Bitlis Eren University Journal of Science
BİTLİS EREN ÜNİVERSİTESİ FEN BİLİMLERİ DERGİSİ
ISSN: 2147-3129/e-ISSN: 2147-3188
VOLUME: 11 NO: 1 PAGE: 249-268 YEAR: 2022
DOI: 10.17798/bitlisfen.1016834

Evaluation of Global Food Security Index Indicators with 2020 COVID-19 Period Data and Country Comparisons

Gökhan ÖZKAYA[1*], Gülsüm UÇAK ÖZKAYA[2]

[1]Yıldız Technical University, Faculty of Economics and Administrative Sciences, Department of Business Administration, Istanbul, Turkey
[2]Bitlis Eren University, Department of Gastronomy and Culinary Arts, Kanik School of Applied Sciences, Bitlis, Turkey
(ORCID: 0000-0002-2267-6568) (ORCID: 0000-0002-4207-6797)

Keywords: Food Security, Climate change, COVID-19, Cluster analysis, Multi-criteria decision making methods

Abstract
Fluctuating global economic growth, rising inequality, political instability and forced migration have a significant impact on whether the population is well-nourished. While climate change and depletion of natural resources increase these negativities, they make it difficult to reach the United Nations' Sustainable Development Goals (UN SDGs) by 2030. According to research by the UN Food and Agriculture Organization (FAO), 35 to 122 million people will fall into poverty by 2030 and there will be less food security due to climate-related problems. The food security and nutritional status of the most vulnerable communities are expected to worsen due to the health and socio-economic impacts of the COVID-19 pandemic. In the study, the comparative situations of the countries including Turkey were planned to be analyzed by Multi-Criteria Decision Making methods with the 2020 COVID-19 period data in terms of food security, which is among the main headings of the United Nations 2030 Development Goals. The study presents an novelty to the literature by drawing attention to the increasing food security problem with the global COVID-19 pandemic, and also by using Multi-Criteria Decision Making methods and cluster analysis from data mining methods.. According to the final ranking obtained by the Borda Count method in the study, Singapore ranks first, followed by Finland, Sweden, Switzerland, the United States and the Netherlands, respectively. In both the COPRAS and MAUT rankings, six of the top 10 nations are European Union members. Indonesia, India, South Africa, Thailand, Brazil, and Slovakia are at the bottom of the Borda ranking.

1. Introduction

The term of food security relates to the accessibility of food and ease of getting it. Affordability is only one of the many factors to consider. Throughout history, food security has been a major concern. It is known that state officials in ancient China and Egypt built food stocks to satisfy the needs of the people and provided them completely for free during times of famine.

The term "food security" was conceptualized at the 1974 World Food Conference, and it was defined as "the allocation of a world food supply of basic food stuffs that is always satisfactory, nutritious, varied, stable, and assessed to support the routine growth in consumption and to stability in generation and prices"(Thomas, 2003). Following that, the issues of consumption and supply were included to this concept. According to the World Food Summit's final document, food security occurs if all individuals get right to have adequate, clean, and healthy food to satisfy their

*Corresponding author: *gozkaya@yildiz.edu.tr*

Received: 31.10.2021, Accepted: 15.02.2022

dietary requirements for an adequate standard of living (Food & Organization, 1996; Patel, 2013).

If all members of a residence get enough food to live an improved standard of living, they are considered to be food secure (Service, 2008). People who are food secure do not have to worry about starvation or famine(Agricultural, 2012). The United States Department of Agriculture (USDA) defines food insecurity as "the limited and inadequate supply of dependable nutrients, or limited capacity of distribution"(Bickel, Nord, Price, Hamilton, & Cook, 2000).

Figure 1 shows the stakeholders and key objectives of the European Union food and nutrition security (SUSFANS) framework.

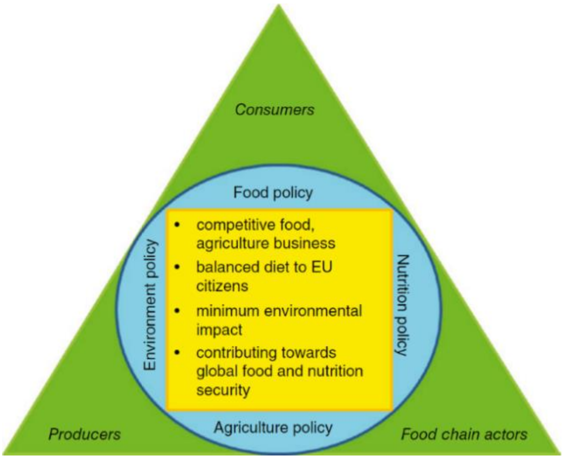

Figure 1. European Union food and nutrition security framework (SUSFANS) [1].

Food security is defined as the capacity to adjust to future disruptions or shortages of critical food reserves owing to a variety of risk factors such as droughts, transportation interruptions, fuel shortages, global recession, and conflicts. From 2011 to 2013, over 842 million were severely food insecure [2]. According to the WHO, food security is based on three factors: food availability, food access, and food consumption and misuse. The FAO proposed a fourth factor: the continuity of the first 3 aspects of food security through time. Consequently, there are four elements of food security according to the United Nations' Food and Agriculture Organization (FAO): availability, access, utilization and stability [3]. U.N. stressed that in order to benefit from the other rights, one must have the right to food [4]. There were declarations made during the 1996 United Nations World Food Summit that food must not become an instrument of social and financial restrictions [5].

Food security has improved globally during the previous decade, thanks to increased agricultural productivity and lower food costs. Thus, economic and financial predictions were met. In spite of these improvements, changing world economies, rising inequalities, COVID-19, governmental instability, and forced migration all have a substantial influence on whether communities have access to sufficient amounts of food. Climate change and the loss of natural resources enhance these problems, and also they create difficulties to meet the Sustainable Development Goals (SDGs) of the United Nations by 2030. Because of these climate-related challenges, another 35 to 122 million people will be poor by 2030[6]. As a result of the COVID-19 pandemic related effects, food security and malnutrition of the most vulnerable groups are expected to worsen further. The potential worst scenarios are becoming more probable, given the existing condition of the ecosystem and the shortage of natural assets. Furthermore, a World Food Program (WFP) study found that for every one percent increase in food insecurity, an extra 1.9 percent of people migrate in quest of food. If finding or purchasing food becomes hard, migration will increase [7].

Figure 2 summarizes the responsibilities of the private sector, individuals and central government for food security.

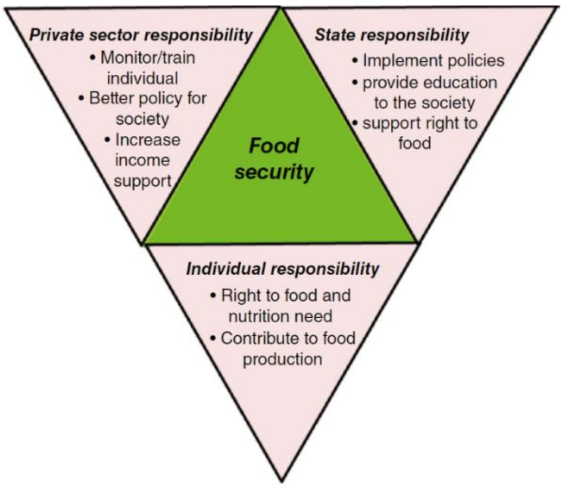

Figure 2. The responsibilities of individuals, businesses, and governments in food security [1].

Within the household budget, the number of calories per capita per day may be used to assess food security [8, 9]. An index's main objective is usually to capture all or most of the available and accessible food and consumption factors that contribute to food security. Availability and consumption variables may be predicted quite easily. On the contrary, accessibility remains a more challenging issue [10]. The factors influencing daily food availability are frequently context-specific [11]. Numerous assessments have been carried out to capture the availability component of food security, including several useful indicators created by the USAID-funded Food and Nutrition Technical Assistance (FANTA) project, in collaboration with Cornell University, Tufts University, Africare, and World Vision [11, 12]. These include:

- The Household Food Insecurity Access Scale (HFIAS) is a monthly questionnaire that assesses the amount of food insecurity (lack of availability) in a house.
- The Household Dietary Diversity Scale (HDDS) determines how much of each food categories ingested during a certain time period (24 hours, 48 hours, or 7 days).
- The Household Hunger Scale (HHS) is a survey and index that aims to evaluate food insecurity in households.

You may measure how effectively your family copes with food scarcity by comparing it to a group of recognized methods by using the Coping Strategies Index (CSI). "What do you do when you do not have the food or ability to afford it?" is the sole question that has been used to obtain data for this research [13-15].

Questionnaire in the Census Bureau's Current Population Survey are used to assess food insecurity in the USA. It includes the aspects of the family budget used to buy enough food, the sense of inadequacy in the quantity or taste of food eaten by people of all ages in the residence, and the behaviors displayed during the poor diet [16]. The State of Food Insecurity in the World is a collaboration of the FAO, the World Food Programme (WFP), and the International Fund for Agricultural Development (IFAD). Developing food supply for cheap nutritional diets was the focus of the 2020 edition. Revised minimum dietary energy requirements for specific nations, revisions to global population statistics, and estimates of wasted food in service supply for every nation are among the new highlights. Nutritional energy supply, agricultural production, food pricing, food budget, and food chain unpredictability are all factors that influence the index [17]. Food insecurity levels vary from excellent food security to full-fledged shortage [18]. According to reports, 852 million people (approximately 15% of the global population) are suffering from malnutrition in underdeveloped nations. According to the UN, over two billion people around the world can not get enough vitamins and minerals. Since the mid-1990s, 30 million people in India have been malnourished, and 46 percent of children are underweight [19].

For millennia, there have been several instances of food insecurity and scarcity. Most of them have resulted in the deaths of millions of people and a considerable drop in the population of a large geographic area. While drought and conflict were the most prevalent causes, economic policies were the primary cause of the world's worst famines.

In order to determine the major effects of food insecurity, the Global Food Safety Index (GFSI) examines the performance of food supply networks at global level. It has been released yearly since 2012 and attempts to determine a nation's level of food security in relation to the level of other countries. Food security is a complex and multi - dimensional phenomenon that is influenced by culture, climate, and region. However, despite its limitations, it provides a helpful approach for evaluating the risks to food security in states, regions, and the globe in terms of fundamental parameters. As a result of GFSI, countries could easily be compared based on their food security. 113 nations are compared in terms of cost, availability, quality, and safety in order to arrive at this conclusion. Global Financial Stability Index (GFSI) also contains a "natural resources and resilience" factor, which assesses how vulnerable nations are to global warming hazards, and how they respond to such challenges. This index has used as a policy check instrument for authorities as well as an investment evaluation tool. As a result of this index, non-governmental and international aid groups are able to identify nations that require assistance and support in their food security policies and challenges. The commercial sector also uses this index as a reference for making critical choices, considering food consumption patterns, and supporting programs for collective social responsibility.

The study aims to present a novelty to the literature by highlighting the growing food security problem caused by the global COVID-19 pandemic, as well as by employing Multi-Criteria Decision Making methods and cluster analysis. The findings and methodology of this study are expected to be useful to researchers and policymakers around the world. The 40 countries were ranked based on 55 variables including affordability, availability, quality, and safety, as well as natural resources and resilience. The Entropy, COPRAS, MAUT, Cluster Analysis, and Spearman Correlation methods were used to conduct the analysis. There is no clear evidence in the literature that one MCDM method is superior to another. As a result, using multiple MCDM methods to check the consistency of the results is critical for the study's reliability. As a result, Spearman Correlation analysis was used to evaluate the obtained results. In addition to these methods, Cluster Analysis, which is frequently used in similar studies in the literature, was also applied in order to make a comparison with the MCDM results of the study.

The remainder of the research is structured as follows: Section 2 goes into detail about the literature review. The proposed methods are explained in Section 3.The findings are presented in Section 4. Sections 5 and 6 present the conclusion and discussion, respectively.

2. Methodology and Data

2.1. Countries

This research aims to assess the 40 nations in the world in terms of food security performance using Multi-Criteria Decision-Making (MCDM) and cluster techniques. Ekonomi ve nüfus açısından, bu ülkeler genellikle kendi bölgelerinde en önemli ülkelerdir. Due to these characteristics, these countries were chosen to represent the regions in which they are located. Table 1 displays the countries considered for the study as well as additional descriptive data.

Table 1. Country names and some brief descriptive information

No	Country	Income	Region	Population (mn)	GDP PPP$	GDP per capita, PPP$
1	Australia	High	SEAO	24.8	1,386.60	52,375.50
2	Austria	High	EU	8.8	464	52,137.40
3	Belgium	High	EU	11.5	549.7	48,244.70
4	Brazil	Upper middle	LCN	210.9	3,370.60	16,154.30
5	Canada	High	NA	37	1,852.50	49,651.20
6	China	Upper middle	SEAO	1,415.00	25,313.30	18,109.80
7	Czech Republic	High	EU	10.6	396.4	37,371.00
8	Denmark	High	EU	5.8	300.3	52,120.50
9	Finland	High	EU	5.5	257.2	46,429.50
10	France	High	EU	65.2	2,968.50	45,775.10
11	Germany	High	EU	82.3	4,379.10	52,558.70
12	Greece	High	EU	11.1	312.5	29,123.00
13	Hungary	High	EU	9.7	308.2	31,902.70
14	India	Lower middle	CSA	1,354.10	10,401.40	7,873.70
15	Indonesia	Lower middle	SEAO	266.8	3,495.90	13,229.50
16	Ireland	High	EU	4.8	378.5	78,784.80
17	Israel	High	NAWA	8.5	336.1	37,972.00
18	Italy	High	EU	59.3	2,398.20	39,637.00
19	Japan	High	SEAO	127.2	5,632.50	44,227.20
20	Malaysia	Upper middle	SEAO	32	999.8	30,859.90
21	Mexico	Upper middle	LCN	130.8	2,575.20	20,601.70
22	Netherlands	High	EU	17.1	972.5	56,383.20
23	New Zealand	High	SEAO	4.7	199.3	40,135.40
24	Norway	High	EU	5.4	398.3	74,356.10
25	Poland	High	EU	38.1	1,201.90	31,938.70
26	Portugal	High	EU	10.3	328.8	32,006.40
27	Qatar	High	NAWA	2.7	356.7	130,475.10
28	Russian Federation	Upper middle	EU	144	4,179.60	29,266.90
29	Singapore	High	SEAO	5.8	556.2	100,344.70
30	Slovakia	High	EU	5.4	191.1	35,129.80
31	South Africa	Upper middle	SSF	57.4	790.9	13,675.30
32	South Korea	High	SEAO	51.2	2,139.70	41,350.60
33	Spain	High	EU	46.4	1,867.90	40,138.80
34	Sweden	High	EU	10	542.8	52,984.10
35	Switzerland	High	EU	8.5	551.4	64,649.10
36	Thailand	Upper middle	SEAO	69.2	1,323.20	19,476.50
37	Turkey	Upper middle	Europe	82.9	2,314.40	27,956.10
38	United Arab Emirates	High	NAWA	9.5	732.9	69,381.70
39	United Kingdom	High	EU	66.6	3,033.70	45,704.60
40	United States	High	NA	326.8	20,513.00	62,605.60

Source: Created by author by using the Global Innovation Index [20] values

CSA: Central and Southern Asia; **EU**: Europe; **LCN**: Latin America and The Caribbean; **NAWA**: Northern Africa and Western Asia; **NA**: Northern America; **SEAO**: South East Asia, East Asia, and Oceania; **SSF**: Sub-Saharan Africa

The Global Innovation Index classifies Turkey as a country in Northern Africa and Western Asia. Turkey is included among the European countries in this study because it is in the process of becoming an EU candidate and is evaluated alongside European countries in all international organizations. In the case of other countries, the Index's regional classification has been taken into consideration.

2.2. Global Food Security Index dimensions and sub-dimensions

This study investigates how exposure to climate risks and three natural assets critical to food security (water, land, and oceans) can affect a country's overall food security situation, in addition to the affordability, availability, quality, and safety factors discussed above in all of their dimensions.

Climate change poses a significant concern, notably in the Middle East and North Africa. In terms of natural resource and resilience issues, the Middle East and North Africa, particularly the Gulf Cooperation Council (GCC) states, are the most vulnerable regions. Food security in GCC countries is threatened due to a variety of climatic issues like as sea level rise, rising temperatures, and drought. Food security in Africa and the Middle East is being strained further by rising urbanization and population expansion, which puts pressure on food systems to satisfy rising demand. Comprehensive analyses and assessments of all of these elements will offer a deeper knowledge of the subject. With its scope and approach, the study will make a significant contribution to the literature.

2.3. Methods

The research ranks the 40 nations based on 55 variables in the categories of affordability, availability, quality & safety, as well as natural resources and resilience. The assessment was carried out using the Entropy, COPRAS, MAUT, Cluster Analysis, and Spearman Correlation methods. In the literature, a dominant superiority of MCDM methods over each other has not been stated. Therefore, it is important for the reliability of the study to use more than one MCDM method in order to check the consistency of the results. Therefore, the obtained results are also evaluated with Spearman Correlation analysis. In addition to these methods, Cluster Analysis, which is frequently used in similar studies in the literature, is also applied in order to make a comparison with the MCDM results of the study.

While the SPSS program was used for Clustering and Spearman Correlation Analysis, the Excel program was used for Entropy and other Multi-Criteria Decision Making methods.

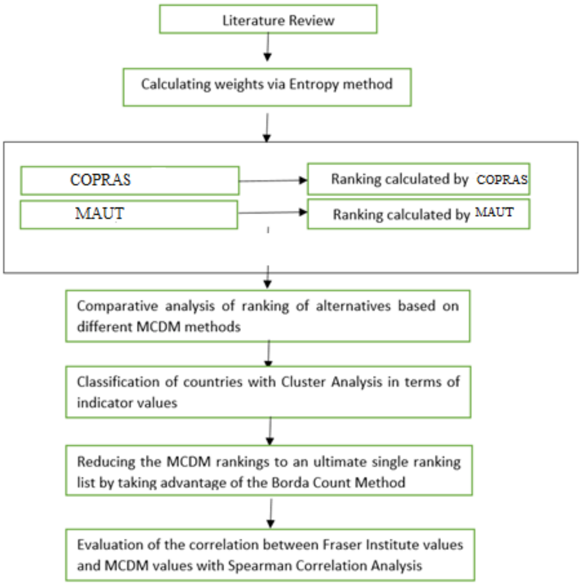

Figure 3. Research framework

2.3.1. Entropy method and objective weights

If you use an Entropy technique, you'll construct a decision matrix using the indicators' numeric value [21]. Entropy, a notion introduced by Shannon and Weaver [22] is used to estimate the relative comparison intensities of the decision-making variables [23]. In spectrum analysis [24], language modeling [25], and economics [26], his technique has been used. The Entropy approach's weight calculation phases are as described in the following: [27-30]:

1st Step: The Decision Matrix

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{x_{11}} & \cdots & \boldsymbol{x_{1n}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{x_{m1}} & \cdots & \boldsymbol{x_{mn}} \end{bmatrix} \tag{1}$$

2nd Step: A normalized decision matrix is constructed.

These indicators have been standardized based on their benefit or cost characteristics, allowing the values of variables with various units to be compared:

$$r_{ij} = x_{ij}/max_{ij}(i = 1, \dots, m; j = 1, \dots, n)$$

$$\boldsymbol{r_{ij} = x_{ij}/min_{ij}(i = 1, \dots, m; j = 1, \dots, n)} \tag{2}$$

$i\ represents\ alternatives$; $j =$ criteria; $r_{ij} =$ normalized values;

$x_{ij} =$ benefit values of the $i.$ alternative for j.

$$P_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}};\ \forall_j \tag{3}$$

P_{ij} represents normalized values, whereas *a* represents utility values.

3rd Step: Calculating the Entropy value

$$E_j = -k \sum_{i=1}^{m} \left[P_{ij} \ln P_{ij}\right]; \forall_j \quad (4)$$

$k = entropy\ coefficient\ \{(\ln(n))^{-1}\}$; $P_{ij} = normalized\ values$; $E_j = entropy\ value$

4th Step: Computing the (dj) uncertainty value

$$d_j = 1 - E_j;\ \forall_j \quad (5)$$

5th Step: wj weights are calculated to reflect the relative importance of j.

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j};\ \forall_j \quad (6)$$

It is calculated that the sum of these weights is 1.

$$w_1 + w_2 + w_j + \cdots + w_n = 1 \quad (7)$$

2.3.2. MAUT (Multi-attribute Utility Theory) method

The Multi-Attributed Utility Theory (MAUT) approach is one of the MCDM methods that allows the qualitative and quantitative criteria to be evaluated together and determines the best alternative in terms of criteria [31, 32]. The procedure is divided into two parts [33]. The decision matrix elements are normalized in the first step.

Step 1. In the normalization process, the values of each criterion are first converted so that the best value is one (1) and the worst value is zero (0). Thus, all values must be in the range [0, 1]. This transformation is done using the following equation [33]:

$$\boldsymbol{u_j(x_j) = \frac{x - \bar{x}_j}{\overset{+}{x}_j - \bar{x}_j}} \quad (8)$$

Definitions of variables in this formula are shown below:

X_j^+: The largest value of the relevant criterion.

X_j^-: The smallest value of the relevant criterion.

X: Current value of the cell under calculation.

Step 2. In the second step after normalization process, the utility values of each alternative are calculated. The formula used in the calculation of these benefit values and the definitions of the variables used are given below [33]:

$$\boldsymbol{U(x) = \sum_{1}^{m} u_j(x_j) * w_j} \quad (9)$$

U(x): Benefit value of the relevant alternative.

$u_j(x_j)$: The utility value of the alternative in terms of the relevant criteria.

w_j: weight value of the relevant criterion.

2.3.3. COPRAS (Complex Proportional Assessment) method

In the MCDM approach of COPRAS (Complex Proportional Assessment), the options are evaluated and ranked. Here are a few of the phases in the assessment of the method [34-36]:

In the COPRAS technique, the parameters are: Ai: *i*-th alternative I = 1, 2, …., m; C_j: j-th criterion j= 1, 2, …., n; w_j: significance weight of the *j*-th criterion *j* = 1, 2, …, n; x_{ij}: j-th level of evaluation criterion *j* = 1, 2, , n.

Step 1. The x_{ij} values are used to create a decision matrix.

$$D = \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ . \\ A_m \end{array} \begin{bmatrix} x_{11} & x_{12} & x_{13} & . & x_{1n} \\ x_{21} & x_{22} & x_{23} & . & x_{2n} \\ x_{31} & x_{32} & x_{33} & . & x_{3n} \\ . & . & . & . & . \\ x_{m1} & x_{m2} & x_{m3} & . & x_{mn} \end{bmatrix} \quad (10)$$

Step 2. Each value in the decision matrix is normalized by dividing it by the total of the column to which it relates.

$$X_{ij}^* = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}},\forall_j = 1, 2, \ldots, n \quad (11)$$

Step 3. The d_{ij} components of the weighted normalized decision matrix D‘ are produced by multiplying the weight value (w_j) of each evaluation metrics with the normalized decision matrix elements.

$$D' = d_{ij} = x_{ij}^* \times w_j \quad (12)$$

Step 4. The total of the benefit and cost criteria' weighted normalized decision matrix values is computed. S_i^+ denotes the total of values in the benefit criteria's *i* weighted normalized decision matrix, whereas Si denotes the entire value of the cost criteria. Equations (13) and (14) illustrate the formulae for computing these values (12).

$$S_{i+} = \sum_{j=1}^{k} d_{ij}, j = 1, 2, \ldots, k \quad (13)$$

$$S_{i-} = \sum_{j=k+1}^{n} d_{ij}, j = k+1, k+2, \ldots, n \quad (14)$$

Step 5. The relative significance value (Q_i) of each choice is computed in this phase.

$$Q_i = S_{i+} + \frac{\sum_{i=1}^{m} S_{i-}}{S_{i-} \times \sum_{i=1}^{m} \frac{1}{S_{i-}}} \quad (15)$$

Step 6. There's a ranking system that determines which priority is greatest.

$$Q_{max} = max\{Q_i\}, \forall_i = 1, 2, \ldots, n \quad (16)$$

Step 7. We calculate the performance index (P_i) score for each choice.

$$P_i = \frac{Q_i}{Q_{max}} \times \%100 \qquad (17)$$

Performance index (Pi) of 100 is considered the greatest choice based on several assessment factors. The COPRAS assessment list is created by descendingly rating the performance index score of each option.

2.3.4. Hierarchical Clustering Methods

First of all, clustering methods can be examined in two main groups. These are hierarchical clustering and non-hierarchical clustering. The most used methods are the hierarchical clustering method group. Hierarchical clustering methods are used to identify clusters sequentially by combining units with each other at different stages and to determine at what distance (or similarity) level the elements that will enter these clusters are cluster elements. The main ones among these methods are single linkage technique, full linkage technique and variance (Ward's Technique) technique.

Clustering takes place in four steps.
Step 1: Consider n individuals, n clusters.
Step 2: The two closest clusters are merged.
Step 3: The number of clusters is reduced by one and the iterated distance matrix is found.
Step 4: Steps 2 and 3 are repeated n-1 times [37].

The tree diagram (dendogram) is used to make the process easy to understand. In Figure 4, we can see an example of dendrogram.

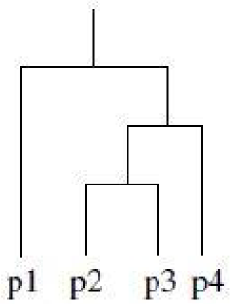

Figure 4. An example of dendrogram

- Single link Technique

It is based on the shortest distance principle. It finds the two observations closest to each other and puts that cluster core in the first stage. Then it finds two other observations closest to each other or another observation closest to this core group and expands the cluster [38].

- The complete linkage Technique

It is very adorned with the single connection method. Cluster structure is formed by starting from the farthest observations.

- Variance Technique (Ward's Technique)

Ward's technique is the most preferred one in the literature. It is based on the average distance of the observation falling in the middle of a cluster from the observations in the same cluster. Thus, it makes use of the total deviation squares. This technique is also used in the analysis of the study.

3. Literature Review

As part of their research, Leroy, et al. [39] determined which indicators are most suited for evaluating the different components of access to food security, and then offered recommendations for further research. Using the Household Food Insecurity Access Scale (HFIAS), Desiere, et al. [40] examined the scale's cross-sectional and intertemporal validity in Burundi. According to a study by Garibaldi, et al. [41], agriculture practices can improve biodiversity and livelihoods, as well as food security. Food safety measurement and governance concerns were taken into consideration by Pérez-Escamilla, et al. [42] while evaluating the relevance of various food insecurity indicators for policymakers in their study. Cafiero, et al. [43] proposed techniques based on the Rasch model created to determine the eight-item Food Insecurity Experience Scale (FIES) through a collection of criteria for global food insecurity observation. Smith, et al. [44] used the FAO's food insecurity experience measure to assess food insecurity across Latin America and the Caribbean. Smith, et al. [45] performed a comprehensive assessment of the literature on the aspects of food insecurity in affluent nations. Poulsen, et al. [46] conducted a comprehensive evaluation of the effects of urban agriculture on food security in least developed nations. According to a study by Kansiime, et al. [47], COVID-19 has a negative impact on household income as well as food security in Kenya and Uganda. A report on food security and sustainability was released by Pachapur, et al. [1] in 2020.

Some sample studies in the literature about the Entropi, MAUT, COPRAS, and BordaCount methods used in the study are shown in Table 2. While preparing the literature review, the study of the Ömürbek and Urmak [48] has been used. In addition, other current studies have been added to the list. The studies presented here generally evaluated the alternatives considered in terms of the determined criteria and tried to determine the alternatives that show the best performance in terms of relevant indicators. As a result of each study analysis, they obtained a ranking or clustering result related to the alternatives they assessed. In these studies, they generally compared the results among themselves by analyzing with more than one MCDM method or they created a final ranking with the Borda Count method. These all studies made significant contributions to all stakeholders related to these issues they study with a results of the studies. They have revealed that these methods are quite satisfactory in terms of comparing alternatives.

Table 2. Literature Review on the Methods Used in the Analysis

Some Studies with the ENTROPI Method	
Evaluation of Turkey's Tourism Performance	Karaatlı, Ömürbek, Budak, and Dağ (2015)
Evaluation of Groundwater Sustainability	J. Chen, Zhang, Chen, and Nie (2015)
Evaluation of Food Waste Safety	T. Chen, Jin, Qiu, and Chen (2014)
Performance Evaluation of Twenty-seven EU Member States and 6 EU Candidate Countries	Çakır and Perçin (2013)
Evaluation of Shipping Companies in Taiwan and Korea	Lee, Lin, and Shin (2012)
Some Studies with the MAUT Method	
Comparing the R&D Performance of Turkey and Last 13 EU Members Countries	Orhan and Aytekin (2020)
Project Portfolio Selection	Lopes and de Almeida (2015)
Material Handling Equipment Selection	Ahmed and Lam (2014)
Regional Airport Selection	Türkoğlu and Uygun (2014)
Supplier Selection	de Freitas, de Freitas, Veraszto, Marins, and Silva (2013)
Evaluation of Eviction Orders	Kailiponi (2010)
Selection of Dismantling Scenario	Kim and Song (2009)
Evaluation of Transport Corridors	Zietsman, Rilett, and Kim (2006)
Some Studies with the COPRAS Method	
Comparison of the EconomicIndicators of the European Union Countries and Turkey	Özbek and Demirkol (2019)
Rapid Prototyping System Selection	Makhesana (2015)
Performance Evaluation of Machinery Chemical Industry Corporation	Karaatlı, Ömürbek, Aksoy, and Atasoy (2015)
Performance Evaluation of Turkish Coal Enterprises	Aksoy, Ömürbek, and KARAATLI (2015)
Evaluation of Hotel Alternatives	Sarıçalı and Kundakcı (2016)
Performance Evaluation of Research Assistants	Organ and Yalçın (2016)
Some Studies with ENTROPI and MAUT Methods	
Evaluation of Corporate Sustainability Performance	İhsan, Öztel, and Köse (2015)
Performance Evaluation of OPEC Countries	Tunca, Ömürbek, Cömert, and Aksoy (2016)
Some Studies with ENTROPI and MAUT Methods	
Measuring Corporate Sustainability Performance in the Rubber Coating Industry	Ersoy (2017)
Performance Evaluation of Automotive Companies	Ömürbek, Karaatlı, and Balcı (2016)
Some Studies with ENTROPI, COPRAS and MAUT Methods	
Evaluation of the Trade Performances of Turkey and EU Countries that are Members of the World Trade Organization	Balcı (2017)

Analysis of Aviation Companies Listed in Forbes 2000	Ömürbek and Urmak (2018)
Science, Technology and Innovation Policy Indicators and Comparisons of Countries	Ozkaya, Timor, and Erdin (2021)
Some Studies with the Cluster Method	
Changes in Global Cropland Area and Cereal Production: An inter-Country Comparison	Yu, Xiang, Wu, and Tang (2019)
National Health Innovation Systems: Clustering the OECD Countries by Innovative Output in Healthcare Using a Multi-Indicator Approach	Proksch, Busch-Casler, Haberstroh, and Pinkwart (2019)
Export credit insurance and export performance	Polat and Yeşilyaprak (2017)
Some Studies Made with Borda Counting Method	
Travel and Tourism Competitiveness Ranking of 133 Countries	Wu (2011)
Evaluation of Railway Connections	Kılıç and Çerçioğlu (2016)
Multidimensional Measurement of Poverty Levels of 24 Countries	Kabaş (2007)
Some Studies with COPRAS, MAUT and Borda Counting Methods	
Analysis of Aviation Companies Listed in Forbes 2000	Ömürbek and Urmak (2018)
Science, Technology and Innovation Policy Indicators and Comparisons of Countries	Ozkaya et al. (2021)

4. Results

According to the entropy analysis calculation logic, the weight of five indicators for which all nations have identical value is computed as zero. As a result, these metrics have no impact on country rankings. Table 3 displays the entropy weights of these and other indicators. Entropy Analysis is a method of objective computation that uses the raw values of the country's indicators for weighting.

Since the four indicators of the Affordability dimension took zero in the Entropy analysis, it was the dimension with the lowest weight with a total value of 0.0222. Natural resources and Resilience dimension, on the other hand, reached 0.651 with the total weights of the 21 criteria and became the highest weighted dimension. The Availability dimension has a total weight of 0.24, while the Quality & Safety has a weight of 0.086.

Table 3. Entropy weights of the GFSI indicators

Indicators	Definitions	Weights	Indicators	Definitions	Weights
1.1	Change in average food costs	0.0000072	**3.3.2**	Dietary availability of iron	0.004807
1.2	Proportion of population under global poverty line	0.0002029	**3.3.3**	Dietary availability of zinc	0.002802
1.3	Gross domestic product per capita (US$ PPP)	0.0164825	**3.4**	Protein quality	0.0057983
1.4	Agricultural import tariffs	0.0045737	**3.5.1**	Agency to ensure the safety and health of food	0
1.5.1	Presence of food safety-net programs	0	**3.5.2**	Percentage of population with access to potable water	0.0001012
1.5.2	Funding for food safety net programs	0	**3.5.3**	Ability to store food safely	0.0000528
1.5.3	Coverage of food safety net programs	0	**4.1.1**	Temperature rise	0.0059578
1.5.4	Operation of food safety-net program	0	**4.1.2**	Drought	0.0043278
1.6	Access to financing for farmers	0.0009975	**4.1.3**	Flooding	0.0071677
2.1.1	Average food supply	0.0033196	**4.1.4**	Storm severity (AAL)	0.0348697
2.1.2	Change in dependency on chronic food aid	0.0000005	**4.1.5**	Sea level rise	0.0030987

2.2	Public expenditure on agricultural R&D	0.1190683	**4.1.6**	Commitment to managing exposure	0.0285032
2.3.1	Existence of adequate crop storage facilities	0.0088934	**4.2.1**	Agricultural water risk—quantity	0.0089869
2.3.2	Road infrastructure	0.007576	**4.2.2**	Agricultural water risk—quality	0.0098161
2.3.3	Port infrastructure	0.0053838	**4.3.1**	Land degradation	0.0021043
2.3.4	Air transport infrastructure	0.0037733	**4.3.2**	Grassland	0.0034986
2.3.5	Rail infrastructure	0.0083258	**4.3.3**	Forest change	0.0006339
2.3.6	Irrigation infrastructure	0.0644589	**4.4.1**	Ocean eutrophication	0.2721651
2.4	Volatility of agricultural production	0.0009931	**4.4.2**	Marine biodiversity	0.0097289
2.5	Political stability risk	0.0040442	**4.4.3**	Marine protected areas	0.0551219
2.6	Corruption	0.0147042	**4.5.1**	Food import dependency	0.0315021
2.7	Urban absorption capacity	0.0002503	**4.5.2**	Dependence on natural capital	0.0000634
2.8	Food loss	0.0002066	**4.5.3**	Disaster risk management	0.1224655
3.1	Dietary diversity	0.0034453	**4.6.1**	Early warning measures/climate smart agriculture	0.0458862
3.2.1	National dietary guidelines	0.0088934	**4.6.2**	National agricultural risk management system	0.0020124
3.2.2	National nutrition plan or strategy	0.0219112	**4.7.1**	Population growth (2015-20)	0.0016345
3.2.3	Nutrition monitoring and surveillance	0.0365598	**4.7.2**	Urbanization (2015-20)	0.0015412
3.3.1	Dietary availability of vitamin A	0.0012817			

Table 4 shows the benefit values generated from the COPRAS analysis using entropy weights, as well as the nation ranking created by sorting these values from greatest to smallest. According to the findings of this analysis, Singapore is in first place with a substantial difference, followed by Switzerland, Finland, the United States, Sweden, and Ireland, respectively. It is worth noting that four of these six nations are members of the European Union. On the other hand, when we look at the end of the list, there is no specific union or region that can be evaluated in this way. As a result, nations such as Indonesia, Thailand, India, South Africa, Turkey, China, Brazil and Russia, which have a large population in comparison with many other countries, are at the bottom of the list.

Table 4. COPRAS Benefit Values (N_j) and Ranking of Countries According to COPRAS Analysis

Countries	COPRAS Benefit Values (N_j)	Countries	COPRAS Benefit Values (N_j)
Singapore	100	United Arab Emirates	67.45543
Switzerland	96.48004	United Kingdom	66.89947
Finland	93.0316	Spain	66.07265
United States	90.61637	Italy	65.71261
Sweden	87.58242	Poland	64.32783
Ireland	86.21677	South Korea	63.34803
Netherlands	83.48091	Czech Republic	62.58251
Qatar	82.13393	Malaysia	61.31493
Norway	81.3543	Greece	60.30856
Israel	79.96912	Hungary	59.95087
Canada	79.20888	Mexico	56.44054
Belgium	77.85202	Slovakia	56.38451
Japan	76.17271	Russia	55.87405
Austria	75.02995	Brazil	54.06991
Germany	73.50313	China	52.56553

Denmark	72.20444	Turkey	51.84064
Australia	71.77626	South Africa	49.95134
New Zealand	69.81419	India	47.87141
France	69.02024	Thailand	40.19424
Portugal	68.80277	Indonesia	36.79253

Table 5 shows the benefit values generated from the MAUT analysis using entropy weights, as well as the nation ranking produced by sorting these values from greatest to smallest. According to the findings of this study, Finland ranks top with a substantial difference, followed by Singapore, Sweden, the United States, the Netherlands, and Switzerland, respectively. Four of the top six nations are European Union members, as is the case with the COPRAS ranking. When looking towards the bottom of the list, Indonesia, India, South Africa, Slovakia, Thailand, and Brazil are in the last row.

Table 5. MAUT Benefit Values (U_i) and Ranking of Countries According to MAUT Analysis

Countries	**MAUT U_i**	**Countries**	**MAUT U_i**
Finland	0.700909	United Kingdom	0.325779
Singapore	0.616035	Spain	0.321168
Sweden	0.487162	South Korea	0.319531
United States	0.484447	Malaysia	0.31842
Netherlands	0.480474	Italy	0.318383
Switzerland	0.454243	Czech Republic	0.318279
Ireland	0.453777	Poland	0.305672
Norway	0.437278	Hungary	0.303121
Canada	0.435235	Portugal	0.301864
Qatar	0.397361	Greece	0.299824
Germany	0.391125	China	0.292867
France	0.379801	Russia	0.285759
Austria	0.374581	Turkey	0.278784
Israel	0.35175	Mexico	0.256343
Belgium	0.349289	Brazil	0.255476
Australia	0.347461	Thailand	0.251661
Denmark	0.339234	Slovakia	0.227977
Japan	0.334231	South Africa	0.205845
New Zealand	0.328068	India	0.204589
United Arab Emirates	0.32671	Indonesia	0.175247

The dendrogram below visualizes the groupings of nations in the clustering produced by the SPSS software's clustering study. Two clusters are identified in the study as a result of merging in Ward's algorithm's 25th unit. According to the dendrogram, the cluster number of countries should be described as "2" in this case. The dendrogram is shown in Figure 5.

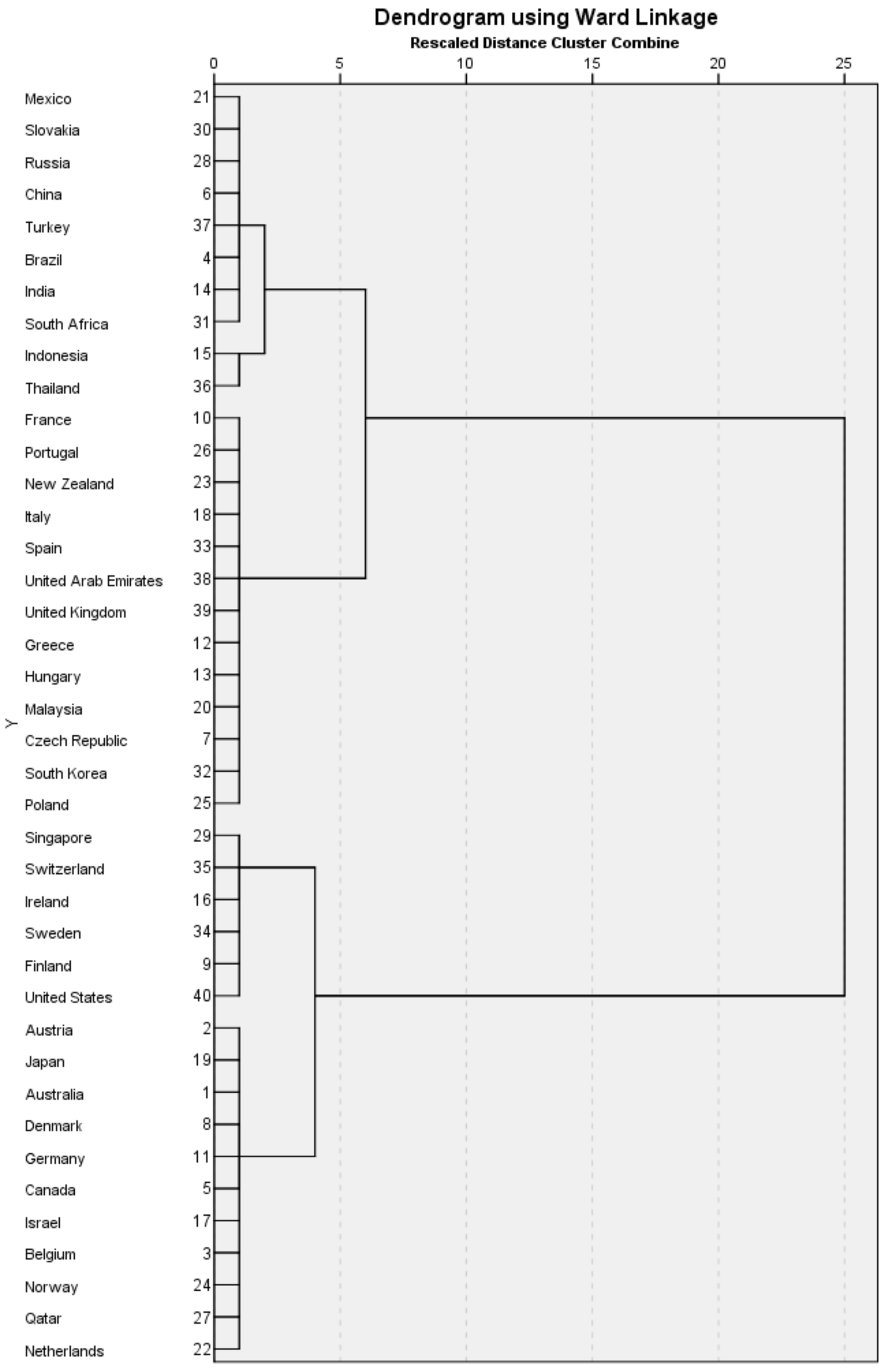

Figure 5. Dendrogram

Table 6 displays the distances between the nations separated into these two groups and the cluster centers, as well as the final ranking and Borda scores produced by reducing the lists obtained from the two MCDM techniques to a single list by the Board Count method. When France's Borda score is taken into account, it is seen that it is higher than Australia and Denmark, which are equal to Japan. France is the only country assigned to an incorrect cluster by the cluster analysis as a result of the Borda score. This indicates that the two results have a high degree of consistency.

Table 6. Clusters and Borda Scores

Countries	Cluster	Distance	Borda Scores	Countries	Cluster	Distance	Borda Scores
Singapore	2	17.259	39.5	Thailand	1	18.397	3.5
Finland	2	10.293	39	Brazil	1	4.521	6.5
Sweden	2	4.841	37	Slovakia	1	2.207	6.5
Switzerland	2	13.738	37	Turkey	1	6.75	6.5
United States	2	7.875	37	China	1	6.026	8
Netherlands	2	0.74	35	Mexico	1	2.151	8.5
Ireland	2	3.475	34.5	Russia	1	2.717	8.5
Norway	2	1.388	32.5	Greece	1	1.718	11.5
Qatar	2	0.609	32	Hungary	1	1.36	12
Canada	2	3.533	31	Czech Republic	1	3.992	14.5
Israel	2	2.774	29	Malaysia	1	2.724	15
Germany	2	9.239	28	Poland	1	5.737	15
Austria	2	7.712	27.5	Italy	1	7.122	16.5
Belgium	2	4.891	27.5	Portugal	1	10.212	16.5
Japan	2	6.57	25.5	South Korea	1	4.757	16.5
Australia	2	10.966	24.5	Spain	1	7.482	18.5
Denmark	2	10.538	24.5	United Kingdom	1	8.308	19.5
Indonesia	1	21.799	1	United Arab Emirates	1	8.864	20.5
India	1	10.72	2.5	New Zealand	1	11.223	22.5
South Africa	1	8.64	3.5	France	1	10.43	25.5

Spearman Correlation analysis, a non-parametric approach, was used to assess the relationship between the scores and rankings obtained from the MCDM methods used in the study and the GFSI score and ranking. When the values in Table 7 are evaluated, it is seen that there is a significant positive high correlation between all rankings.

Table 7. Spearman Correlation Analysis Outputs

Correlations

			GFSI	MAUT	COPRAS
Spearman's rho	GFSI	Correlation Coefficient	1.000	.905**	.903**
		Sig. (2-tailed)		0.000	0.000
		N	40	40	40
	MAUT	Correlation Coefficient	.905**	1.000	.917**
		Sig. (2-tailed)	0.000		0.000
		N	40	40	40
	COPRAS	Correlation Coefficient	.903**	.917**	1.000
		Sig. (2 tailed)	0.000	0.000	

**. Correlation is significant at the 0.01 level (2-tailed).

5. Discussion

In this study, it is emphasized how the objective weights should be and which indicators come to the fore in the comparison of these countries by analyzing the GFSI indicators, taking into account the values of the countries being compared. The strengths and weaknesses and relative comparisons of these countries in their current situation are presented. By adding “Natural Resources and Resilience”, which was included in the assessment for the first time by GFSI, the index's effort to emphasize the relationship between climate issue and food security has been considered. The dimension with the largest weight, according to the study's Entropy analysis, is "Natural Resources and Resilience". In addition to these, the Index includes important indicators such as income adjusted for inequality, gender disparity, and armed conflict. Unlike the studies described in the research's literature review section, this study compares the leading nations from all continents using objective evaluation methodologies. As in other studies, it does not assess the situation of a specific region or country. Due to the high number of GFSI criteria and their contradictory nature, it was decided to apply MCDM approaches. The use of MCDM and clustering analysis, one of the data mining methods, as well as the processing of their results together, are notable novelties in the literature in this field. Also, the "Natural Resources and Resilience" dimension, which was added to the GFSI evaluation for the first time in 2019, is also included in this study, contributing to the literature.

6. Conclusion

World food prices have risen over the previous five years. While food costs have increased most dramatically in conflict war-torn nations, the mean basket of food costs has been steadily rising across the world. As a result, certain Middle East and African nations have seen food prices treble in the previous five years. There was a 5 percent or higher food price inflation rate in 26 nations in the GFSI over the last year. Argentina had the highest food inflation in the last year (51%), followed by Turkey (25 percent). As a result of currency devaluation and economic instability, Turkey's food prices have skyrocketed.

It is of great importance with the increase in the number of these and similar studies and their use in the policies to be produced. We'll be able to better grasp the underlying causes of food insecurity and the need for a more sustainable global food system as a result. When the GFSI's 2012-18 reports are examined, it is observed that, while there is a continual increase in food security in general, there is a significant decline in food at the global level in the 2019 report. Furthermore, the released 2020 report indicates a severe decline. However, the pandemic experience has demonstrated how critical it is to investigate the major variables impacting food security and come up with strategies.

Infrastructure plays a significant role in ensuring food security. Agricultural infrastructure is essential for a variety of factors, including the efficient transfer of food between farms, markets, and consumers. Many nations depend on airports and railroads for delivering agricultural products and supplies, therefore the GFSI indicators were used to assess infrastructure beyond roads and ports. The index also contains an indicator for assessing access to on-farm infrastructure, particularly irrigation infrastructure. The new irrigation indicator underlines the necessity of focusing on irrigation infrastructure; according to FAO data, more than 70% of countries report that less than 10% of agricultural land is suitable for irrigation.

Climate change and the emissions will make issue of inadequate storage of food much more of a problem. It's estimated that 1.3 billion metric tons of edible food is squandered or thrown away every year. Even if this meal has no nutritional value, its ecological cost is still there in the air. During the period 2010-2016, worldwide food waste accounted for 8-10% of all human-caused greenhouse gas emissions. Therefore, conditioning and refrigeration infrastructure are required to keep food fresher for extended periods of time, as well as to transport and store food. It is possible to reduce food waste through increasing food supply chain productivity, such as by allowing the preservation of food at strategic locations and simplifying exports and imports processes. This improvements strengthens farmers by providing them extra time to the sale of their fresh products on a local level.

The research's first dimension assesses food affordability by evaluating characteristics such as household ability to buy food, tolerance to market volatility, and the availability of practices and initiatives to assist households if crises arise. Europe is the highest-scoring area in terms of this dimension indicators after North America, thanks to high wages, low poverty rates, steady food costs, strong welfare systems, and powerful agricultural credit mechanisms.

The study's second component evaluates variables such as the country's food supply's adequacy, the danger of supply interruption, the capability to spread food, and scientific projects to increase agricultural productivity. Although Countries in Europe score well in terms of agricultural infrastructure, there are considerable opportunities for development, notably in terms of transportation systems and agricultural production instability. Countries should also continually check the quantity of agricultural warehouses and the condition of irrigation facilities on a regular basis to ensure continued food security, especially in cases of serious weather conditions and poor harvests.

The conventional diet's variety and nutritional characteristics, as well as its safety, has been evaluated as part of the study's third dimension. Six of the top ten performing nations in the result list are in Europe, suggesting that food quality and safety is a region-wide strength. Due to high income levels and access to varied food sources, the region has one of the greatest levels of dietary variety, as well as excellent supply of minerals, vitamins and protein-rich foods. Authorities pay an attention to nutritional requirements, and the most of these nations provide some sort of nutritional dietary guidelines in place to encourage eating a healthy diet. In addition to a food safety agency, every country should have a reliable energy infrastructure to allow for the safe storage and usage of fresh products, such as fruits and veggies.

This study's last dimension examines how global climatic hazards related to weather, water, land and seas affect a country's overall food security situation. In general, European countries have the greatest values in this dimension, while the Czech Republic, Finland and Denmark are the countries with the best indicator values in this category. As Europe takes the lead in tackling natural resource and resilience problems from an agricultural perspective, many countries are experimenting with new approaches to manage these concerns. For instances, Dutch floating agricultural initiatives are being implemented because of rising sea levels.

According to entropy analysis results, ocean eutrophication (0.27), disaster risk management (0.122), public expenditure on agricultural R&D (0.119), irrigation infrastructure (0.065), marine protected areas (0.055), early warning measures/climate smart agriculture (0.055), nutrition monitoring and surveillance (0.037) are the indicators with the highest weight. Four of these indicators belong to the natural resources and resilience dimension. Natural resources and resilience dimension, on the other hand, reached 0.651 with the total weights of the 21 criteria and became the most weighted dimension. Also, change in dependency on chronic food aid, change in average food costs, ability to store food safely, dependence on natural capital indicators have the lowest weights in the Entropy calculation made based on the values of these indicators of countries.

According to the ranking of the Borda Count method obtained by utilizing the results of the COPRAS and MAUT methods applied by using these weights, Singapore and Finland are in the first two places with a significant difference, while the five countries following this country are Sweden, Switzerland, Finland, USA, Netherlands and Ireland respectively. It is worth noting that six of these eight nations are members of the European Union. There is no specific union or region that may be assessed in this manner at the bottom of the list. Indonesia, Thailand, India, South Africa, Slovakia, Turkey, China, Brazil, and Russia, all of which have a big population in comparison to many other nations, are at the bottom of the list.

According to the clustering method, in the first stage, Mexico, Slovakia, Russia, China, Turkey, Brazil, India and South Africa were clustered together. In the later stage, they merged with the cluster formed by Indonesia and Thailand. These are the countries that have very close values to each other in the scores they obtained from the Borda Count method and are in consecutive rankings. France, Portugal, New Zealand, Italy, Spain, United Arab Emirates, United Kingdom, Greece, Hungary, Malaysia, Czechia, South Korea and Poland also formed a cluster that came together in the first stage. The clusters mentioned here merged in the last stage and formed the first cluster indicated in Table 6. On the other hand, Singapore, Switzerland, Ireland, Sweden, Finland and the USA came together in the first stage and gathered in a cluster. These countries have very close values to each other in terms of Borda Scores and are at the top of the final ranking. Meanwhile, Austria, Japan, Australia, Denmark, Germany, Canada, Israel, Belgium, Norway, Qatar and the Netherlands clustered together. These two clusters combined in the last stage and formed the second cluster indicated in Table 4. When France's Borda score is taken into account, it is seen that it is higher than Australia and Denmark, which are equal to Japan. France is the only country assigned to an incorrect cluster by the cluster analysis as a result of the Borda score. When an evaluation is made about these two clusters, the final ranking obtained by Borda method from MCDM analysis and cluster analysis results are quite consistent.

Climate change is the most significant impediment to sustainable agriculture and efficient harvesting. The Nordic countries Denmark, Sweden and Norway, which performed well in this study, had the worst yields in both vegetable and grain production of the last fifty years in 2018, due to drought and the above-seasonal summer season. Climate change causes similar variations in countries such as Australia. As a result, countries that are in a favorable position during stable periods should now consider these periods to be preparations for future famine periods and establish global collaboration platforms and facilities.

Singapore, the United Arab Emirates and Qatar evaluated in this study which are high-income nations with scarce resources, are heavily reliant on food imports.

The United Arab Emirates is aiming to minimize its demand on foreign products by funding vertical farms, hydroponics, and aquaponics.

Especially, making investments in modern farming systems and artificial meat and protein is becoming increasingly attractive. Singapore is also diversifying its food source in order to decrease its reliance on imports. Both the United Arab Emirates and Singapore encourage the utilization of contemporary agriculture technologies and developments. Such countries with insufficient farmland and resources will benefit from seeking answers within the country as well as changing their approach to trade strategies regarding local and international food supply.

Flooding is becoming a greater threat in many African and Asian nations, resulting in yield reduction and a fluctuating availability of food. China, South Korea, and India are all at risk of major flooding in the near future. According to the agricultural water risk indicators in the study, several emerging nations, including India, are also at danger of water resource pollution. Nations are planning action plans that combine government investment with private sector entrepreneurship to be ready for water-based hazards.

Water-saving measures including efficient irrigation approaches, flood control, and environmental preservation are being heavily funded in China as part of the country's agricultural sustainability and development. Israel, which is at danger of running out of agricultural irrigation resources, is reducing water leaks and recycling wastewater for farming use through utilizing AI methods and smart meters.

Countries that intend to adapt to technology advancements, and agricultural R&D will be better equipped to face future difficulties. Almost all of Europe's nations have built early-warning mechanisms for agriculture, established national goals to minimize potential losses, and developed national environmental regulations that take agricultural adjustment into consideration. On another continent, two million African farmers are cultivating drought-resistant corn under the Drought Tolerant Maize for Africa program.

The epidemic has exacerbated the global decline in the poverty rates that occurred in 2019 and before, particularly in poor and emerging nations. Quarantines, business closures, and rising unemployment have caused a significant influence on people who have low income and live in abject poverty.

While rising food costs impacted unregistered employees, unskilled labor, immigrants, and the owners and employees of SMEs who had to stop their businesses in cities, farmers in rural regions experienced a considerable drop in revenue owing to interruptions in food production and delivery. This circumstance made it impossible for them to repay the borrowings and loans they had received in earlier years.

Although many countries provided temporary financial support to various segments of the society through aid programs, this was quite insufficient for the citizens of many countries. As the pandemic process and economic instability continue, it is expected that the difficulties faced by the vulnerable people in terms of food security will deepen. Many countries do not have a transparent, properly programmed and sustainable organizational infrastructure in the distribution of support packages and aid. Consequently, there is a need to learn from the epidemic and make the required adjustments.

Acknowledgment

This work has been supported by Yildiz Technical University Scientific Research Projects Coordination Unit under project number SKD-2021-4403**.**

Contributions of the authors

Gökhan ÖZKAYA contributed to the planning of the study, literature review, writing the manuscript, applying the statistical and MCDM methods, and interpretation of the results.

Gülsüm UÇAK ÖZKAYA contributed to the planning of the study, literature review, writing the manuscript, applying the statistical methods, and interpretation of the results.

Conflict of Interest Statement
There is no conflict of interest between the authors.

Statement of Research and Publication Ethics
The study is complied with research and publication ethics

References

[1] P. K. Pachapur, V. L. Pachapur, S. K. Brar, R. Galvez, Y. Le Bihan, and R. Y. Surampalli, "Food Security and Sustainability," *Sustainability: Fundamentals and Applications,* pp. 357-374, 2020.

[2] F. Nouh, "Prevalence of Food Insecurity in Eastern Part of Libya: A Study of Associated Factors," *Sch Acad J Biosci,* vol. 8, pp. 192-198, 2021.

[3] F. Food Summit, "Declaration of the world summit on food security," *World Food Summit,* pp. 16-18, 2009.

[4] C. Rights, "General Comment No. 19," *Geneva: United Nations,* 1999.

[5] Food and A. Organization, *Rome Declaration on World Food Security and World Food Summit Plan of Action: World Food Summit 13-17 November 1996, Rome, Italy*: FAO, 1996.

[6] Food and A. Organization, "The state of food and agriculture: Climate change, agriculture and food security," ed: FAO Rome, 2016.

[7] W. F. Program, "At the Root of Exodus: Food Security, Conflict and International Migration," 2017.

[8] P. Webb, J. Coates, E. A. Frongillo, B. L. Rogers, A. Swindale, and P. Bilinsky, "Measuring household food insecurity: why it's so important and yet so difficult to do," *The Journal of nutrition,* vol. 136, pp. 1404S-1408S, 2006.

[9] R. Pérez-Escamilla and A. M. Segall-Corrêa, "Food insecurity measurement and indicators," *Revista de Nutrição,* vol. 21, pp. 15s-26s, 2008.

[10] C. B. Barrett, "Measuring food insecurity," *Science,* vol. 327, pp. 825-828, 2010.

[11] A. Swindale and P. Bilinsky, "Development of a universally applicable household food insecurity measurement tool: process, current status, and outstanding issues," *The Journal of nutrition,* vol. 136, pp. 1449S-1452S, 2006.

[12] T. Ballard, J. Coates, A. Swindale, and M. Deitchler, "Household hunger scale: indicator definition and measurement guide," *Washington, DC: Food and nutrition technical assistance II project, FHI,* vol. 360, p. 23, 2011.

[13] D. G. Maxwell, "Measuring food insecurity: the frequency and severity of "coping strategies"," *Food policy,* vol. 21, pp. 291-303, 1996.

[14] W. H. Oldewage-Theron, E. G. Dicks, and C. E. Napier, "Poverty, household food insecurity and nutrition: coping strategies in an informal settlement in the Vaal Triangle, South Africa," *Public health,* vol. 120, pp. 795-804, 2006.

[15] D. Maxwell, R. Caldwell, and M. Langworthy, "Measuring food insecurity: Can an indicator based on localized coping behaviors be used to compare across contexts?," *Food Policy,* vol. 33, pp. 533-540, 2008.

[16] K. Aboaba, D. M. Fadiji, and J. A. Hussayn, "Determinants of food security among rural households in Nigeria: USDA food insecurity experience based measurement (forms) approach," *Journal of Agribusiness and Rural Development,* vol. 56, pp. 113-124, 2020.

[17] I. FAO and UNICEF, "WFP, & WHO.(2020). The state of food security and nutrition in the world: Transforming food systems for affordable healthy diets," *The state of the world,* 2020.

[18] A. Saint Ville, J. Y. T. Po, A. Sen, A. Bui, and H. Melgar-Quiñonez, "Food security and the Food Insecurity Experience Scale (FIES): ensuring progress by 2030," ed: Springer, 2019.

[19] K. Chetia, "Food Security in India: A critical study on its Issus, Efforts and Challenges," 2021.

[20] G. I. Index, "Global Innovation Index," *The Global Innovation Index Report. GII,* 2019.

[21] Ç. Kahraman, E. Abdulhamit, and O. Özevin, "Futbol Takımlarının Finansal Ve Sportif Etkinliklerinin Entropi ve TOPSIS Yöntemiyle Analiz Edilmesi: Avrupa'nın 5 Büyük Ligi ve Süper Lig Üzerine Bir Uygulama," *Uluslararası Yönetim İktisat ve İşletme Dergisi,* vol. 13, pp. 199-222, 2017.
[22] C. E. Shannon and W. Weaver, "A mathematical model of communication," *Urbana, IL: University of Illinois Press,* vol. 11, 1949.
[23] M. Zeleny, *Multiple criteria decision making Kyoto 1975* vol. 123: Springer Science & Business Media, 2012.
[24] J. P. Burg, "Maximum entropy spectral analysis," *Astronomy and Astrophysics Supplement,* vol. 15, p. 383, 1974.
[25] R. Rosenfeld, "Adaptive statistical language modeling," *PhD Thesis, Carnegie Mellon University,* 1994.
[26] A. Golan, G. Judge, and D. Miller, "Maximum entropy econometrics: Robust estimation with limited data," 1997.
[27] M. Lihong, Z. Yanping, and Z. Zhiwei, "Improved VIKOR algorithm based on AHP and Shannon entropy in the selection of thermal power enterprise's coal suppliers," in *2008 International Conference on Information Management, Innovation Management and Industrial Engineering*, 2008, pp. 129-133.
[28] T.-C. Wang and H.-D. Lee, "Developing a fuzzy TOPSIS approach based on subjective weights and objective weights," *Expert systems with applications,* vol. 36, pp. 8980-8985, 2009.
[29] A. Shemshadi, H. Shirazi, M. Toreihi, and M. J. Tarokh, "A fuzzy VIKOR method for supplier selection based on entropy measure for objective weighting," *Expert Systems with Applications,* vol. 38, pp. 12160-12167, 2011.
[30] M. Apan, A. Öztel, and M. İslamoğlu, "Teknoloji Sektörünün Entropi Ağırlıklı Uzlaşık Programlama (CP) ile Finansal Performans Analizi: BİST'de Bir Uygulama," in *19th Finance Symposium, Hitit University Çorum, Turkey [online] https://www. researchgate. net/publication/283299704 (accessed 7 December 2017)*, 2015.
[31] P. C. Fishburn and R. L. Keeney, "Seven independence concepts and continuous multiattribute utility functions," *Journal of Mathematical Psychology,* vol. 11, pp. 294-327, 1974.
[32] E. Løken, "Use of multicriteria decision analysis methods for energy planning problems," *Renewable and sustainable energy reviews,* vol. 11, pp. 1584-1595, 2007.
[33] Ö. Konuşkan, A. Endüstri Mühendisliği, and Ö. UYGUN, "ÇOK NİTELİKLİ KARAR VERME (MAUT) YÖNTEMİ VE BİR UYGULAMASI," 2014.
[34] P. Chatterjee, V. M. Athawale, and S. Chakraborty, "Materials selection using complex proportional assessment and evaluation of mixed data methods," *Materials & Design,* vol. 32, pp. 851-860, 2011.
[35] M. C. Das, B. Sarkar, and S. Ray, "A framework to measure relative performance of Indian technical institutions using integrated fuzzy AHP and COPRAS methodology," *Socio-Economic Planning Sciences,* vol. 46, pp. 230-241, 2012.
[36] A. Kaklauskas, E. K. Zavadskas, J. Naimavicienė, M. Krutinis, V. Plakys, and D. Venskus, "Model for a complex analysis of intelligent built environment," *Automation in construction,* vol. 19, pp. 326-340, 2010.
[37] H. TATLIDİL and U. Ç. D. İ. Analiz, "Akademi Matbaası," *Ankara-2002,* 1996.
[38] Ş. Kalaycı, *SPSS uygulamalı çok değişkenli istatistik teknikleri* vol. 5: Asil Yayın Dağıtım Ankara, Turkey, 2010.
[39] J. L. Leroy, M. Ruel, E. A. Frongillo, J. Harris, and T. J. Ballard, "Measuring the food access dimension of food security: a critical review and mapping of indicators," *Food and nutrition bulletin,* vol. 36, pp. 167-195, 2015.
[40] S. Desiere, M. D'Haese, and S. Niragira, "Assessing the cross-sectional and inter-temporal validity of the Household Food Insecurity Access Scale (HFIAS) in Burundi," *Public Health Nutrition,* vol. 18, pp. 2775-2785, 2015.
[41] L. A. Garibaldi, B. Gemmill-Herren, R. D'Annolfo, B. E. Graeub, S. A. Cunningham, and T. D. Breeze, "Farming approaches for greater biodiversity, livelihoods, and food security," *Trends in ecology & evolution,* vol. 32, pp. 68-80, 2017.

[42] R. Pérez-Escamilla, M. B. Gubert, B. Rogers, and A. Hromi-Fiedler, "Food security measurement and governance: Assessment of the usefulness of diverse food insecurity indicators for policy makers," *Global Food Security,* vol. 14, pp. 96-104, 2017.
[43] C. Cafiero, S. Viviani, and M. Nord, "Food security measurement in a global context: The food insecurity experience scale," *Measurement,* vol. 116, pp. 146-152, 2018.
[44] M. D. Smith, W. Kassa, and P. Winters, "Assessing food insecurity in Latin America and the Caribbean using FAO's food insecurity experience scale," *Food policy,* vol. 71, pp. 48-61, 2017.
[45] M. D. Smith, M. P. Rabbitt, and A. Coleman-Jensen, "Who are the world's food insecure? New evidence from the Food and Agriculture Organization's food insecurity experience scale," *World Development,* vol. 93, pp. 402-412, 2017.
[46] M. N. Poulsen, P. R. McNab, M. L. Clayton, and R. A. Neff, "A systematic review of urban agriculture and food security impacts in low-income countries," *Food Policy,* vol. 55, pp. 131-146, 2015.
[47] M. K. Kansiime, J. A. Tambo, M. I. Mugambi, M. M. Bundi, A. Kara, and M. C. Owuor, "COVID-19 implications on household income and food security in Kenya and Uganda: Findings from a rapid assessment," *World Development,* p. 105199, 2020.
[48] N. Ömürbek and E. D. A. Urmak, "Forbes 2ooo Listesinde Yeralan Havacilik Sektöründeki Şirketlerin Entropi, MAUT, COPRAS ve SAW Yöntemleri İle Analizi," *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi,* vol. 23, pp. 257-278, 2018.