}BD})^{-1}]$, which is called as the Leontief inverse, shows the total requirement matrix. The matrix multiplication part, $\boldsymbol{BD}$, which is shown by $\boldsymbol{A}$ in Leontief's model, known as the direct requirement matrix (Kucukvar and Samadi, 2015). Then, the overall sustainability influences and impact can be defined as equation (4) below:

$$r = \boldsymbol{E}_{dir}k = \boldsymbol{E}_{dir}k = \left[\boldsymbol{D}\ (I - \boldsymbol{BD})^{-1}\right]\mathrm{f} \tag{4}$$

where r, the overall influences/impacts vector, indicates the total sustainability effects per one unit of final demand. $\boldsymbol{E}_{dir}$ matrix provides the value of direct effects per one dollar of the output of each food manufacturing sector. $\boldsymbol{E}_{dir}$ is calculated by dividing the overall direct sectorial effect like income by the overall economic sectoral output. Furthermore, the term $\boldsymbol{E}_{dir}\ [\boldsymbol{D}\ (\boldsymbol{I\text{-}BD})^{-1}]$ is named the multiplier matrix (Kucukvar, 2013).

2.2. Non-dimensional normalization

Since the composite sustainability index involves indicators with different units of measure, the dataset is normalized considering the fact that all the indicators should have an equal opportunity to contribute to the sustainability index. Although several normalization methods are widely researched and examined in literature, still there is no particular methods to be used exclusively in practice (Freudenberg, 2003) and (Leiva et al., 2017). This study uses unity-based normalization as one of the simplest non-dimensional normalization methods.

To continue, $\boldsymbol{Y}^s_{i,j} = [y^s_{1,j}, y^s_{2,j}, \ldots, y^s_{m,P_s}]^T$ shows the j_{th} column under the s_{th} sustainability aspect and the i_{th} observation (industrial sector), where $i = 1{,}2, m$, $j = 1{,}2, \ldots P_s$, and $s = 1, 2, \ldots, S$. The term P_s is used here to refer to the indicator number – or density under the s_{th} sustainability aspect. The overall indicator-matrix, $\mathbf{Y}$, when $S = 3$ can be shown as:

$$\mathbf{Y} = \begin{bmatrix} y^1_{1,1} & y^1_{1,2} & \cdots & y^1_{1,p_1} & y^2_{1,p_1+1} & y^2_{1,p_1+2} & \cdots & y^2_{1,p_1+p_2} & y^3_{1,p_1+p_2+1} & y^3_{1,p_1+p_2+2} & \cdots & y^3_{1,p_1+p_2+p_3} \\ y^1_{2,1} & y^1_{2,2} & \cdots & y^1_{2,p_1} & y^2_{2,p_1+1} & y^2_{2,p_1+2} & \cdots & y^2_{2,p_1+p_2} & y^3_{2,p_1+p_2+1} & y^3_{2,p_1+p_2+2} & \cdots & y^3_{2,p_1+p_2+p_3} \\ y^1_{3,1} & y^1_{3,2} & \cdots & y^1_{3,p_1} & y^2_{3,p_1+1} & y^2_{3,p_1+2} & \cdots & y^2_{3,p_1+p_2} & y^3_{3,p_1+p_2+1} & y^3_{3,p_1+p_2+2} & \cdots & y^3_{3,p_1+p_2+p_3} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \cdots & \vdots \\ y^1_{m,1} & y^1_{m,2} & \cdots & y^1_{m,p_1} & y^2_{m,p_1+1} & y^2_{m,p_1+2} & \cdots & y^2_{m,p_1+p_2} & y^3_{m,p_1+p_2+1} & y^3_{m,p_1+p_2+2} & \cdots & y^3_{m,p_1+p_2+p_3} \end{bmatrix}$$

The indicators are redefined with respect to the polarity of their

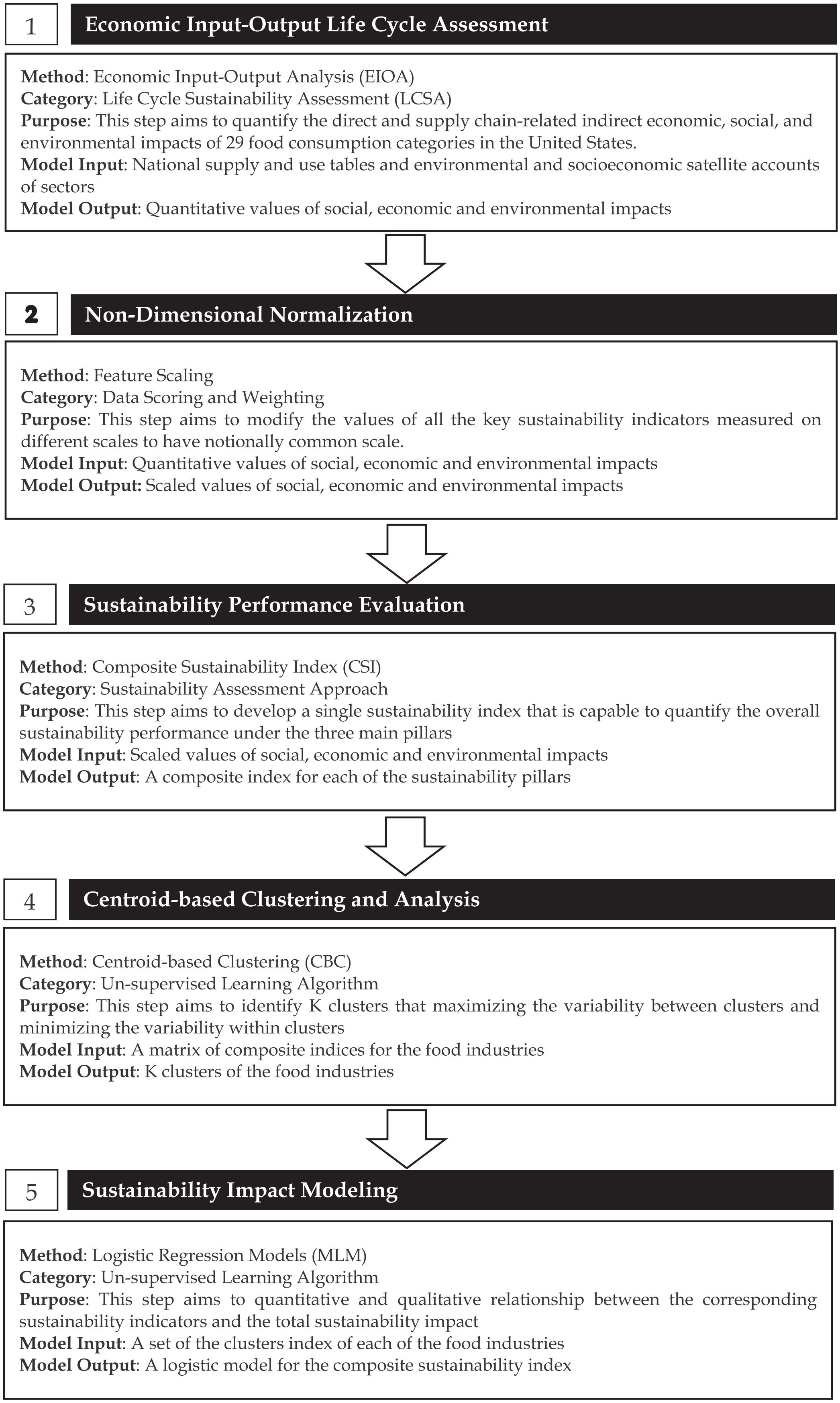

Fig. 2. The 5-steps of sustainability assessment method.

contribution. If the value of the indicator corresponds to a positive effect, then the indicator assigned as a positive-polarity indicator, other else, the indicator is assigned as a negative-polarity (Ciommi et al., 2017).

Set that Ω^+ and Ω^- as the subsets of the positive and negative subsets, then the normalized values of the positive indicators are computed as follows:

$$y_{ij}^{s'} = a_0 + \frac{\left(y_{ij}^{s} - \mathrm{M}_{min,\,j}^{s}\right)(a_1 - a_0)}{\left(\mathrm{M}_{max,\,j}^{s} - \mathrm{M}_{min,\,j}^{s}\right)}; \quad \nabla\Omega^+ \tag{5}$$

where $\mathrm{M}_{max,\,j}^{s}$ *and* $\mathrm{M}_{min,\,j}^{s}$ are the maximum and minimum value under the j_{th} indicator and the s_{th} sustainability aspect, respectively. For the indicators in Ω^-, Equation (5) is modified as follows:

$$y_{ij}^{s'} = a_0 + \frac{\left(\mathrm{M}_{min,\,j}^{s} - y_{ij}^{s}\right)(a_1 - a_0)}{\mathrm{M}_{max,\,j}^{s} - \mathrm{M}_{min,\,j}^{s}}; \quad \nabla\Omega^- \tag{6}$$

The constants a_0 *and* a_1 , in Equations (5) and (6), are the lower and upper bounds of the normalization range. In this study, a_0 *and* a_1 are set at 0 and 1, respectively. That allows us to normalize the indicators into an interval of length 1 (Mazziotta and Pareto, 2016) and (Ciommi et al., 2017). The reason behind the modification in Equation (6) is to reverse the normalization range such that the indicators in Ω^- will negatively contribute. Another way to reverse the normalization range is by setting a_0 *and* a_1 in Equation (5) equal to 0 and -1, respectively. The values obtained above are scaled such that the column-vector associated with each value will have length one. That can be succeeded in a simple way by dividing each normalized value by the Euclidean length of its column-vector. The new value under each indicator and sustainability aspect is found as follows:

$$y_{ij}^{s''} = \frac{y_{ij}^{s'}}{\|y_{ij}^{s'}\|} = \frac{y_{ij}^{s'}}{\sqrt{\sum_{i=1}^{n}\left(y_{ij}^{s'}\right)^2}}; \quad j = 1, 2, \ldots, P_s; \quad \nabla S \tag{7}$$

where $y_{ij}^{s''}$ is the scaled values and $\|y_{ij}^{s'}\|$ is the Euclidian norm operator of the vector containing the $y_{ij}^{s'}$ values under the s_{th} aspect. The step described in Equation (7) is known in the literature as scaling to unit length. This kind of scaling provides more consistency in the statistical properties of the normalized values.

2.3. Sustainability performance evaluation

The integration of key sustainability indicators is important to handle the broad concept of sustainable development (Beekaroo et al., 2019). In this section, the second step of the proposed method is explained with respect to a new composite index that addresses sustainable performance development under the three main aspects of sustainability (environmental, economic, and social). The resulting index deviates from several existing indices in the sense that it is not only considering the individual impacts of the sustainability indicators but also the variability within these indicators. This feature provides an index with the advantage of being useful for comparing different sectors and between different periods in the same sector.

To calculate the total weighted impact per unit of standard deviation (TWI) of the i_{th} sector, we propose the following:

$$\mathrm{TWI}_i = \sum_{s=1}^{S} \frac{\left|w_j y_{i,j}^{s''}\right|^2}{(P_s - 1)^{-1/2}\sqrt{\left(y_{i,j}^{s''} - \bar{y}_i^{''}\right)^2}}; j = 1, 2, \ldots, P_s \tag{8}$$

where $0 \le w_j \le 1$ is the weight assigned to the indicator. The weight w_j is added here to provide sustainability assessment with more flexibility for sensitivity analysis. The term $\bar{y}_i^{''}$ is the average of the individual impacts of all sustainability indicators under the i_{th} sector and k_{th} sustainability aspect. The value of this parameter is calculated as follows:

$$\bar{y}_i^{''} = \frac{1}{S}\sum_{s=1}^{S}\sum_{j=1}^{P_s} y_{i,j}^{s''} \tag{9}$$

For a better understanding of the individual impact of the industry sectors, the sum of individual impact (SUM-I) is used as follows:

$$\mathrm{SUM} - \mathrm{I}_i = \sum_{s=1}^{S} w_j y_{i,j}^{s''}; j = 1, 2, \ldots, P_s \tag{10}$$

where P_s represents the density number of the s_{th} sustainability aspect.

2.4. Centroid-based clustering analysis

The centroid-based, K-means, clustering is one of the simplest unsupervised machine-learning methods, which is customarily used in practice due to its robustness to the “curse of dimensionality” problem and discriminative characteristic. In this step, the k-means clustering is used to create homogeneous groups of food and beverage sectors based on their total sustainability impact developed in the previous step (Azadniaa et al., 2012) and (Alonso et al., 2015).

The method proposed in this study uses the Wilks' lambda criterion to optimize the clustering process. That means the optimum k-means clustering is achieved when the variability within a K number of clusters is reached the minimum. The Wilks' lambda is a test statistic used here to test whether there are differences between the means of identified groups of sectors on a combination of the TWI. The Wilks' lambda criterion corresponds to the division of determinant (***A***) by determinant (***T***), where ***A*** is the within sum-of-squares and cross products matrix, and ***T*** is the total inertia matrix. Let ***B*** is the between sum-of-squares and cross-products matrix, then the Wilks's lambda $(0 \le \Lambda \le 1)$ can be found as

$$\Lambda = \frac{\det \boldsymbol{A}}{\det(\boldsymbol{T})} = \frac{\det \boldsymbol{A}}{\det(\boldsymbol{A} + \boldsymbol{Z})}; \tag{11}$$

However, as can be seen from Equation (11), the optimal performance of the K-means clustering is a trade-off process involving both the within and between-clusters variability. Let $\mathrm{H} = \{h_1, h_2, \ldots, h_K\}$ be a subset of the K clusters, then the objective of the clustering process can be mathematically expressed as follows:

$$\underset{\mathrm{H}}{\operatorname{argmin}} \left(\sum_{k=1}^{K}\sum_{\mathrm{TWI} \in h_k} \|\mathrm{TWI} - \mu_k\|^2\right); \tag{12}$$

where $\|\mathrm{TWI} - \mu_k\|^2$ is the L_2-norm or the Euclidian distance, h_k is the k_{th} cluster, and μ_k is the centroid of the cluster h_k. Equation (12) is equivalent to minimizing the squared deviations of the TWI pairwise in the same cluster; then

$$\underset{\mathrm{H}}{\mathrm{arg}min}\left(\sum_{k=1}^{\mathrm{K}}\frac{1}{2|h_k|}\sum_{\mathrm{TWI},\mathrm{TWI}^{'}\varepsilon\ h_k}\mathrm{TWI}-\mathrm{TWI}^{'2}\right); \tag{13}$$

or

$$\underset{\mathrm{H}}{\mathrm{arg}min}\left(\sum_{k=1}^{\mathrm{K}}\frac{1}{2|h_k|}\sum_{\mathrm{TWI}\neq\mathrm{TWI}^{'}\varepsilon\ h_k}(\mathrm{TWI}-\mu_k)(\mu_k-\mathrm{TWI}^{'})\right) \tag{14}$$

One of the challenges for the K-means clustering is the uncertainty in identifying the optimal number of clusters. This study uses the “clvalid” package, available at the Comprehensive R Archive Network[1], to determine the optimal K-value. The package provides several validation measures that can be used to determine the optimal number of clusters. This study uses three different internal measures, including the connectivity (C), Silhouette Width (SW), and Dunn Index (DI). These measures are based on quantifying the connectedness, homogeneity, and the degree of separation between the clusters. Further details about these measures are available in Brock et al. (2008). The “clvalid” package requires the user to set a specific range of the number of clusters (K) as input before starting the validation process. This step is somehow subjective and depends on the method used for clustering and validation.

2.5. Sustainability impact modeling

Sustainability models are important in providing data-driven approaches through which the organization can reduce the uncertainty about the overall organizational performance under one or more of the main sustainability aspects (Bebbington et al., 2007; Alonso et al., 2015). In this step, the multinomial logistic regression, as a simple machine learning method, is used to model the relationship between the sustainability indicators and the distribution of the TWIs. The multinomial logistic regression is a general formulation of the binary logistic regression that allows for more than two levels of the outcome. The multinomial logistic models mainly use the maximum likelihood estimation rather than the least-squares estimation method used in classical multiple regression to assess the probability of categorical membership.

Similar to several of the regression models, the multinomial logistic regression uses the linear formulation to predict the probability that a sector i is located in a cluster k. That is

$$f(i,k)=\alpha_k+\beta_{1k}y^{''}_{1,i}+\beta_{2k}y^{''}_{2,i}+\ldots+\ \beta_{Pk}y^{''}_{P,i}=\alpha_k+\ \sum_{p=1}^{P}\beta_{pk}y^{''}_{p,i}\ ;$$
$$k=1,2,\ldots,\ \mathrm{K} \tag{15}$$

where α_k is a constant, β_{pk}'s are the regression coefficients associated with the cluster k, $y^{''}_{p,i}\varepsilon\mathbb{R}$ is the normalized value of the i_{th} sector, and P is the total number of the SIs. The logistic regression is applied to understand to what extent the WTIs values of the food and beverage sectors are sensitive to uncertainty in the SIs scores. To achieve this, the probability of the categorical membership under different potential settings of the SIs scores is examined. The probability that the i_{th} industrial sector will be located in a cluster c can be found as follow:

$$Pr(k_i=c)=\left(e^{\alpha_c+\sum_{p=1}^{P}\beta_{p,c}y^{''}_{p,i}}\right)\left(\sum_{k=1}^{K}e^{\alpha_k+\sum_{p=1}^{P}\beta_{pk}y^{''}_{p,i}}\right)^{-1} \tag{16}$$

where k_i is the response variable. In the multinomial logistic regression, one of the K clusters is designated as the reference cluster, and then the probability of membership in other clusters is compared to the probability of membership in the reference cluster. Moreover, for a particular cluster, the values of the coefficients estimators in Equation (16) represents the probability of being located in the reference cluster versus a one-unit change of the corresponding sustainability indicator(s).

3. Case study

In this paper, the U.S. food consumption is selected as a case study. First, the social, economic and environmental impacts of 29 food consumption categories are analyzed. To be able to carry out a more precise and comprehensive sustainable assessment evaluation of food industries, a high sector resolution economic input-output table of the U.S. economy is used. The economic value of food consumption for each food category is obtained from the Bureau of Economic Analysis database (BEA, 2007). In the case study, national supply-chain linked sustainability impacts of 29 food consumption categories are estimated, and a comprehensive sustainability assessment and modeling are performed. Table 1 shows the descriptive statistic results of dataset in addition to the polarity of all the corresponding indicators. The description of each indicator is presented in Kucukvar et al. (2019b) with corresponding descriptions and units.

3.1. Scope-based carbon footprint analysis

Fig. 3 demonstrates the scope-based carbon emissions. Scope 1 emissions are the emissions stemming from directly from the food production sector. Scope 2 emissions account for GHG emissions that result from the consumption of purchased electricity in the food production sector, which are emitted directly through the combustion of fossil fuels on electric power plants. Finally, all of the emissions from the supply chain of Scope 1 and 2 activities are allocated into Scope 3 emissions (Kucukvar et al., 2015). The results of the scope-based carbon footprint analysis show that animal (except poultry) slaughtering, rendering, & processing sector is responsible for around 30% carbon emissions related to food consumption. Scope 3 has the largest contribution to total carbon emissions with 89%. Scope 1 and scope 2 categories have lower shares with 6% and 5%, respectively. Overall, animal (except poultry) slaughtering, rendering, & processing, fluid milk and butter manufacturing, and poultry processing are the top 3 sectors in terms of total carbon footprints when compared to other sectors. The results clearly proved that direct impacts has a little contribution to overall carbon footprints and supply chain-related carbon emissions (Scope 2 and 3) should be further investigated. The percentage contribution of Scope 1, 2 and 3 are presented in Fig. 3 for all categories.

3.2. Supply chain decomposition analysis for Top-3 food consumption categories

In the supply chain decomposition analysis, the direct is considered as the on-site impact in carrying out the food manufacturing processes and operations. The indirect impact is linked to supply chain operations that contribute indirectly to the overall carbon footprint. In this research, the effect of detailed

[1] http://CRAN.R-project.org.

Table 1
Descriptive statistics and polarity of the sustainability indicators of the food and beverages industry.

Aspect	Indicator	Unit	Polarity	Statistics				
				Minimum	Maximum	Median	Mean	Variance
Environmental	CO	mt[(1)]	Negative	2.90E+02	1.60E+05	2.50E+04	3.20E+04	1.10E+09
	NH_3	mt		1.30E+02	4.90E+05	1.50E+04	4.60E+04	9.70E+09
	NO_X	mt		2.30E+02	1.30E+05	1.60E+04	2.40E+04	6.60E+08
	PM_{10}	Mt		2.70E+02	9.70E+04	2.80E+04	3.40E+04	7.50E+08
	$PM_{2.5}$	Mt		8.80E+01	3.50E+04	1.00E+04	1.10E+04	8.50E+07
	SO_2	Mt		1.30E+02	3.00E+04	7.70E+03	8.70E+03	5.40E+07
	VOC	Mt		1.80E+02	5.40E+04	1.30E+04	1.60E+04	1.50E+08
	GHG	mt CO_2-eq		1.20E+05	1.40E+08	1.20E+07	1.60E+07	6.40E+14
	Energy	TJ[(2)]		1.90E+01	5.50E+05	7.40E+04	1.20E+05	2.10E+10
Economy	Total Output	$M[(3)]	Positive	4.60E+02	1.70E+05	3.40E+04	4.10E+04	1.50E+09
	Total Intermediate	$M		2.20E+02	1.10E+05	2.20E+04	2.60E+04	6.20E+08
	Tax	$M		0.00E+00	9.30E+03	7.10E+02	1.40E+03	3.80E+06
	Gross Surplus	$M		1.50E+02	3.00E+04	6.10E+03	7.60E+03	5.60E+07
	Import	$M	Negative	1.40E+02	1.30E+04	3.70E+03	4.50E+03	1.50E+07
Social	Men Employment	Emp[(4)]	Positive	5.90E+02	2.30E+05	6.00E+04	7.60E+04	4.70E+09
	Women Employment	Emp		3.30E+02	2.00E+05	2.80E+04	4.20E+04	2.10E+09
	Injuries Occurred	Emp	Negative	3.10E+01	2.80E+04	3.60E+03	6.00E+03	4.50E+07
	LABHS Workers	Emp	Positive	3.30E+02	1.50E+05	2.80E+04	4.00E+04	1.50E+09
	LABMS Workers	Emp	Positive	5.10E+02	2.30E+05	4.90E+04	6.70E+04	4.00E+09
	LABLS Workers	Emp	Positive	7.80E+01	3.90E+04	7.00E+03	1.10E+04	1.10E+08
	Compensation	$M	Positive	8.40E+01	2.10E+04	5.20E+03	6.90E+03	3.90E+07

Units: [(1)] Metric ton [(2)] Tera-joule [(3)] Million Dollar [(4)] Number of Employee.

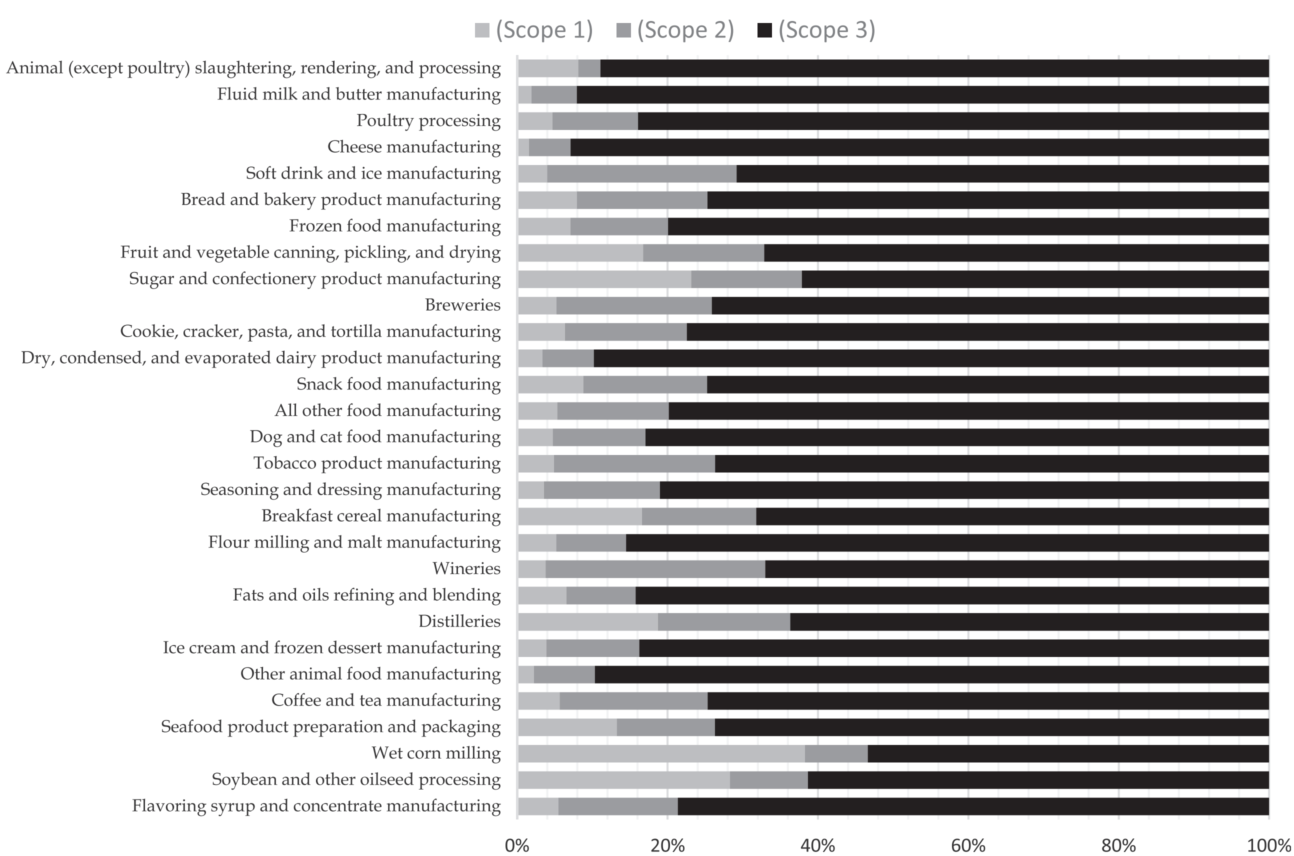

Fig. 3. Percentage contribution of GHG Scope 1, 2 and 3 for all food consumption categories.

supply chain industries is interconnected with the carbon footprints.

Table 2 illustrates the indirect supply chain decomposition results for the top three carbon emissions that relied on food manufacturing sectors based on total consumption. The direct and indirect carbon footprints of animal (except poultry) slaughtering, rendering, and processing category are found 2.2% and 97.8%, respectively. Based on the top 5 sectors analysis in the supply chains of animal (except poultry), Fresh Wheat, Corn, Rice, and other Grains (FWCRG), electricity, fertilizers, truck transport and Cattle Ranches and Feedlots (CRF) are accounted nearly 72.8% of the overall indirect carbon footprints. The direct and indirect carbon

Table 2
Chain Decomposition Analysis for Top Three GHG Emissions based on Total consumption amounts.

Consumption Category	Percentage	mt CO_2-eq
Animal (except poultry) slaughtering, rendering, and processing		
Avg. Onsite Carbon Footprint	2.2%	1.66E+06
Avg. Supply Chain Carbon Footprint	97.8%	7.35E+07
Top 5 Sectors in the Supply Chains		
Fresh Wheat, Corn, Rice, And Other Grains	47.0%	3.46E+07
Electricity	8.3%	6.10E+06
Fertilizers	6.9%	5.10E+06
Truck Transport	5.6%	4.12E+06
Cattle Ranches and Feedlots	5.0%	3.65E+06
Fluid milk and butter manufacturing		
Avg. Onsite Carbon Footprint	1.9%	7.30E+05
Avg. Supply Chain Carbon Footprint	98.1%	3.79E+07
Top 5 Sectors in the Supply Chains		
Dairies	34.5%	2.54E+07
Electricity	3.2%	2.33E+06
Fresh Wheat, Corn, Rice, And Other Grains	2.9%	2.10E+06
Truck Transport	2.4%	1.75E+06
Cattle Ranches and Feedlots	2.3%	1.66E+06
Poultry Processing		
Avg. Onsite Carbon Footprint	4.7%	1.26E+06
Avg. Supply Chain Carbon Footprint	95.3%	2.56E+07
Top 5 Sectors in the Supply Chains		
Poultry Farms	6.8%	5.00E+06
Fresh Wheat, Corn, Rice, And Other Grains	6.2%	4.54E+06
Electricity	4.2%	3.06E+06
Truck Transport	4.0%	2.96E+06
Cattle Ranches and Feedlots	3.7%	2.71E+06

emissions of Fluid Milk and Butter (FMB) category are found 1.9% and 98.1%, respectively. By considering the supply chains of this sectors, dairies, electricity, FWCRG, truck transport, and CRF have a 45.2% portion for the overall indirect carbon footprints. As another dominant category in terms of total carbon emissions, supply chain-related indirect carbon footprint of poultry processing and manufacturing is computed 95.3%. Moreover, top 5 sectors in the supply chains of poultry processing, poultry farms, FWCRG, electricity, truck transport, and CFR contributed around 24.8% to the overall indirect carbon footprints. Consequently, supply chain-linked carbon hotspots of these food consumption categories shall be investigated and emphasized to optimize the usage of several energy consumption systems for the supply chain of food processing sectors in the U.S. More energy-efficient production processes utilizing renewable electricity resources such as solar, hydro, and/or wind can be viable approaches to minimize the supply chain-related carbon emissions, as suggested by Egilmez et al. (2014) and Kucukvar et al. (2015).

3.3. *Sustainability impact assessment*

In this section, the operational procedures of the sustainability assessment method reported using the dataset of the food and beverage industry are presented. As a first step in the proposed method, the indicators in Table 1 were normalized according to their polarity (i.e. Equation (5) was used for the indicators in Ω^+, and Equation (6) was used for the indicators in Ω^-). The normalization range is set from 0 to 1. For further reading about the determination of the polarity see Silvestre and Mihaela (2019); De Oliveira Neto et al. (2018). Each indicator was scaled, using Equation (7), such that its length becomes equal to one. Then, the total weighted impact per unit of standard deviation (TWI) of the *ith* sector is calculated and presented, as indicated in Table 3. It should be considered that the weight value is set equal to one for all the indicators.

Among the 29 industrial sectors, the “Animal (except poultry) slaughtering, rendering, and processing” sector has the highest TWI value (TWI = 11.248); see Table 3. Also, Fig. 4 shows the highest 3 contributor sectors in terms of TWI comparison and Fig. 5 shows the variance comparisons between the first three-highest contributor sectors. Animal (except poultry) slaughtering, rendering, and processing lead the list of the highest variability. From managerial insight, the increase in the variability is an indicator that the sector’s performance is varying from one indicator to another. Table 3 also shows that the Flavoring Syrup and Concentrate Manufacturing sector has the smallest TWI value ($TWI_1 = 0.001$). The very low value of the variance of this sector (0.0001) leads to that the sustainability contribution of this sector is slightly changing from one aspect to another. However, the rank of the industrial sectors in terms of the TWI (Table 3) is slightly consistent with the rank based on the amount of personal consumption expenditures. Table 3 also shows that the Animal (Except Poultry) sector has the greatest SUM-I score. The negative sign of the SUN-I of this sector refers to that the individual impact of the negative-polarity sustainability indicators is greater than the positive-polarity indicators.

The initialization method is critical to the solution of the K-means clustering problem. The results of the clustering process may depend on the initial clusters (solution). This study uses the random partition method, in which each data point is randomly assigned to a random center, and then the initial location of each center is specified as the centroid of all the points assigned to the corresponding cluster. The random partition method provides the k-means clustering with the advantages of being more independent of on initial clustering and instance order (Pena et al., 1999; Greg and Charles, 2002).

Table 4 presents the scores of the three CRAN internal validation methods over the proposed range of k. In this study, the minimum and maximum number of clusters are set at 3 and 9, respectively.

Table 4 reports three optimal values of K. The underlined scores in Table 4 represent the optimum performance of the corresponding validation method over the selected range of K. Fig. 6 graphically shows the distribution of the validation scores over the specified range of K. The Silhouette Width measure reveals a significant fluctuation comparing with the other two measures. In this study, more weight is given to the connectivity between the sectors, and hence k = 3 is selected as the optimal number. Table 5 summarizes the descriptive results of the clustering process.

Table 5 and Fig. 7 indicate that most of the industrial sectors (48.27%) are in the “Low” cluster, in which the “Seafood product preparation and packaging” is the central cluster. The relatively low value of the variance of the “Low” cluster (variance = 0.439) reveals that most of the industrial sectors located in this cluster have a similar sustainability performance impact (i.e., low TWI values). Also, 13.7% of the food and beverage sectors are clustered as “High,” in which the “Bread and bakery product manufacturing” is the central sector. The large value of the variance (5.242) is attributed to the large TWI value of the “Animal (except poultry) slaughtering, rendering, and processing” cluster.

The most notable finding here is that the “Tobacco product manufacturing” sector is at the “Medium” cluster. This, no doubt, explains the interest of the United Nations in incorporating the “Tobacco product manufacturing” industry under the UN Sustainable Development Goals (SDGs) for sustainable consumption and production goal.

To demonstrate the individual impact of the sustainability indicators on the composite index TWI, three logistic models, one for each of the three sustainability aspects, were developed. In this study, the Cross-Validation (CV) is used for assessing how

Table 3
The TWI and SUM-I scores of the food and beverages industry in the USA under the three sustainability aspects.

Sector	Variance	Score	
		SUM-I	TWI
Animal (except poultry) slaughtering, rendering, and processing	0.2663	**−2.108**	**11.248**
Soft drink and ice manufacturing	0.1018	0.167	6.704
Poultry processing	0.0900	−0.133	6.302
Bread and bakery product manufacturing	0.1089	1.288	7.163
Fruit and vegetable canning, pickling, and drying	0.0475	−0.087	4.581
Frozen food manufacturing	0.0408	−0.344	4.269
Fluid milk and butter manufacturing	0.0313	−0.460	3.773
Sugar and confectionery product manufacturing	0.0454	−0.985	4.685
Breweries	0.0328	−0.399	3.835
Cookie, cracker, pasta, and tortilla manufacturing	0.0219	−0.001	3.117
Tobacco product manufacturing	0.0369	0.691	4.149
Snack food manufacturing	0.0269	−0.318	3.463
All other food manufacturing	0.0164	0.026	2.682
Wineries	0.0135	0.164	2.442
Cheese manufacturing	0.0114	−0.333	2.288
Dog and cat food manufacturing	0.0100	−0.295	2.131
Seasoning and dressing manufacturing	0.0076	−0.220	1.846
Dry, condensed and evaporated dairy product manufacturing	0.0034	−0.198	1.250
Distilleries	0.0061	−0.190	1.665
Breakfast cereal manufacturing	0.0031	−0.158	1.197
Coffee and tea manufacturing	0.0014	−0.003	0.782
Seafood product preparation and packaging	0.0017	0.008	0.855
Fats and oils refining and blending	0.0038	−0.402	1.421
Flour milling and malt manufacturing	0.0021	−0.402	1.140
Ice cream and frozen dessert manufacturing	0.0004	−0.007	0.413
Other animal food manufacturing	0.0005	−0.165	0.541
Soybean and other oilseed processing	0.0001	−0.060	0.186
Wet corn milling	0.0001	−0.077	0.168
Flavoring syrup and concentrate manufacturing	0.0001	**0.001**	**0.001**

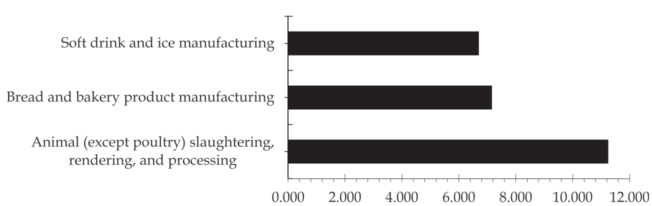

Fig. 4. The TWI comparisons between the first three-highest contributor sectors.

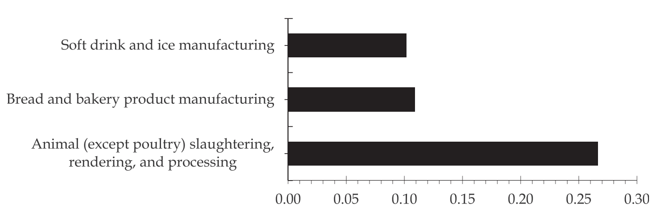

Fig. 5. The variance comparisons between the first three-highest contributor sectors.

accurately the logistic model will perform in practice. The original dataset is partitioned into two complementary subsets, and then one of these subsets is used to develop the model and the other to validate its accuracy.

It is conventional in the literature to refer to these two subsets as training and validating datasets. This selection of the training and validating datasets is randomly performed using the XLSTAT software. The cross-validation is repeated with each of the three models. Only the case of the cross-validation of the building the environmental model is detailed here (Table 6). For the other two models, economic and social models, the regression coefficients are presented.

Tables 7 and 8 show indicators that can be utilized to evaluate the accuracy of the environmental model. In this research, the probability of the log-likelihood ratio is utilized, as shown in Table 7. However, since the probability is less than 0.0001, the significance of the developed model can be simple confirmed.

Table 9 below gives details on the coefficients of the environmental logistic model. These coefficients clarify the impact of the environmental indicators on the categories of the TWI. The model parameters are obtained for each environmental indicator and for each TWI category (except the reference category) using the XLSTAT software. Table 9 indicates if there is a unit of increase in the emission that for one unit increase in emission rate of the CO, the log-likelihood ratio between the “Low” and “High” clusters will decrease by −0.004. In other words, the increase in the emission rate of the CO increases the possibility of moving from “Low” to “High” and from “Medium” to “High.” Table 9 also shows that for a

Table 4
Internal validation scores of the K-means clustering.

Validation Measure	Number of Clusters							Expected	Target	Optimal K
	3	4	5	6	7	8	9			
Connectivity	7.499	14.41	19.75	26.25	31.14	33.14	38.19	[0,∞]	Min	3
Silhouette Width	0.107	0.067	0.109	0.233	0.331	0.333	0.170	[-1,1]	Max$^+$	8
Dunn Index	0.592	0.598	0.565	0.563	0.545	0.491	0.424	[0,∞]	Max	4

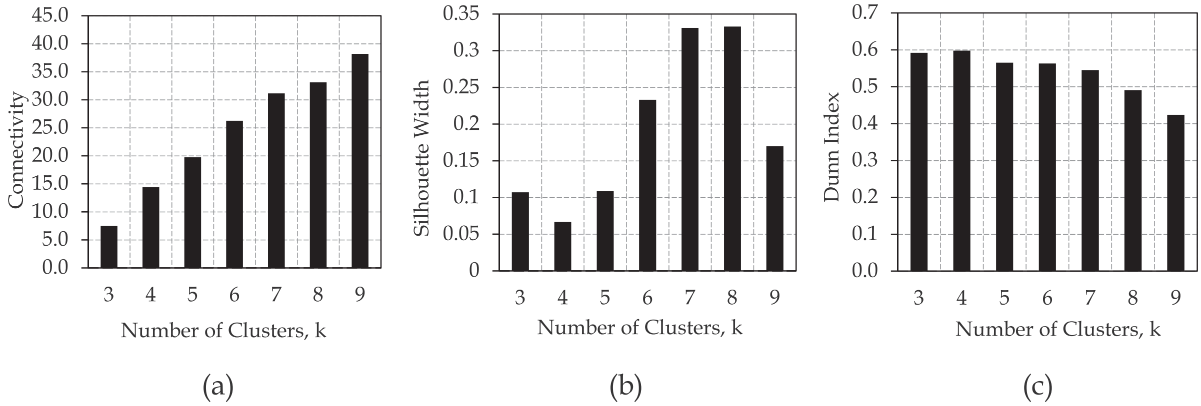

Fig. 6. Internal validation distribution versus the number of clusters: (a) Connectivity, (b) Silhouette Width, (c) Bund Index.

Table 5
The descriptive results of the 3-means clustering.

Clusters	Centroid	Sector	TWI Score	Density, %	Variance
High	7.854	Bread and bakery product manufacturing	7.163	13.80	5.242
Medium	3.571	Snack food manufacturing	3.463	37.93	0.712
Low	0.971	Seafood product preparation and packaging	0.855	48.27	0.439

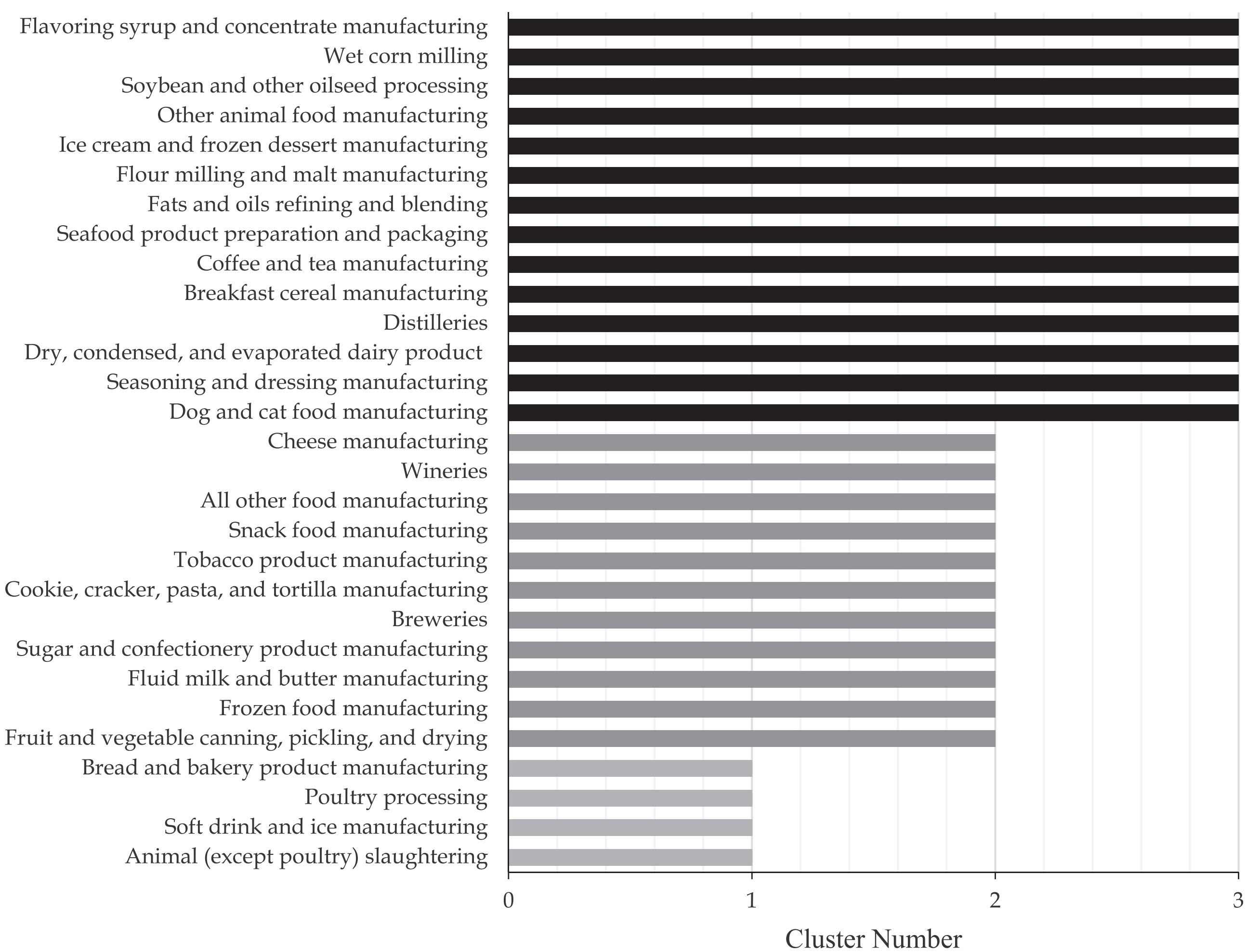

Fig. 7. The TWI-based cluster distribution of the food and beverage sectors in the U.S.

Table 6
The parameter description of the cross-validation.

Dataset	Industry Sectors	Response Variable	Type	Percentage,%		
				High	Medium	Low
Training Dataset	19	TWI	Ordinal	10	40	50
Validating Dataset	10	TWI	Ordinal	10	40	50

Table 7
The parameter description of the cross-validation.

Statistic	Independent	Full
Sectors	19	19
Sum of Weights	19.000	19.000
Degree of freedom	18	1
−2 Log(Likelihood)	40.285	0.011
R^2(Cox and Snell)	0.000	0.880
AIC	44.285	36.011

Table 8
The results of the goodness of fit using the XLSTAT software.

Statistic	Degree of freedom	Chi-square	Probability > Chi^2
−2 Log(Likelihood)	16	40.273	0.0001
Score	16	25.231	0.066

unit of increase in SO_2, the log-likelihood ratio between the “Low” and “High” and “Medium” and “High” clusters will increase by 0.007 and 0.008, respectively.

Among all the environmental indicators, the PM2.5 has the largest impact ($\beta_i = 0.017$and$\beta_i = 0.011$)in increasing the probability of moving from “Low” to “High” and “Medium” to “High. Table 9 shows that the coefficient estimates of the NH_3, NOx, GHG, and energy are all equal to zeros. That means these indicators have no impact on the probability of being clustered as “Low” or “Medium. Figs. 8 and 9 show a graphical comparison between the impacts of the environmental indicators.

The logistic model equation for both the “Low” and “Medium” clusters are shown below:

i The model equation for Low-Class:

$$\text{Log}\frac{\Pr(TWI = Low)}{\Pr(TWI = High)} = 24.512 - 0.004CO - 0.005PM_{10} + 0.017PM_{2.5} + 0.007SO2 - 0.001VOC \quad (17)$$

ii The model equation for Medium-Class:

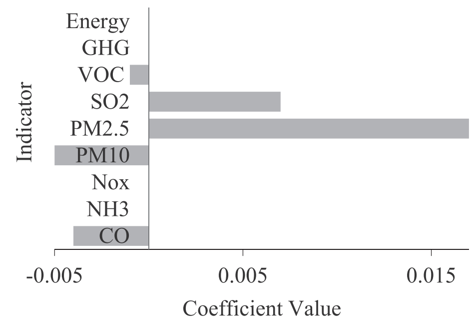

Fig. 8. The environmental model coefficients (Low-Case).

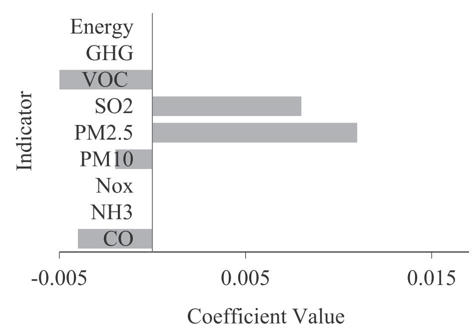

Fig. 9. The environmental model coefficients (Medium-Case).

$$\text{Log}\frac{\Pr(TWI = Medium)}{\Pr(TWI = High)} = 43.838 - 0.004CO - 0.002PM_{10} + 0.011PM_{2.5} + 0.008SO2 - 0.005VOC \quad (18)$$

Table 9 also shows that the intercept is significant for both the “Low” and “Medium” cases. In general, we can say that the CO, NH_3, NO_x, GHG, and energy are the indicators that are not affecting the outcome of the clustering process of the TWI.

When developing predictive models, it is important to quantify how well the model fits the future expectations. There are many ways in the literature to check model accuracy. This study mainly

Table 9
The regression coefficients of the environmental logistic model.

TWI Cluster	Indicator	β_i	Standard error	TWI Cluster	Indicator	β_i	Standard error
Low	Intercept	24.51	4603.41	Medium	Intercept	43.83	4603.38
	CO	−0.004	0.268		CO	−0.004	0.269
	NH3	0.000	0.067		NH3	0.000	0.066
	NOx	0.000	0.000		NOx	0.000	0.000
	PM_{10}	−0.005	0.360		PM10	−0.002	0.360
	$PM_{2.5}$	0.017	2.204		PM2.5	0.011	2.204
	SO2	0.007	1.017		SO2	0.008	1.017
	VOC	−0.001	0.135		VOC	−0.005	0.135
	GHG	0.000	0.000		GHG	0.000	0.000
	Energy	0.000	0.013		Energy	0.000	0.013

Table 10
The prediction step of the "validating" sample.

Food and Beverage Sector	TWI Cluster		Probability		
	Actual	Predicted	High	Low	Medium
Soft drink and ice manufacturing	High	High	1.000	0.000	0.000
Snack food manufacturing	Medium	High	0.995	0.000	0.005
Fluid milk and butter manufacturing	Medium	Medium	0.000	0.212	0.788
Wineries	Medium	Medium	0.000	0.407	0.593
Dog and cat food manufacturing	Medium	Medium	0.000	0.070	0.930
Dry, condensed and evaporated dairy product manufacturing	Low	Low	0.000	0.983	0.017
Ice cream and frozen dessert manufacturing	Low	Low	0.000	1.000	0.000
Other animal food manufacturing	Low	Low	0.000	1.000	0.000
Soybean and other oilseed processing	Low	Low	0.000	1.000	0.000
Flavoring syrup and concentrate manufacturing	Low	Low	0.000	1.000	0.000

Table 11
Measuring the model accuracy.

From\to	Cluster			Total	Correct, %
	High	Low	Medium		
High	1	0	0	1	100.00%
Low	0	5	0	5	100.00%
Medium	1	0	3	4	75.00%
Total	3	5	2	10	**91.67%**

uses the percentage of prediction as a criterion of decision about model accuracy. Based on that, the accurate model is the mode that is capable of predicting the highest percent of future observations. The TWI clusters of ten randomly selected industrial sectors were predicted using the developed model and compared with the actual clusters. Table 10 shows that the model was capable of predicting the actual cluster of 9 out of the 10 clusters. The "Probability" column in Table 10 reports the probability that the fitted model will assign the corresponding industry under a specific cluster (Low, Medium, or High). For instance, the probability of assigning the "Dog and cat food manufacturing" under the "Medium" cluster is 0.930, while the probability of assigning the same industry under the "Low" cluster is 0.070." Overall, the model accuracy was estimated to equal 91.67%, as shown in Table 11. The overall model accuracy has been found equal to 91.67%, which seems quite good. The case of low accuracy for the medium case might be attributed to the size of the training sample and also the collinearity among the sustainability indicators. Other logistic models, such as penalized logistic or ordinal regression models could be used as well and could provide a more accurate model.

The same procedures above were also followed to develop the economic and social logistic models. The regressing coefficients of these models were estimated in reported in Table 12 and Table 13. Table 12 shows that one unit decrease in the "Total Output" or "Tax" will reduce the probability of moving from "Low" to "High" cluster by 0.002 and 0.001, respectively. More specifically, an increase in any of these two indicators will lead to a significant increase in the value of the TWI. Considering the large value of the regression coefficient of the "Tax" indicator under the "Medium" case ($\beta_i = -0.009$), we conclude that the "Tax" is the most significant indicator comparing with the other economic indicators.

Table 13 shows the regression coefficients of the social logistic model. The zero-values of the regression coefficients of the "Men Employment," "Women Employment," and "LABLS Workers," under both the "Low" and "Medium" cases, reveal that these indicators have no significant impact on the probability of transition between the clusters.

4. Conclusion and recommendations

In this research, the sustainability impacts of 29 food consumption categories are performed. The results showed that animals (except poultry), soft drink & ice manufacturing, and bread

Table 12
The regression coefficients of the economic-logistic model.

TWI Cluster	Indicator	β_i	Standard error	TWI Cluster	Indicator	β_i	Standard error
Low	Intercept	30.95	141.08	Medium	Intercept	91.63	177.94
	Total Output	−0.002	0.072		Total Output	0.000	0.079
	Total Intermediate	0.001	0.087		Total Intermediate	−0.004	0.094
	Tax	−0.001	0.094		Tax	−0.009	0.128
	Gross Surplus	0.002	0.087		Gross Surplus	0.002	0.096
	Import	0.001	0.035		Import	−0.002	0.043

Table 13
The regression coefficients of the social logistic model.

TWI Cluster	Indicator	β_i	Standard error	TWI Cluster	Indicator	β_i	Standard error
Low	Intercept	−17.62	294.54	Medium	Intercept	15.41	279.43
	Men-Employment	0.000	0.000		Men-Employment	0.000	0.000
	Women Employment	0.000	0.020		Women Employment	0.000	0.020
	Injuries Occurred	−0.012	0.114		Injuries Occurred	0.000	0.068
	LABHS Workers	−0.003	0.071		LABHS Workers	0.000	0.070
	LABMS Workers	0.002	0.027		LABMS Workers	0.000	0.025
	LABLS Workers	0.000	0.000		LABLS Workers	0.000	0.000
	Compensation	0.013	0.189		Compensation	0.002	0.198

manufacturing were found as the main top three food consumption sectors. These sectors are also found to be located at the same cluster based on the TWI-based cluster distribution of the sectors. It is found that tobacco production is considered second in the ranking based on personal consumption to have the largest taxes and gross operating surplus.

The results also showed that injury has a high regression coefficient. It means that this social indicator has a significant impact on the moving from low performing cluster to high-performing cluster. Therefore, it is highly recommended to consider the strategies for minimizing work-related injuries in animal and soft drink production sector. The occupational health & safety should be highlighted as a sustainable indicator to ensure a high compliance level of safety and health performance and avoid life losses.

For carbon emissions, it is recommended to have solid efforts in emission reduction for animal production by optimizing energy production and consumption. The findings of Egilmez et al. (2014) and Kucukvar et al. (2015) proved that electric power generation, transmission, and distribution sector is found to be responsible for high carbon emissions within regional and global supply chains of food production sectors. Therefore, it should be emphasized that energy-efficient production processes and the use of renewable electricity such as solar, hydro, and/or wind can be vital strategies to minimize the supply chain-related carbon emissions. De Oliveira Neto et al. (2018) also discussed a framework of actions toward strong sustainability for companies such as increasing sustainable production, replacing energy from non-renewable sources with that from renewable ones, increasing the efficiency of resource consumption, lower energy consumption and waste generation that can be adapted by food production companies.

The method presented in this paper applied feature scaling, weighting, centroid-based clustering, and logistic regression methods. These methods are then applied for designing the 4-steps sustainability assessment method involving economic input-output life cycle sustainability assessment, data normalization, sustainability performance evaluation, sectoral analysis and modeling the sustainability impacts based on changes in indicators. This generic method can be applied to other research areas in transportation, energy, and manufacturing, where there is a need for the normalization, weighting of multi-unit indicators and clustering for sustainability assessment and modeling.

In future work, the Ecological Footprint Analysis could be value-added to measure and quantify the impacts of food consumption on the ecological systems, as presetented in Park et al. (2016) for the U.S. agrifood production sectors. Furthermore, water footprint, land use and gender equality can be included in the future work when assessing and modeling the sustainability of food consumption. Another important extension of this research will be using a global multiregional input-output analysis databases such as Eora, GTAP, EXIOBASE, WIOD, OECD etc., and compare country-specific sustainability impacts of food consumption considering social, economic and environmental indicators and the Environmental Footprint Explorer software can help us to obtain the regional and global sustainability impacts of food consumption (Stadler et al., 2015).

Authors contribution section

Murat Kucukvar contributed to the conceptualization and method sections. Dr. Galal M. Abdella contributed to the statistical modeling and data analysis and wrote the sections related to results and discussion. Nuri C. Onat contributed to the life cycle assessment and conducted the supply chain analysis. Hussein M. Al-Yafay contributed to the data collection and input-output analysis. Muhammet Enis Bulak contributed to the literature review and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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