Endüstri Mühendisliği / Journal of Industrial Engineering 36(2), 236-270, 2025

Endüstri Mühendisliği / Journal of Industrial Engineering

https://dergipark.org.tr/tr/pub/endustrimuhendisligi

EVALUATION OF OECD COUNTRIES' AGRICULTURAL TRADE PERFORMANCE: PROPOSAL OF A DYNAMIC MODEL

Melis Almula KARADAYI[1*], Umut AYDIN[2], Füsun ÜLENGİN[3], Burç ÜLENGİN[4]

[1]Istanbul Medipol University, School of Engineering and Natural Sciences, Department of Industrial Engineering, Istanbul
ORCID No : http://orcid.org/0000-0002-6959-9168
[2]Istanbul Ticaret University, Faculty of Business Administration, Department of Management Information Systems, Istanbul
ORCID No : http://orcid.org/0000-0003-4802-8793
[3]Sabancı University,School of Management,Istanbul
ORCID No : http://orcid.org/0000-0003-1738-9756
[4]Istanbul Technical University, Faculty of Management, Management Engineering Department, Istanbul
ORCID No : http://orcid.org/0000-0001-5276-8861

Keywords

Agricultural Products, Trade, Efficiency, Categorical-DEA, Malmquist Total Factor Productivity Index, Dynamic Social Network Analysis

Abstract

Given the increasing complexity of global food systems and the growing emphasis on sustainability and resilience, accurately assessing agricultural trade performance has become a strategic priority for OECD countries. However, existing evaluation methods often fall short of addressing the multidimensional and dynamic nature of trade. This study proposes a novel hybrid model that integrates Categorical DEA, Malmquist TFPI, and Dynamic Social Network Analysis (SNA) to assess both the efficiency and trade centrality of OECD countries over time.

Within the scope of the study, the performance of the OECD (Organisation for Economic Co-operation and Development) nations on agricultural product trade is analyzed using the proposed dynamic model. Categorical Data Envelopment Analysis (DEA)-Malmquist Total Factor Productivity Index (TFPI) approaches are employed to examine in detail the changes in the agricultural trade performance of OECD

*Sorumlu yazar; e-posta : makaradayi@medipol.edu.tr

doi : https://doi.org/10.46465/endustrimuhendisligi.1674970

members in terms of efficiency, technology, and Total Factor Productivity (TFP) over time. Additionally, Dynamic Social Network Analysis is conducted to reveal the eigenvector centrality of the countries investigated during the same period for both import- and export-related trade, identifying which countries have the highest trade connections and the highest trade volumes with other countries. Finally, regression analysis takes those eigenvector centrality measures as dependent variables. The Categorical-DEA values, as well as maximum reservoir of water, reservoir minimum water area (% of total land area), Logistics Performance Index, and Red List Index, are used as independent variables in order to reveal the primary reasons behind these eigenvector centrality values and the actions that should be taken to improve them are specified.

OECD ÜLKELERİNİN TARIMSAL TİCARET PERFORMANSININ DEĞERLENDİRİLMESİ: DİNAMİK BİR MODEL ÖNERİSİ

Anahtar Kelimeler

Tarımsal Ürünler, Ticaret, Etkinlik, Kategorik VZA, Malmquist Toplam Faktör Verimliliği Endeksi, Dinamik Sosyal Ağ Analizi

Öz

Artan küresel gıda sistemleri karmaşıklığı ile sürdürülebilirlik ve dayanıklılığa verilen önemin büyümesi, tarım ticareti performansının doğru şekilde değerlendirilmesini OECD ülkeleri için stratejik bir öncelik hâline getirmiştir. Ancak mevcut değerlendirme yöntemleri, ticaretin çok boyutlu ve dinamik yapısını ele almakta çoğu zaman yetersiz kalmaktadır. Bu çalışma, OECD ülkelerinin zaman içindeki hem verimlilik hem de ticaret merkeziliğini değerlendirmek üzere Kategorik VZA, Malmquist TFPI ve Dinamik Sosyal Ağ Analizi (SNA) yöntemlerini entegre eden yeni bir hibrit model önermektedir. Çalışma kapsamında, OECD (Ekonomik İşbirliği ve Kalkınma Teşkilatı) ülkelerinin tarımsal ürün ticaretindeki performansı önerilen dinamik model kullanılarak analiz edilmiştir. Kategorik Veri Zarflama Analizi (VZA)–Malmquist Toplam Faktör Verimliliği Endeksi (TFPI) yaklaşımları, OECD üyelerinin tarımsal ticaret performansında zaman içindeki değişimleri; verimlilik, teknoloji ve toplam faktör verimliliği (TFV) açısından ayrıntılı biçimde incelemek amacıyla kullanılmıştır. Ayrıca, aynı dönemde ithalat ve ihracat temelli ticarette ülkelerin özvektör merkeziliklerini ortaya koymak amacıyla Dinamik Sosyal Ağ Analizi yapılmış, en yüksek ticaret bağlantılarına ve en yüksek ticaret hacimlerine sahip ülkeler belirlenmiştir. Son aşamada, bu özvektör merkezilik ölçüleri bağımlı değişken olarak alınarak regresyon analizi yapılmıştır. Bağımsız değişkenler olarak Kategorik VZA değerleri, maksimum su rezervi, minimum su rezervi alanı (toplam kara alanının yüzdesi), Lojistik Performans Endeksi ve Kırmızı Liste Endeksi kullanılmış; bu merkezilik değerlerinin temel nedenleri ortaya konmuş ve bunları iyileştirmek için atılması gereken adımlar belirlenmiştir.

Araştırma Makalesi		Research Article	
Başvuru Tarihi	: 14.04.2025	Submission Date	: 14.04.2025
Kabul Tarihi	: 15.07.2025	Accepted Date	: 15.07.2025

1. Introduction

In the context of growing global challenges, such as climate change, resource scarcity, and shifting trade dynamics, the agricultural sector has become increasingly central to economic and policy agendas. For OECD countries, which play a pivotal role in shaping international agricultural trade, a nuanced and dynamic evaluation of trade performance is essential. However, conventional evaluation tools often fail to capture the structural heterogeneity among countries and the evolving nature of trade networks. This study addresses this critical gap by introducing an integrated approach that combines Categorical DEA, Malmquist TFPI, and Dynamic SNA to provide a comprehensive, time-sensitive assessment of agricultural trade performance.

OECD countries account for a significant portion of global agricultural production and trade and also shape the sector through technological developments, agricultural policies, and sustainability practices. Therefore, measuring the agricultural performance of OECD countries is a critical necessity for assessing their internal dynamics and understanding their impact on the global agricultural system. In order to objectively assess the agricultural trade performance of OECD countries, this study adopts an integrated methodology combining Categorical DEA, the Malmquist TFPI, and Dynamic SNA. Categorical DEA enables meaningful comparison of countries by accounting for structural differences such as trade volume. At the same time, the Malmquist TFPI captures temporal dynamics by decomposing performance changes into efficiency and technological components. Dynamic SNA is employed to examine countries' positions within trade networks over time. By integrating these three complementary methodologies, this study offers a multidimensional perspective that simultaneously considers technical efficiency and strategic network positioning, providing deeper insights for policymakers seeking to enhance agricultural trade performance. Accordingly, this study analyzes the trade performance of agricultural products in OECD countries over the 2010–2019 period using a proposed dynamic and multi-stage model. In this context, the inputs and outputs that affect agricultural trade performance are initially investigated through detailed literature analysis. In the second stage, the revealed inputs and outputs are clustered using Principal Component Analysis (PCA) to mitigate the high level of correlation between variables. Subsequently, countries are divided into homogeneous groups based on these inputs and outputs using hierarchical clustering analysis. The agricultural trade performance of each cluster is evaluated with categorical DEA. Subsequently, the technical, technological, and total changes in the agricultural trade performance during the investigated period are specified.

Moreover, the agricultural products import and export traffic of 38 OECD countries is analyzed during the 2011-2019 period with the dynamic SNA approach. Dynamic SNA is a branch of SNA, and it is a valuable tool for understanding the evolution of social networks over time and for examining the impact of network dynamics on individuals and groups within the network.

In section 2, a literature search is conducted based on studies related to agricultural trade performance. The methodology and data set used to analyze the evolution of the agricultural trade performance of 38 OECD countries are explained in detail in Section 3. The fourth section presents the research findings obtained through the application of the proposed methodology. The eigenvector centrality of each country's trade is specified and treated as a dependent variable in the regression models. At the same time, the efficiency values, as well as the maximum reservoir of water, the minimum water area in the reservoir (% of total land area), the logistics performance index, and the red list index are used as independent variables to reveal the primary reasons behind the import and export eigenvector centrality values.

The primary reason for combining Categorical DEA, Malmquist TFPI, and Dynamic SNA in this study is that they provide an integrated framework for evaluating agricultural trade performance in a multidimensional and time-dynamic manner. While classical DEA is based on the assumption that all units are homogeneous, this assumption is often not met in real-life applications. Categorical DEA enables decision-making units (DMUs) with different environmental or structural characteristics to be categorized into similar categories rather than being compared directly. OECD countries are categorized annually according to their total agricultural trade volumes. In this way, this approach enables us to measure the relative efficiency of countries objectively. The Malmquist TFPI, on the other hand, details the changes in these efficiencies over time, particularly about the components of technological change and productivity change. Dynamic SNA, on the other hand, analyses not only performance but also the structure of trade links between countries and their evolution over time, revealing which countries are more central in trade networks. When these three methods are employed together, it becomes possible to evaluate not only the efficiency levels of countries and how these change over time but also their positions within international trade networks. This integrated approach enables policymakers to gain more meaningful insights by jointly assessing both technical efficiency and strategic positioning within the network structure.

Section 2 presents a literature review on the application of DEA for assessing agricultural efficiency. Section 3 introduces the proposed methodology, and the data used in this study. Section 4 presents the key findings on the agricultural performance of OECD countries based on the proposed methodology. Finally, conclusions and further suggestions are given in section 5.

2. Literature Review

DEA is also widely used to analyze efficiencies. Mainly, Malmquist TFPI is used to determine the change in agricultural efficiency levels over time. For example, Coelli and Rao (2005) examined the changes in international agricultural productivity between 1980 and 2000. Chen, Yu, Chang, and Hsu (2008) used the Malmquist TFPI based on DEA output-oriented CCR model to perform productivity analysis in the agricultural sector of 29 regions in China between 1990-2003. The results showed that technical progress was the primary source of productivity growth, and the regional differences in productivity growth worsened over time. Armagan, Ozden, and Bekcioglu (2010) analyzed productivity changes in the Turkish agricultural sector from 1994 to 2003. Telleria and Aw-Hassan (2011) calculated the Malmquist Index for 12 countries in the West Asia-North Africa regions known as WANA between 1961 and 1997. Turkey, Tunisia, Syria, and Algeria were among the most productive countries in terms of agricultural productivity, while Pakistan, Sudan, Yemen, and Ethiopia were among the least productive countries. Tunca and Deliktaş (2015) used the dynamic DEA method to calculate the agricultural efficiency levels of OECD countries between 1966 and 2007. They found that Italy, Belgium-Luxembourg, Netherlands, and New Zealand were the most effective countries in agricultural production. Karaman and Özalp (2017) analyzed the technological change, efficiency, and TFP changes in the agricultural sector for 12 regions in Level 1 in Turkey between 2003 and 2014 using the Malmquist TFPI. In this period, it was stated that there was an annual average growth of 1% in TFP at the national level.

Hajihassaniasl (2021), on the other hand, analyzed the total productivity growth trend of production factors in three critical sectors of the Iranian economy (agriculture, industry, and service) between 2012 and 2017, using the Malmquist productivity index. Djoumessi (2022) analyzed the increase in agricultural productivity for 23 sub-Saharan African countries during the 1991-2015 period by estimating the TFPI in agriculture; Şişman and Tekiner-Mogulkoc (2022) analyzed the productivity of the Turkish agricultural sector between 2006 and 2015 for ten regions in 26 NUTS2 regions of Turkey using DEA based Malmquist TFP method.

Recent studies have shown that, in addition to classical Malmquist-based analyses, Data Envelopment Analysis (DEA) is also effectively used in agricultural productivity assessments with various applications. For example, in a study conducted in Bangladesh by Sultana, Hossain, and Haque (2023), the technical efficiency of 300 potato producers was compared with both DEA and Stochastic Frontier Analysis (SFA) methods; it was revealed that the input-based DEA model is a powerful tool in assessing the technical efficiency level of small-scale producers. The average technical efficiency obtained in the study was 72%.

In another study conducted in Greece, Kouriati, Tafidou, Lialia, Prentzas, Moulogianni, Dimitriadou, and Bournaris (2023) evaluated the efficiency levels of farms in the Pieria region based on input use. In the analyses conducted using the DEA model, it was determined that a significant portion of farmers were operating below the efficiency limit. It was emphasized that structural problems and management deficiencies were the primary causes of this situation.

Similarly, Boakye, Lee, Annor, Dadzie, and Salifu (2024) examined the technical and scale efficiency of small-scale pineapple producers in Ghana using DEA and found that the average technical efficiency was 50.5%. This result demonstrates the productivity growth potential of rural agricultural enterprises in developing countries.

In addition, Islam, Sabau, Dawson, Cheema, Daraio, and Galagedara (2025) employed the DEA method to assess sustainable agricultural production performance in the Canadian context, considering not only economic but also environmental sustainability criteria. The findings demonstrate that DEA can serve as a multidimensional decision support tool for sustainability-based production management, providing valuable insights for policymakers.

On the other hand, SNA is also widely used to understand the patterns of interaction and communication within a network and to identify key players, clusters, and other structures that emerge from these relationships. By providing a comprehensive view of network structure, SNA can inform policymaking and management decisions in various fields, as well as analyze trade networks. Using SNA, Lovrić, Da Re, Vidale, Pettenella, and Mavsar (2018) examined the trade of wood and non-wood forest products between countries from 1988 to 2006. Liu, Liu, Huang, and Sun (2019) employed SNA to analyze the structure of the global polysilicon trade network and the characteristics of each country within the network based on international trade data from 2006 to 2016. Yu and Ma (2020) conducted a network density and centrality analysis of countries for international seafood trade between 2008 and 2017.

The literature review revealed that the Malmquist TFPI is a practical approach frequently used to analyze the performance changes of regions or countries over time and to investigate the causes of inefficiency. Additionally, SNA is an efficient method used to identify and analyze various aspects of trade between countries, as well as the existing network characteristics, and to identify the strongest countries in the trade network. That is why, in this study, Categorical DEA, Malmquist TFPI, and dynamic SNA are jointly used to analyze the primary reasons behind the agricultural trade performance of 38 countries in the 2010-2019 period and to specify. To the best of our knowledge, this will be a novel approach to evaluating the agricultural performance of the countries.

3. Proposed Methodology and Data

This study complies with research and publication ethics.

To analyze the agricultural trade performance of 38 OECD countries, data are sourced from the World Economic Forum Global Competitiveness Index (World

Economic Forum [WEF], 2020) and the World Trade Organization (WTO) database. The total import and total export data of the countries on an annual basis for the period 2010-2019 were used utilizing the WTO database. Agricultural imports and exports data obtained from the WTO database are used as output variables in the performance analysis section. Moreover, the eigenvector centrality values of the countries are calculated using the bilateral agricultural imports and exports data of 38 OECD countries obtained from the same database.

The steps of the proposed dynamic model are summarized below:

Step 1: Determination of the input and output variables for DEA

The first step is to identify the variables for performance measurement through an in-depth literature review. Within the scope of this study, the quality of the road, rail, sea, and airway infrastructure (Liu & Luo, 2019; Kyriacou, Muinelo-Gallo, & Roca-Sagalés, 2019; Muinelo-Gallo, & Roca-Sagalés, 2019); the availability of financial services, accessibility of financial services and personal internet use (Nin-Pratt, 2021); illegal payment (bribery) (Liu & Luo, 2019); tax situation other than customs duty and level of customs procedure (Kyriacou et al., 2019); Intellectual property protection, state regulation, dispute resolution legislation, transparency of government policies, and the cost of crime to business (Kyriacou et al., 2019) are used as input variables. The total agricultural trade volume between OECD countries is used as the output variable.

Step 2: Application of Principal Component Analysis

In the DEA approach, the existence of correlated variables is inconvenient in terms of discriminating power. For this reason, the Principal Component Analysis (PCA) approach is used to create components that are not correlated (Pınarbaşı, Aydın, Karadayı, & Tozan, 2022; Aydın, Karadayı, Ülengin, & Ülengin, 2021).

As a result of PCA applied in this study, the "Port efficiency and transportation quality" component is used instead of the quality of the road, rail, sea, and airline infrastructure; the “Customs and border management” component replaced the variables of availability of financial services, accessibility of financial services and individual internet usage; “Government regulations” component is used to replace the variables of illegal payment (bribery), tax situation other than customs duty, and customs procedure level; The “Finance and e-commerce” component was created with the variables of intellectual property protection, state regulations, legal regulations for the resolution of disputes, transparency of government policies and the cost of crime to the business world. The regression factor scores are used to create the PCA components.

Step 3: Hierarchical Clustering Analysis

Using hierarchical clustering analysis, the OECD countries (DMUs) are divided into groups separately for each year. In the cluster analysis stage, OECD countries are categorized annually according to their total agricultural trade volumes.

Step 4a: Categorical-DEA Approach

This step involves applying the categorical DEA approach to the new dataset created using PCA component values.

Step 4b: Dynamic SNA

This step applies the Dynamic SNA method, utilizing the agricultural trade export and import values in the dataset. The aim is to determine the status of OECD countries in terms of the import and export of agricultural products.

Step 5: Malmquist Total Factor Productivity Index

We are applying the Malmquist TFPI to observe the variation in efficiency scores calculated using the PCA-Categorical DEA approach over time and to analyze the sources of the observed change in detail.

Step 6: Regression Analysis

The last step utilizes the eigenvector values calculated based on the export and import traffic obtained by the Dynamic SNA approach as dependent variables. Dong (2021) found that a country's trade facilitation significantly promotes its degree of centrality, betweenness centrality, and closeness centrality in trade networks. With this motivation, regression equation estimations are made to calculate efficiency scores with categorical DEA and other environmental factors (such as reservoir water area, logistics performance index, and red list index) as independent variables. In this way, the impact of the efficiency scores and other environmental factors on the centrality scores of the countries is revealed. The regression equation used in the research is given below.

$$\begin{aligned} Centrality_{it} = \hat{\beta}_0 &+ \hat{\beta}_1 Efficiency_{it} \\ &+ \hat{\beta}_2 (Reservoir\ Maximum\ Water\ Area_{it} \\ &- Reservoir\ Minimum\ Water\ Area_{it}) \\ &+ \hat{\beta}_3 Logistics\ Performance\ Index_{it} \\ &+ \hat{\beta}_4 Red\ List\ Index_{it} + \mu_i + u_{it} \end{aligned} \tag{1}$$

The subscripts i and t represent the country and year, respectively. In the model, we control the country-fixed effects (μ_i). Mathematically, the difference between "Reservoir Maximum Water Area" and "Reservoir Minimum Water Area" refers to the range of changes in the water level in the reservoir. The use of water resources is a crucial measure for the operation of the reservoir and meeting water demands. The Logistics Performance Index is an indicator that measures the effectiveness and efficiency of a country's or region's logistics infrastructure and services. The Country Red List Index is an indicator that assesses and monitors the status of a country's threatened species. This index establishes a benchmark by evaluating the population trends and conservation status of threatened species within a country. Apart from these variables, fertilizer consumption, agricultural land, arable land, GDP per capita, and agriculture share of government expenditure were also added as explanatory variables in the regression. However, they were excluded from the model since they were to be found statistically insignificant. The flow chart of the proposed dynamic model to analyze the agricultural performance of 38 OECD countries is summarized in Figure 1.

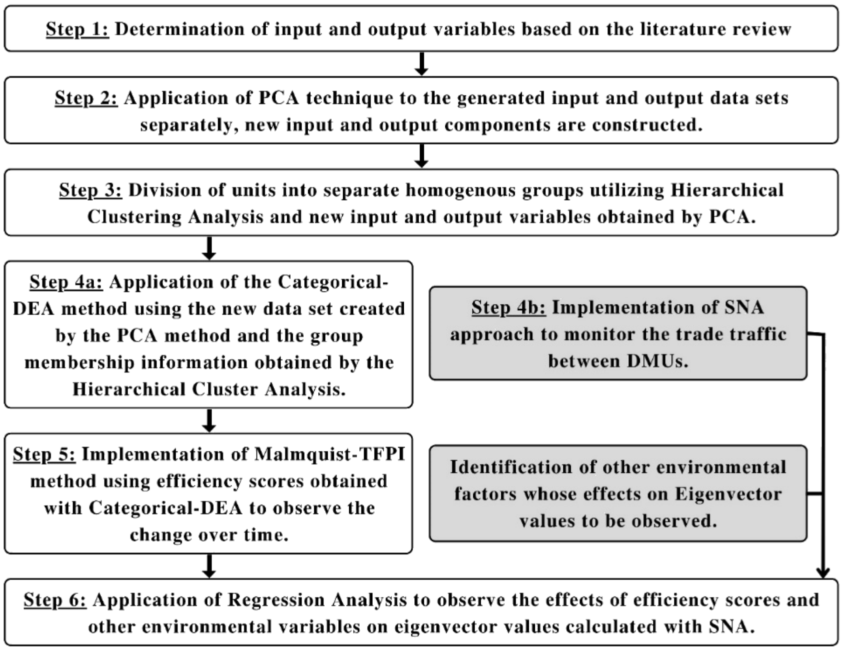

Figure 1. The Flowchart of the Proposed Methodology

3.1. *Principal Component Analysis*

Principal Component Analysis (PCA) is a linear transformation technique widely used in multivariate statistical analysis, which aims to reduce the dimensionality of the dataset by taking into account the correlation structure between variables.

The primary purpose of PCA is to represent a high-dimensional data set with fewer dimensions (components) by minimizing the loss of information (variance) in the data (Jolliffe & Cadima, 2016).

PCA creates a new component space using the covariance or correlation matrix between the original variables. These components are orthogonal to each other, and each explains a certain proportion of the total variance of the data. The first principal component represents the highest variance in the data, while the second principal component represents the second highest variance, perpendicular to the first, and so on. Each component is a linear combination of the original variables.

Mathematically, the PCA solution is based on the eigenvalue and eigenvector decomposition of the data matrix. While the eigenvalues show the variance ratio that each component will explain, Eigenvectors are the weights that determine the extent to which the components are affected by which variables. When deciding how many of the obtained components to use, the Kaiser criterion (those with eigenvalues greater than 1), Scree Plot analysis, or the goal of explaining a certain percentage of the total variance (e.g., 80%) are usually taken into account.

One of the advantages of PCA is that it eliminates the problem of multicollinearity by reducing unnecessary data redundancy in cases where there is a high correlation between variables. In this respect, it is frequently preferred as a preliminary analysis technique, especially in non-parametric efficiency analyses such as Data Envelopment Analysis (DEA), to reduce the number of input variables and increase the model's discriminatory power (Adler & Yazhemsky, 2010; Aydın et al., 2021).

3.2. *Hierarchical Cluster Analysis*

Hierarchical Cluster Analysis is a classification method frequently used in multivariate statistical analyses, creating clusters in a hierarchical structure by considering the similarity or distance relationships between observations. This method analyzes observations with either an "agglomerative" or "divisive" approach; the most common in practice is the agglomerative method (Hair, Black, Babin, & Anderson, 2010).

In aggregative Hierarchical Cluster Analysis, each observation (e.g., a country) is initially considered a cluster on its own. Then, a new cluster is created by combining the two observations that are most similar. This process continues until all observations are collected in a single cluster. The similarity between clusters is typically calculated using distance measures, such as Euclidean distance and Manhattan distance. In the clustering algorithm, methods such as Ward, Single Linkage, and Complete Linkage are used. The hierarchical structure formed as a result of this process is visualized with a tree diagram called a dendrogram.

The primary advantage of Hierarchical Cluster Analysis is that it eliminates the need to determine the number of clusters in advance. Instead, the similarity structure obtained from the dendrogram is examined, and the researcher interprets meaningful clusters. In addition, HCA is especially effective in cases where the number of samples is limited compared to the number of variables (e.g., in country-based studies) and provides visually understandable results (Everitt, Landau, Leese, & Stahl, 2011).

In efficiency analyses, especially before DEA, the Hierarchical Cluster Analysis method is used to test the structural similarity of decision units (e.g., countries), create homogeneous analysis groups, and increase the comparability of the results (Wu, Liang, & Song, 2010). In this way, the units evaluated in the DEA model are ensured to have closer characteristics to each other, and the distinguishing power of the model increases.

3.3. Categorical Data Envelopment Analysis

Banker and Morey (1986) introduced the Categorical DEA method to the literature, assuming that uncontrollable categorical variables also have an impact on the efficiency of DMUs. This approach enables researchers to categorize the DMUs into homogeneous subgroups during efficiency analysis and to consider these subgroups when calculating efficiency scores.

In this study, a categorical version of the input-oriented CCR model is used, and its mathematical representation is as follows:

$$Min\theta_k$$

$$\sum_{j\in\cup_{f=1}^{l}D_f}^{n} \lambda_j X_{ij} \leq \theta_k X_{ik} \tag{2}$$

$$\sum_{j\in\cup_{f=1}^{l}D_f}^{n} \lambda_j Y_{rj} \geq Y_{rk} \quad , \tag{3}$$

$$\lambda_j \geq 0 \text{ ve } j \in\cup_{f=1}^{L} D_f$$

where

Y_{rk} : amount of *the* output produced by *kth* DMU,

X_{ik} : the amount of *ith* input consumed by *kth* DMU,

Y_{rj} : amount of *the* output produced by *jth* DMU,

X_{ij} : the amount of *ith* input consumed by *jth* DMU,

n : total number of DMUs,

λ_j : weight of the jth DMU,

D_f : the set of number of categories that belong to the kth DMU *f = {1, 2, ... , l,}*

L : total number of defined categories.

3.4. The Malmquist Total Factor Productivity Index

The Malmquist TFPI, which is based on the logic of index construction using distance functions, was first proposed by Sten Malmquist in 1953, and the DEA-based TFPI technique was developed by Caves, Christensen, and Diewert (1982). The TFPI approach is a dynamic approach based on DEA that analyzes the efficiency changes experienced by DMUs over time and the sources of these changes. It is also based on calculating distance functions for two different periods. Parametric and non-parametric methods can be used in calculating distance functions (Tarım, 2001). TFP allows the incorporation of external factors, such as technological change, market conditions, and other environmental factors, that can impact a DMU's efficiency. The Malmquist TFPI between period *t* and the following period *t+1* can be calculated as shown in the equation below:

$$M_0(x^t, y^t, x^{t+1}, y^{t+1}) = \left(\left(\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}\right) \times \left(\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}\right)\right)^{\frac{1}{2}} \tag{4}$$

In the above equation, $D_0^t(x, y)$ denotes the technological change from period *t* to period *t+1*. If the M_0 function is calculated as a value greater than 1, there is an increase in TFP between periods *t* and *t+1*; if it is calculated as a value less than 1, there is a decrease in TFP. Eq.3 can also be expressed as in the following equation:

$$M_0(x^t, y^t, x^{t+1}, y^{t+1}) = \left(\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}\right) \times \left(\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}\right)^{\frac{1}{2}} \tag{5}$$

In the above equation, the part without square root is used to calculate the technical efficiency change between periods *t* and *t+1*. The part whose square root is taken expresses the technological change for the same period. Thus, when calculating technical efficiency according to the efficiency frontier, the change in technology and its impact on the efficiency frontier can also be considered in the performance evaluation process (Kula, Kandemir, and Özdemir, 2009).

3.5. Dynamic Social Network Analysis

SNA uses several appropriate methods to analyze and map the connections between individuals and communities (Wasserman & Faust, 1994). In the SNA analysis, nodes represent the individuals subject to the analysis, and arrows represent the relationships between individuals, indicating the direction of these relationships.

Dynamic SNA is a branch of SNA that focuses on studying network structure and dynamics over time. Dynamic SNA uses time-stamped data to study the evolution of networks over time. Dynamic SNA demonstrates that it is essential to measure the connection strength between layers in the network structure, and this approach plays a crucial role in identifying influential nodes (Yin et al., 2018). In this study, we use the Eigenvector-based Centrality Measures calculation algorithm proposed by Yin et al. 2018 for temporal networks. The stepwise representation of the algorithm can be summarized as follows:

Step 1: Let $A^{(t)} = \{a_{ij}^{t}\}, where\ A^{(t)}$represents the adjacency matrix at each layer of time *t*, a_{ij}^{t} denotes the presence of the edge between node *i* and node *j* in time layer *t*, $a_{ij}^{t} = 1$ if node is connected with node *j* in time layer *t*, and $a_{ij}^{t} = 0$ otherwise.

Step 2: Let $C^{(t,t+1)} = diag\left(c_1^{(t,t+1)}, \dots, c_N^{(t,t+1)}\right)$ where $C^{(t,t+1)}$ is the inter-layer similarity between the time layer *t* and *t+1*. $c_j^{(t,t+1)} = \sum_i \ a_{ij}^{t}\, a_{ij}^{t+1}$ indicates the similarity of node j for two-time layers, say *t* and *t+1*.

Step 3: The improved supra-adjacency matrix should be described as

$$\mathrm{A} = \begin{bmatrix} A^{(1)} & C^{(1,2)} & 0 \\ C^{(1,2)} & A^{(2)} & C^{(2,3)} \\ 0 & C^{(2,3)} & A^{(3)} \end{bmatrix}$$

Step 4: The eigenvector corresponding to the most significant singular value of the improved supra-adjacency matrix *A* denotes the centrality of each node *i* at each time *t.* The node similarity can be measured using the Common Neighbour (CN) approach, where the similarity between two nodes is directly given by the number of common neighbors they share connections. In this study CN index is calculated using the Adamic–Adar Index (AA) (Adamic & Adar, 2003).

$$AA{:}\ c_j^{(t,t+1)} = \sum_i \frac{1}{logk_i} \tag{6}$$

The popularity k_i, the number of nodes that node i have selected between two sequential snapshots, can be obtained by calculating the average and the number of the common neighbors between two sequential snapshots between k_i^t and k_i^{t+1}

$$k_i = (k_i^t + k_i^{t+1})/2 \tag{7}$$

where

$k_i^t = a_{ij}^t a_{ij}^{t+1} \sum_j a_{ij}^t$ and $k_i^{t+1} = a_{ij}^t a_{ij}^{t+1} \sum_j a_{ij}^{t+1}$ to present the selection times of node *i* in time layer *t* and *t+1* respectively.

The data collected in this study were transformed into principal components, and their descriptive statistics are presented in Table 1. Port efficiency and the transportation quality variable have sub-dimensions, including the quality of roads, railroad infrastructure, port infrastructure, and air transport infrastructure. The sub-dimensions for the other variables are as follows: irregular payments bribes, the prevalence of non-tariff barriers, the burden of customs procedures for the government regulation variable; intellectual property protection, the burden of government regulation, the efficiency of the legal framework in settling disputes, transparency of government policymaking, business costs of crime and violence for the finance and e-commerce variable; availability of financial services, affordability of financial services, individuals using the internet for the customs and the border management variable.

Table 1

Descriptive Statistics for Components

	Obs.	Mean	Std. Dev.
Port Efficiency and Transportation Quality	380	2,30	0,98
Customs and the Border Management	380	2,14	1,00
Government Regulation	380	1,88	0,99
Finance and E-Commerce	380	1,97	1,02

In the Categorical-DEA application phase, components were created by applying PCA to the items, and the descriptive statistics of the components are shown in Table 1.

Regression analysis was conducted using the factors obtained from the UNDP database and the variables identified through the analysis conducted in the previous phases of this study. The descriptive statistics of all variables used in the regression analysis are presented in Table 2.

Table 2

Descriptive Statistics for Variables Used in Regression Analysis

Variable	Obs	Mean	Std. Dev.
Export_Centrality	342	0.69	0.20
Import_Centrality	342	0.72	0.20
Efficiency	342	0.39	0.32
Reservoir Maximum Water Area-Reservoir Minimum Water Area (% of total land area)	396	0.00	0.00
Logistics Performance Index	342	98.32	6.13
Red List Index	418	0.89	0.10

4. Evaluation of Agricultural Trade Performance of OECD Countries

Eigenvector centrality values were calculated for the evaluation of OECD countries by taking into account the import and export traffic of agricultural products between them. These values were used to measure the agricultural foreign trade of 38 OECD countries with each other using the dynamic SNA approach. The eigenvector centrality values of the countries by year are shown in Table 3.

Table 3.

Eigenvector Centrality Values Based on OECD Agriculture Export Data

	2011	2012	2013	2014	2015	2016	2017	2018	2019
(1) Australia	0.52	0.11	0.68	0.64	0.80	0.73	0.64	0.82	0.59
(2) Austria	0.52	0.21	0.68	0.85	0.88	0.72	0.64	0.82	0.59
(3) Belgium	0.05	0.21	0.66	0.85	0.88	0.72	0.64	0.82	0.59
(4) Canada	0.09	0.90	0.66	0.98	0.91	0.72	0.64	0.94	0.82
(5) Chile	0.09	0.90	0.91	0.98	0.91	0.72	0.64	0.94	0.82
(6) Colombia	0.39	0.11	0.91	0.98	0.97	0.72	0.64	0.94	0.82
(7) Costa Rica	0.35	0.42	0.77	0.98	0.90	0.59	0.64	0.94	0.72
(8) Czechia	0.35	0.42	0.77	0.73	0.89	0.59	0.64	0.59	0.72
(9) Denmark	0.44	0.36	0.57	0.73	0.73	0.59	0.64	0.82	0.72
(10) Estonia	0.44	0.36	0.61	0.76	0.61	0.59	0.64	0.94	0.59
(11) Finland	0.35	0.68	0.61	0.76	0.64	0.82	0.64	0.64	0.59
(12) France	0.27	0.68	0.99	0.68	0.59	0.64	0.72	0.72	0.59
(13) Germany	0.27	0.96	0.99	0.65	0.64	0.82	0.72	0.64	0.64
(14) Greece	0.24	0.96	0.97	0.65	0.64	0.92	0.72	0.59	0.64
(15) Hungary	0.20	0.76	0.97	0.67	0.59	0.82	0.72	0.59	0.64
(16) Iceland	0.35	0.76	0.90	0.59	0.59	0.72	0.72	0.82	0.64
(17) Ireland	0.12	0.43	0.90	0.59	0.59	0.72	0.72	0.72	0.64
(18) Israel	0.12	0.34	0.67	0.61	0.59	0.59	0.72	0.59	0.72
(19) Italy	0.15	0.40	0.67	0.62	0.59	0.59	0.72	0.59	0.72
(20) Japan	0.23	0.40	0.98	0.62	0.72	0.64	0.72	0.59	0.72
(21) Latvia	0.23	0.34	0.98	0.62	0.64	0.82	0.72	0.94	0.72
(22) Lithuania	0.53	0.50	0.58	0.59	0.81	0.82	0.72	0.82	0.72
(23) Luxembourg	0.53	0.50	0.58	0.72	0.92	0.94	0.72	0.64	0.72
(24) Mexico	0.48	0.69	0.77	0.72	0.92	0.94	0.82	0.59	0.82
(25) Netherlands	0.48	0.69	0.77	0.83	0.93	0.82	0.82	0.59	0.82
(26) New Zealand	0.27	0.50	0.59	0.83	0.64	0.94	0.82	0.64	0.82
(27) Norway	0.27	0.50	0.59	0.77	0.64	0.94	0.82	0.64	0.82
(28) Poland	0.74	0.83	0.61	0.76	0.82	0.94	0.82	0.82	0.82
(29) Portugal	0.74	0.83	0.61	0.92	0.62	0.82	0.94	0.94	0.82
(30) Korea	0.72	0.96	0.61	0.92	0.74	0.82	0.94	0.94	0.82
(31) Slovakia	0.72	0.96	0.61	0.86	0.72	0.82	0.94	0.94	0.94
(32) Slovenia	0.15	0.56	0.77	0.86	0.72	0.82	0.94	0.94	0.94
(33) Spain	0.79	0.56	0.77	0.59	0.72	0.94	0.94	0.72	0.94
(34) Sweden	0.79	0.73	0.67	0.59	0.64	0.94	0.94	0.72	0.94
(35) Switzerland	0.53	0.73	0.67	0.74	0.64	0.94	0.94	0.72	0.94
(36) Turkey	0.53	0.53	0.59	0.74	0.64	0.94	0.94	0.64	0.94
(37) United Kingdom	0.12	0.80	0.59	0.71	0.64	0.94	0.82	0.64	0.94
(38) USA	0.12	0.80	0.59	1.00	0.89	0.82	0.82	0.64	0.94

As shown in Table 3, green represents the highest centrality values, and red represents the lowest. When the table is explicitly examined for Turkey, it is evident that it provided limited access to countries in agricultural exports in 2013, 2015, and 2018 and exhibited low centrality values. However, in 2016, 2017, and 2019, Turkey ranked among the top 10 countries in terms of both the number of countries exported and export traffic. In 2019, Turkey ranked high in terms of agricultural exports, alongside the USA, the United Kingdom, Switzerland, Sweden, Spain, Slovakia, and Slovenia. This situation demonstrates that Türkiye can periodically diversify its foreign trade relations. It is particularly striking that it exhibits similar network behavior to countries with high centrality values, such as Sweden and Switzerland.

When the changes over the years are considered, the trends in annual export centrality values of the five highest- and lowest-performing OECD countries are presented in Figures 2 and 3, respectively.

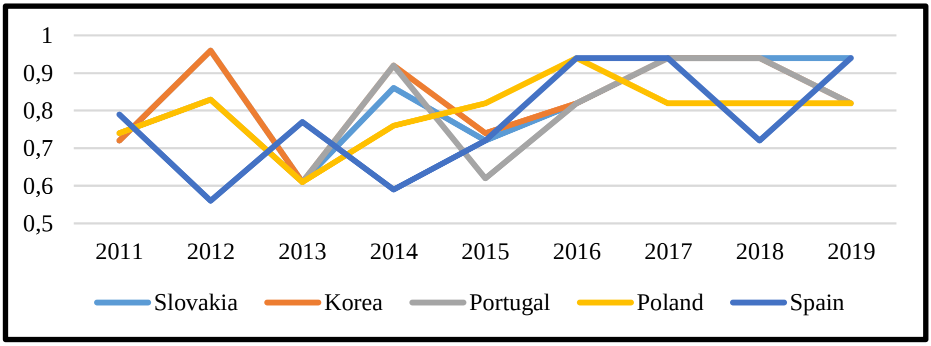

Figure 2. The Yearly Change of the Top 5 OECD Countries Based on Agriculture Export Data

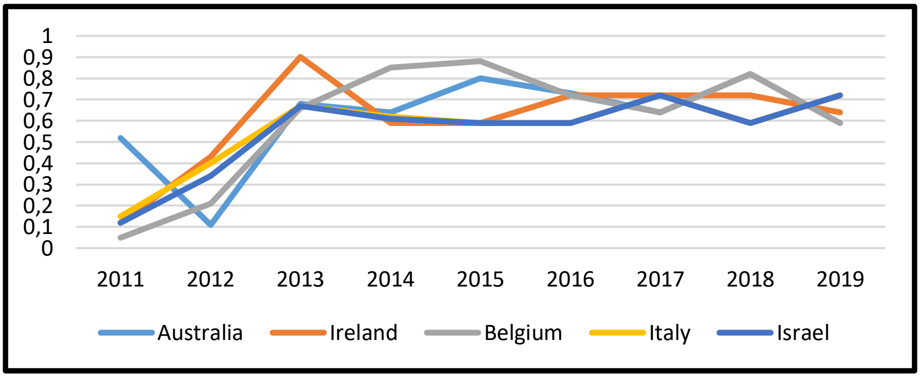

Figure 3. The Yearly Change of the Bottom 5 OECD Countries Based on Agriculture Export Data

Figure 2 illustrates that countries other than Spain followed a similar course during the 2011–2019 period, while Spain's values decreased during this period. The Republic of Korea, on the other hand, followed a fluctuating course throughout the period, exhibiting sudden increases and decreases. It can be said that the position in the export network for such countries tends to fluctuate strategically. On the other hand, countries such as Belgium and Ireland are part of a group with low export performance, exhibiting stable but low centrality, as shown in Figure 3. Italy and Israel, on the other hand, have remained in secondary positions in the agricultural export network, with similarly low values over the years.

The import performances of OECD countries were analyzed in a similar manner. The import-based eigenvector centrality values are presented in Table 4.

Table 4

Eigenvector Centrality Values Based on OECD Agriculture Import Data

	2011	2012	2013	2014	2015	2016	2017	2018	2019
(1) Australia	0.25	0.56	0.57	0.83	0.88	0.65	0.67	0.89	0.89
(2) Austria	0.25	0.56	0.57	0.59	0.74	0.65	0.67	0.49	0.98
(3) Belgium	1.04	0.60	0.57	0.73	0.78	0.90	0.67	0.49	0.98
(4) Canada	1.04	0.60	0.62	0.73	0.81	0.90	0.67	0.86	0.98
(5) Chile	0.81	0.52	0.62	0.77	0.88	0.70	0.98	0.74	0.98
(6) Colombia	0.81	0.52	0.57	0.77	0.88	0.70	0.65	0.74	0.98
(7) Costa Rica	0.23	0.34	0.93	0.66	0.92	0.71	0.65	0.90	0.67
(8) Czechia	0.43	0.78	0.93	0.66	0.92	0.65	0.71	0.98	0.67
(9) Denmark	0.43	0.78	0.83	0.70	0.99	0.88	0.71	0.98	0.67
(10) Estonia	0.29	0.62	0.83	0.70	0.99	0.98	0.86	0.98	0.67
(11) Finland	0.29	0.62	0.59	0.77	0.85	0.98	0.86	0.98	0.67
(12) France	0.13	1.03	0.59	0.78	0.85	0.69	0.86	0.89	0.67
(13) Germany	0.02	1.03	0.59	0.57	0.95	0.70	0.49	0.89	0.67
(14) Greece	0.53	0.36	0.65	0.75	0.88	0.70	0.71	0.89	0.67
(15) Hungary	0.53	0.35	0.65	0.75	0.88	0.74	0.74	0.89	0.67
(16) Iceland	0.10	0.35	0.63	0.98	0.95	0.74	0.74	0.71	0.67
(17) Ireland	0.10	0.47	0.63	0.98	0.95	0.74	0.74	0.71	0.67
(18) Israel	0.45	0.65	0.49	0.65	0.65	0.74	0.74	0.71	0.67
(19) Italy	0.45	0.65	0.49	0.80	0.65	0.74	0.86	0.71	0.65
(20) Japan	0.93	0.50	0.49	0.82	0.70	0.74	0.86	0.71	0.89
(21) Latvia	0.93	0.50	0.49	0.82	0.99	0.71	0.67	0.74	0.98
(22) Lithuania	0.86	0.51	0.49	0.85	0.88	0.71	0.67	0.74	0.86
(23) Luxembourg	0.86	0.50	0.80	0.85	0.74	0.68	0.90	0.74	0.86
(24) Mexico	0.11	0.48	0.80	0.73	0.74	0.68	0.89	0.74	0.86
(25) Netherlands	0.11	0.60	0.72	0.73	0.74	0.90	0.89	0.74	0.74
(26) New Zealand	0.23	0.60	0.72	0.76	0.74	0.67	0.89	0.74	0.74
(27) Norway	0.23	1.03	0.63	0.76	0.74	0.67	0.89	0.65	0.74
(28) Poland	0.22	1.03	0.63	0.72	0.74	0.90	0.67	0.65	0.74
(29) Portugal	0.14	0.83	0.61	0.49	0.65	0.70	0.67	0.89	0.65
(30) Korea	0.27	0.83	0.61	0.49	0.92	0.85	0.67	0.89	0.65
(31) Slovakia	0.14	0.64	0.61	0.49	0.88	0.86	0.67	0.89	0.71
(32) Slovenia	0.14	0.64	0.99	0.64	0.68	0.86	0.67	0.67	0.71
(33) Spain	1.07	0.69	0.99	0.65	0.68	0.71	0.67	0.67	0.71
(34) Sweden	1.07	0.69	0.91	0.70	0.74	0.49	0.65	0.67	0.98
(35) Switzerland	1.02	0.90	0.91	0.70	0.74	0.49	0.89	0.67	0.86
(36) Turkey	1.02	0.90	0.49	0.71	0.74	0.49	0.98	0.86	0.89
(37) United Kingdom	0.89	0.75	0.49	0.71	0.74	0.67	0.98	0.86	0.89
(38) USA	0.89	0.75	0.83	0.88	0.65	0.67	0.98	0.86	0.98

As shown in Table 4, while some countries have consistently exhibited high values in import traffic over the years (for example, the USA), others have maintained low values (for example, Israel). As of 2011, it is evident that the values have varied in terms of the number of countries from which it imports and the volume of imports. It has been observed that countries such as Chile and Canada, in particular, have established stable import networks. In contrast, the level of centralization is relatively low in countries such as Iceland and Slovakia.

The changes in these trends over the years are presented in Figure 4 for the five highest-performing countries and in Figure 5 for the five lowest-performing countries.

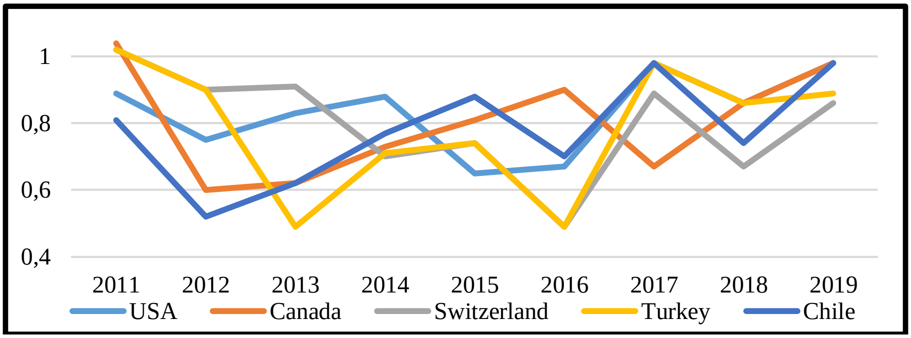

Figure 4. The Yearly Change of the Top 5 OECD Countries Based on Agriculture Import Data

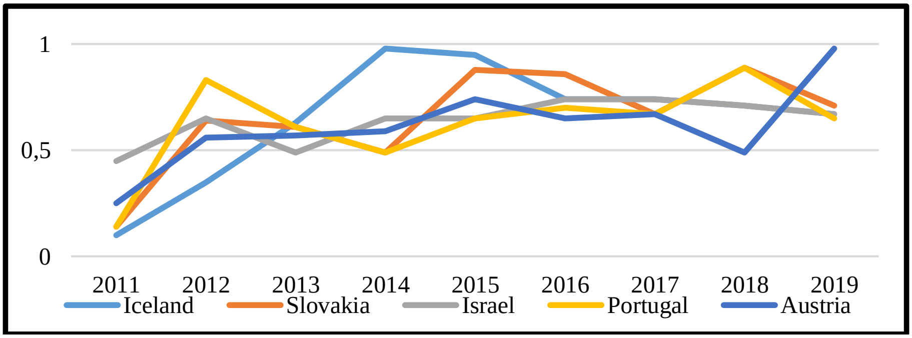

Figure 5. The Yearly Change of the Bottom 5 OECD Countries Based on Agriculture Import Data

Figure 4 shows that countries such as the USA, Turkey, and Chile are at the top of the list in terms of imports. These countries generally stand out with their wide range of suppliers. Canada's rise during the 2012–2016 period can most likely be attributed to changes in North American free trade agreements. Figure 5 shows that Israel has the lowest performance, while Iceland and Slovakia have increased their performance in the 2011–2014 period. The limited infrastructure capacity and logistics connections in these countries may have contributed to marginalization in the trade network.

The hierarchical clustering method was used to group countries based on trade volume, and in this context, countries were divided into three clusters in 2010, 2012, and 2013, and four clusters in 2011 and 2014–2019. According to these clustering results, the data set was prepared for DEA analysis, and then performance scores were calculated using the categorical DEA method.

Following these analyses, the Malmquist TFPV (Total Factor Productivity) index and the change in agricultural productivity over the years are presented in Figure 6.

According to Figure 6, Sweden had the highest increase in 2019. Sweden has increased its TFVP value in 9 of the 10 years. Slovenia and Luxembourg are in second place with an increase in 8 years. These three countries stand out with the importance they attach to structural reforms and agricultural technologies. On the other hand, in countries such as Colombia, Italy, and Mexico, the values mostly remain equal to 1 or decrease. The fact that performance remains constant in these countries indicates either insufficient technology investments or a failure to sustain increases in agricultural productivity.

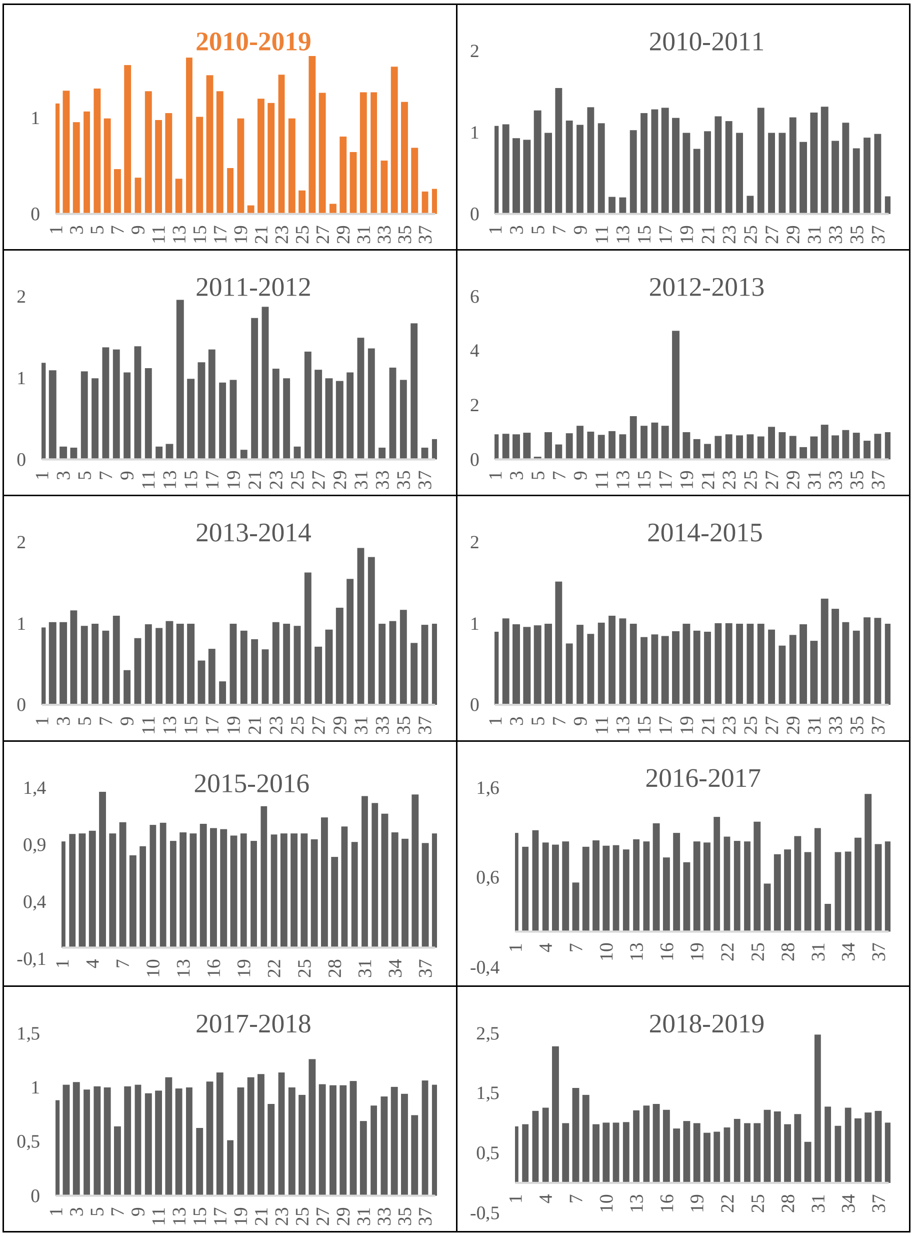

Figure 6. The Categorical Malmquist TFVE Values of the OECD Countries Between 2010-2019

The categorical assessment, created to clarify the annual change of the TFPV index, is summarized in Figure 7.

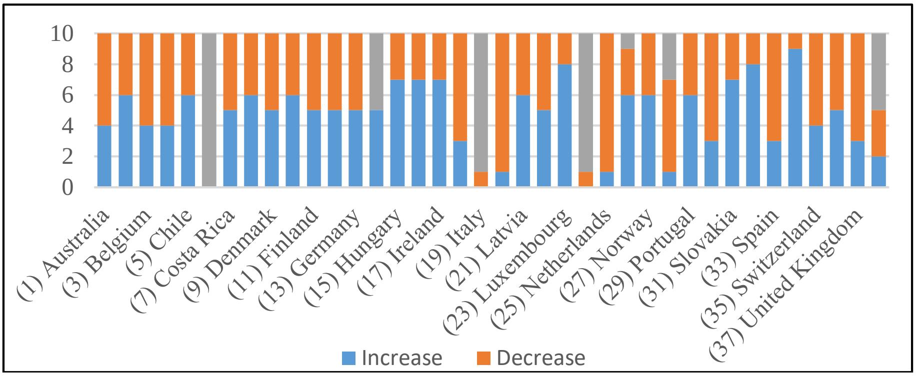

Figure 7. The Yearly Change of TFVE Values in OECD Countries Between 2010-2019

Figure 7 shows that Sweden is the country that has shown the most development on an annual basis. At the same time, more limited increases are observed in countries such as Switzerland, Finland, and Estonia. It is particularly striking that Switzerland and Finland have become more efficient over time, gaining stability.

The two sub-components that make up the TFPV index —technological development and technical efficiency scores —have been analyzed separately. In this context, the annual technological change levels of the countries are detailed in Figure 8.

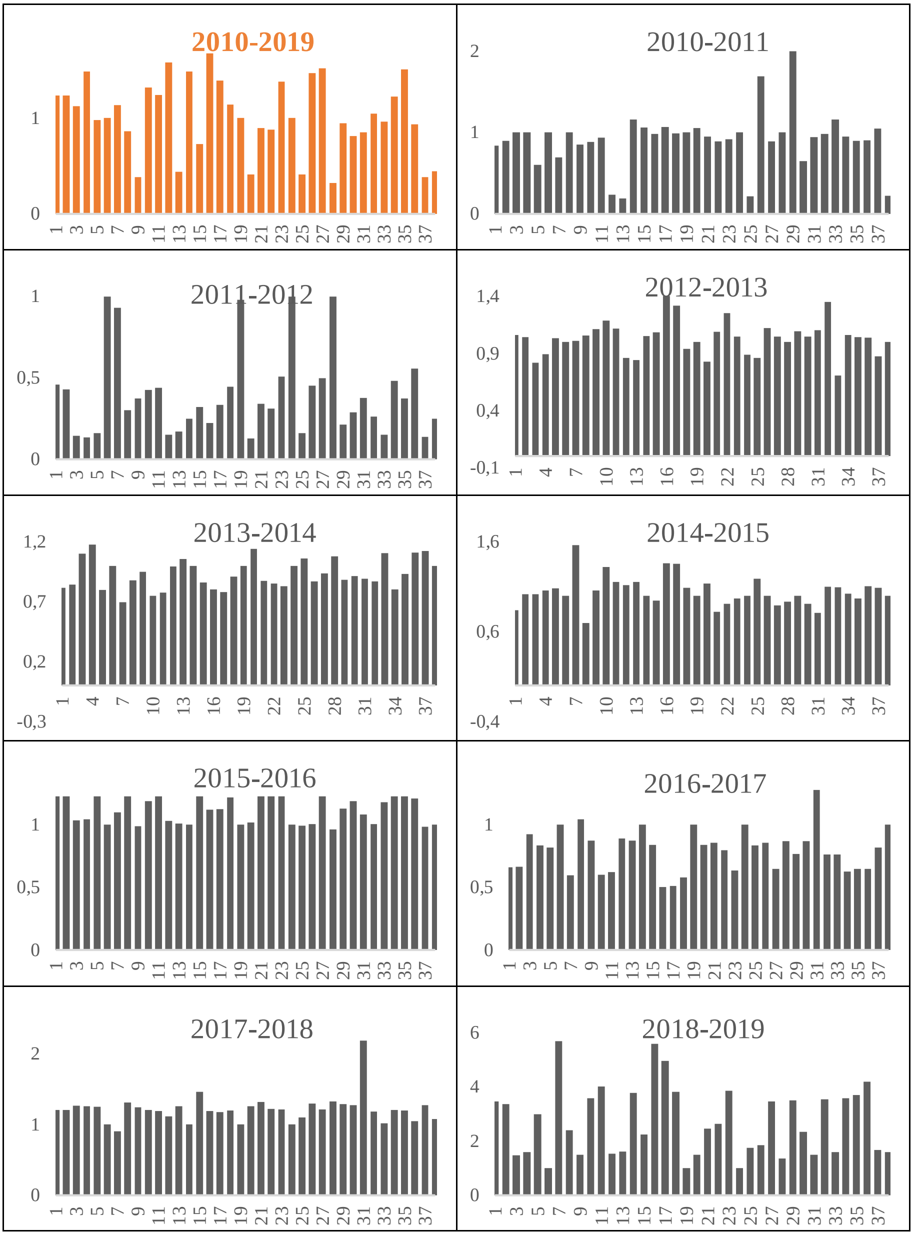

Figure 8. The Categorical-Malmquist Technological Change Values of OECD Countries Between 2010-2019

Here, despite technological regression, countries such as Chile, Czechia, Hungary, Latvia, Lithuania, and Slovakia have seen an overall increase in TFVP. This shows that technical efficiency can compensate for the technological gap. Countries like Slovakia and Latvia must make progress despite their technological backwardness by utilizing their resources more efficiently.

The total status of annual technological changes is summarized in Figure 9.

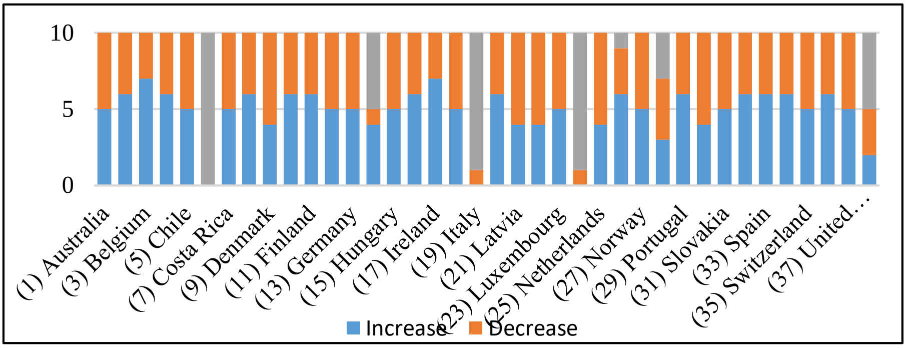

Figure 9. The Yearly Technological Change of OECD Countries in the Period Of 2010-2019

Figure 9 illustrates that countries such as Belgium and Ireland have made the most significant technological progress, while others (e.g., Mexico) have experienced a decline in technology. This situation demonstrates that technology-based growth strategies employed by small-scale countries, such as Ireland, have yielded effective results.

Annual changes in technical efficiency scores obtained by decomposing TFPV scores are presented in Figure 10, and increasing or decreasing trends over time are shown on a country basis.

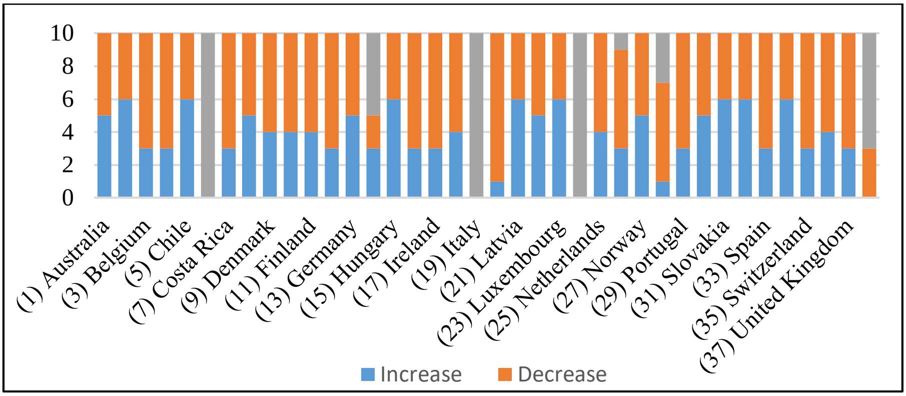

Figure 10. The Yearly Change in Technical Efficiency Scores in OECD Countries in 2010-2019.

In particular, during the 2015–2018 period, notable increases were observed in the technical efficiency scores of countries such as Slovakia, Latvia, and Slovenia. Conversely, Norway and Canada entered a downward trend during the same period. Finally, when Turkey's agricultural trade performance was examined, it was determined that TFVP values decreased in the 2013–2017 period and increased in 2018–2019; this increase was mainly due to technological development rather than technical efficiency. It can be said that the reflections of the R&D and support policies Türkiye followed in this period on technological efficiency are important.

When the agricultural trade performance of Turkey with the OECD countries is examined, it is observed that its TFVE value increased for five periods, while a decrease was experienced for another five periods compared to the previous period. In Turkey, between the 2014-2017 period, there has been an increase in TFVE scores. However, this increase is primarily due to technical efficiency scores in 2015-2016 and 2016-2017, while the source of the increase in 2014-2015 is attributed to technological improvement, similar to the period of 2018-2019.

In the final stage, using the eigenvector centrality values obtained from the import and export data, regression equations analyze the basic environmental factors underlying the realization of these values. The resulting regression equations are summarized in Tables 3 and 4.

Using the dynamic SNA approach, the eigenvector centrality of each of the 38 OECD countries is evaluated to reveal agricultural import and export trade relations among them. In this way, it was possible to specify the number of OECD countries to which each country imports and exports agricultural products, taking into account the volume of this trade. A high level of centrality means that the related country has a relatively higher level of agricultural trade relations, as indicated by the number of OECD countries in which trade is realized and the volume of agricultural trade.

In the final step of the proposed integrated approach, the eigenvector centrality values were used as the dependent variable in the regression model, and the efficiency scores obtained from the categorical DEA were used as the explanatory variable. In addition to DEA efficiency scores, reservoir maximum water area, reservoir minimum water area (as a percentage of total land area), logistics performance index, and red list index variables are considered explanatory to analyze the effects on eigenvector centrality. According to the results of the Hausman test, it was found that the fixed effects model was appropriate (Prob > chi2 = 0.00). Lastly, Pesaran's test of cross-sectional independence test (Prob = 0.00), modified Wald test for groupwise heteroskedasticity test (Prob>chi2 = 0.00) and modified Bhargava et al. Durbin-Watson's (DW = 1.20) statistics indicated that the regression model had issues with cross-sectional dependence, heteroscedasticity, and autocorrelation. Therefore, the regression with Driscoll-Kraay standard errors was estimated and is presented in Table 5. According to the regression analysis results, efficiency, reservoir water area, and logistics performance index have positive and significant effects on centrality. In contrast, the red list index has a negative and significant effect on centrality at a 0.05 significance level.

In the import-based regression model, the same test procedure was applied as in Table 5. The regression with fixed effects is estimated using Driscoll-Kraay standard errors and is presented in Table 6. According to the results, the reservoir water area and logistics performance index have positive and significant effects on import centrality. In contrast, the red list index has a negative and significant effect on import centrality at the 0.05 significance level. However, the effect of efficiency on import centrality is insignificant.

Table 5

Regression Analysis Results Based on Agriculture Export Data

Number of obs = 324 Number Groups= 36 F (4, 35) = 4.62 Prob > F = 0 R-squared = 0.156						
Export Eigenvalues (Dependent)	**Coefficient**	**Robust Std. Err.**	**t**	**P > t**	**95% Conf. Interval**	
Efficiency	0.21	0.10	2.19	0.036	0.02	0.41
Reservoir Maximum Water Area-Reservoir Minimum Water Area (% of total land area)	893.72	274.90	3.25	0.003	335.65	1451.79
Logistics Performance Index	0.006	0.002	2.42	0.021	0.001	0.01
Red List Index	-8.74	3.80	-2.30	0.027	-16.44	-1.03
Constant	7.56	3.07	2.46	0.019	1.33	13.79

Table 6

Regression Analysis Results Based on Agriculture Import Data

Number of obs = 324 Number of Groups=36 F (4, 35) = 19.87 Prob > F = 0.00 R-squared = 0.12						
Import Eigenvalues (Dependent)	**Coefficient**	**Robust Std. Err.**	**t**	**P > t**	**95% Conf. Interval**	
Efficiency	0.11	0.09	1.28	0.209	-0.07	0.30
Reservoir Maximum Water Area-Reservoir Minimum Water Area (% of total land area)	374.28	157.63	2.37	0.023	54.28	694.29
Logistics Performance Index	0.004	0.002	2.37	0.023	0.001	0.007
Red List Index	-12.28	2.56	-4.80	0.000	-17.47	-7.08
Constant	11.09	2.16	5.14	0.000	6.71	15.46

4. Conclusion and Further Suggestions

This study aimed to comprehensively evaluate the agricultural trade performance of OECD countries over the period 2010–2019, motivated by the need to understand better how efficiency, technology, and strategic positioning within trade networks influence international agricultural trade dynamics. As global food security, sustainability, and economic resilience become increasingly urgent policy issues, it is crucial to identify which countries are making progress or lagging behind in their agricultural trade performance and to understand the reasons behind these differences.

The OECD was selected as the focus because its member countries are major actors in global agricultural trade, both as exporters and importers and because they possess relatively advanced institutional and infrastructural systems, which make them suitable candidates for benchmarking trade efficiency and connectivity. By combining Categorical DEA, Malmquist TFPI, and Dynamic Social Network Analysis (SNA), this study introduces an integrated and dynamic methodology that captures temporal changes and network-based performance dimensions—something that traditional DEA or productivity analysis alone cannot offer.

Key findings indicate that while many OECD countries improved either their technical efficiency or technological capabilities over the decade, fewer consistently managed to excel in both dimensions. Countries like Sweden, Slovenia, and Luxembourg stood out for their sustained productivity growth, whereas others, such as Mexico, Italy, and Colombia, experienced stagnation or decline. These results suggest that not all OECD countries are leveraging their structural advantages equally.

Dynamic SNA further revealed the central actors in the agricultural trade network. Countries with higher eigenvector centrality—such as the USA, Germany, and the Netherlands—exhibited robust trade connections and large volumes, reflecting not only competitiveness but also strategic trade relations. The regression analysis confirmed that higher DEA efficiency scores, better logistics infrastructure, and adequate water resource availability are positively associated with centrality in trade networks. In contrast, high Red List Index values—which reflect biodiversity pressures—correlated negatively with trade centrality, possibly due to stricter sustainability-related trade regulations.

These findings underscore the importance of investing not only in productivity-enhancing technologies but also in logistics performance and environmental sustainability. Policymakers can utilize this model to pinpoint the sources of inefficiency and develop targeted interventions. For instance, countries with low technical efficiency but strong network centrality might focus on internal process optimization. In contrast, those with high efficiency but peripheral positions in the network may need to strengthen trade partnerships or address environmental constraints.

In conclusion, the agricultural trade performance of OECD countries varies significantly in terms of efficiency, technological progress, and network centrality. The integrated framework developed in this study not only provides a comprehensive benchmarking tool but also contributes to the academic literature by linking trade efficiency with structural and environmental variables. Future research could apply this model to other regional blocs or incorporate climate risk and digital trade variables to enrich the analysis further.

If the findings are provided in detail, it can be seen that 68.42% of the analyzed countries that experienced the catching-up effect showed an average increase in technical performance, 23.69% experienced a decrease, and 7.89% did not change their technical efficiency during the observation period. The most significant increase in technical efficiency change occurred in New Zealand, Greece, and Chile, respectively.

On the other hand, Iceland, Costa Rica, and Ireland were the countries that realized the frontier effect by shifting their production frontier curves upwards, and they experienced the most significant increase in technological change.

While 71.05% of the countries within the scope of the analysis recorded an increase in the value of technological change, 26.32% recorded a decline, and 2.63% were unable to realize technological change. Portugal experienced the most significant decrease in technological change, 1.2%.

Finally, suppose the change value in the TFPI is obtained by multiplying the technical efficiency change values with the technological efficiency change value, which is less than, equal to, or greater than 1. In that case, this can be interpreted as the TFP decreasing, remaining unchanged, or increasing compared to the previous year (Coelli, 1996).

The annual average decrease in the TFPI values of 38 OECD countries was 8.5%. While New Zealand, Slovakia, and Israel recorded the most significant increases in the TFPI, Japan experienced the largest decrease, at 18.22%.

In conclusion, when port efficiency and transportation quality, as well as border management, government regulations, levels of finance, and e-commerce, are considered in the evaluation of TFP index values for the international agricultural trade of 38 OECD countries in 2010-2019 period it can be seen that Canada, Chile, Czechia, Estonia, France, Greece, Hungary, Iceland, Ireland, Latvia, Lithuania, Luxembourg, New Zealand, Norway, Slovakia, Slovenia, Sweden, and Switzerland are countries with a TFVE value above 1. On the other hand, Mexico, Italy, and Colombia have a TFVE value of 1, and their index value remained constant during the evaluation period. However, the remaining OECD countries, including Turkey, experienced a decrease in both technology and technical efficiency in 2019 compared to 2010. The primary reasons behind this are analyzed through a regression equation, and it is found that the efficiency value of the country, the country's reservoir water area, and the logistics performance index all positively affect export centrality. On the other hand, the country's reservoir water area and logistics performance index have a positive impact on import centrality. Lastly, the red list index has a negative and significant effect on both centralities.

The Red List Index indicates the extinction risk for the species. As a country's Red List Index increases, the impact of imported products on the sustainability of natural resources and the conservation of endangered species may become more critical. Some countries may impose strict import controls that restrict or control the importation of products of threatened species. This may require companies wishing to import to undergo further certification and permitting processes. The logistics performance index, on the other hand, is an index calculated by averaging six scores of countries, including customs performance, infrastructure quality, ease of arranging shipments, logistics service quality, consignments tracking and tracing, and timeliness of shipments. As in many studies, it has been found that the logistics performance index plays a crucial role in agricultural trade. For example, Suroso (2022) found that the logistics performance index affects the export of palm oil and palm-based products in Indonesia and Malaysia. Luttermann et al. (2020) also found a significant relationship between the logistic performance index and trade. Finally, the increase in water reservoirs is also a crucial factor affecting agricultural productivity (Ward and Michelsen, 2002).

Acknowledgment

The authors would like to express their sincere gratitude to Assoc. Prof. Dr. Gizem Kaya Aydın for her valuable insights and constructive discussions during the manuscript preparation process.

Author Contributions

Umut Aydın contributed to data collection, analysis method implementation, reporting, and manuscript writing. Melis Almula Karadayı supported the data collection, analysis method implementation, reporting, and manuscript writing. Burç Ülengin supervised the study and contributed to editing the manuscript. Füsun Ülengin supervised the study, contributed to editing the manuscript, participated in the preparation of the original draft, and assisted in data acquisition.

Conflict of Interest

The authors declare that there is no conflict of interest.

References

Adamic, L. A., & Adar, E. (2003). Friends and neighbors on the web. *Social Networks, 25*(3), 211–230. Doi : https://doi.org/10.1016/S0378-8733(03)00009-1

Adler, N., & Yazhemsky, E. (2010). Improving discrimination in data envelopment analysis: PCA–DEA or variable reduction. *European Journal of Operational Research, 202*(1), 273–284. Doi : https://doi.org/10.1016/j.ejor.2009.03.050

Armagan, G., Ozden, A., & Bekcioglu, S. (2010). Efficiency and total factor productivity of crop production at NUTS1 level in Turkey: Malmquist index approach. *Quality & Quantity, 44*(3), 573–581. Doi : https://doi.org/10.1007/s11135-008-9216-y

Aydın, U., Karadayı, M. A., Ülengin, F., & Ülengin, K. B. (2021). Enhanced performance assessment of airlines with integrated balanced scorecard, network-based superefficiency DEA and PCA methods. In Y. I. Topcu, Ö. Özaydın, Ö. Kabak, & Ş. Önsel Ekici (Eds.), *Multiple criteria decision making. MCDM 2019. Contributions to management science* (pp. 151–164). Springer. Doi : https://doi.org/10.1007/978-3-030-52406-7_9

Banker, R. D., & Morey, R. C. (1986). Efficiency analysis for exogenously fixed inputs and outputs. *Operations Research, 34*(4), 513–521. Doi : https://doi.org/10.1287/opre.34.4.513

Boakye, A., Lee, H., Annor, F., Dadzie, S. K., & Salifu, M. (2024). Data envelopment analysis (DEA) to estimate technical and scale efficiencies of smallholder pineapple farmers in Ghana. *International Journal of Agricultural Economics, 9*(2), 45–56. Doi : https://doi.org/10.11648/j.ijae.20240902.11

Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica, 50*(6), 1393–1414. Doi : https://doi.org/10.2307/1913388

Chen, P.-C., Yu, M.-M., Chang, C.-C., & Hsu, S.-H. (2008). Total factor productivity growth in China's agricultural sector. *China Economic Review, 19*(4), 580–593. Doi : https://doi.org/10.1016/j.chieco.2008.07.001

Coelli, T. J. (1996). Measurement of total factor productivity growth and biases in technological change in Western Australian agriculture. *Journal of Applied Econometrics, 11*(1), 77–91. Doi : https://doi.org/10.1002/(SICI)1099-1255(199601)11:1

Coelli, T. J., & Rao, D. S. P. (2005). Total factor productivity growth in agriculture: A Malmquist index analysis of 93 countries, 1980–2000. *Agricultural Economics, 32*(s1), 115–134. Doi : https://doi.org/10.1111/j.0169-5150.2004.00018.x

Djoumessi, Y. F. (2022). New trend of agricultural productivity growth in sub-Saharan Africa. *Scientific African, 18*, e01410. Doi : https://doi.org/10.1016/j.sciaf.2022.e01410

Dong, H. (2022). The impact of trade facilitation on the networks of value-added trade—Based on social network analysis. *Emerging Markets Finance and Trade, 58*(8), 2290–2299. Doi : https://doi.org/10.1080/1540496X.2021.1974393

Everitt, B. S., Landau, S., Leese, M., & Stahl, D. (2011). *Cluster analysis* (5th ed.). Wiley.

Hajihassaniasl, S. (2021). Measurement of total factor productivity in Iranian economic sectors: Malmquist index analysis. *İzmir İktisat Dergisi, 36*(3), 589–600. Doi : https://doi.org/10.24988/ije.202136306

Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 374*(2065), 20150202. Doi : https://doi.org/10.1098/rsta.2015.0202

Karaman, S., & Özalp, A. (2017). Türkiye tarım sektörü bölgesel toplam faktör verimliliğinin Malmquist endeks ile belirlenmesi. *Gaziosmanpaşa Üniversitesi Ziraat Fakültesi Dergisi, 34*(1), 209–217. Doi : https://doi.org/10.13002/jafag4200

Kouriati, A., Tafidou, A., Lialia, E., Prentzas, A., Moulogianni, C., Dimitriadou, E., & Bournaris, T. (2023). The impact of data envelopment analysis on effective management of inputs: The case of farms located in the Regional Unit of Pieria. *Agronomy, 13*(8), 2109. Doi : https://doi.org/10.3390/agronomy13082109

Kyriacou, A. P., Muinelo-Gallo, L., & Roca-Sagalés, O. (2019). The efficiency of transport infrastructure investment and the role of government quality: An empirical analysis. *Transport Policy, 74*, 93–102. Doi : https://doi.org/10.1016/j.tranpol.2018.11.008

Liu, D., Liu, J. C., Huang, H., & Sun, K. (2019). Analysis of the international polysilicon trade network. *Resources, Conservation and Recycling, 142*, 122–130. Doi : https://doi.org/10.1016/j.resconrec.2018.11.025

Lovrić, M., Da Re, R., Vidale, E., Pettenella, D., & Mavsar, R. (2018). Social network analysis as a tool for the analysis of international trade of wood and non-wood forest products. *Forest Policy and Economics, 86*, 45–66. Doi : https://doi.org/10.1016/j.forpol.2017.10.006

Luttermann, S., Kotzab, H., & Halaszovich, T. (2020). The impact of logistics performance on exports, imports and foreign direct investment. *World Review of Intermodal Transportation Research, 9*(1), 27–46. Doi : https://doi.org/10.1504/WRITR.2020.106444

Malmquist, S. (1953). Index numbers and indifference surfaces. *Trabajos de Estadística, 4*(2), 209–242. Doi : https://doi.org/10.1007/BF03006863

Marchetti, D., & Wanke, P. (2017). Brazil's rail freight transport: Efficiency analysis using two-stage DEA and cluster-driven public policies. *Socio-Economic Planning Sciences, 59*, 26–42. Doi : https://doi.org/10.1016/j.seps.2016.10.005

Pınarbaşı, A., Aydın, U., Karadayı, M. A., & Tozan, H. (2022). An integrated performance measurement framework for restaurant chains: A case study in Istanbul. *Endüstri Mühendisliği, 33*(3), 484–499. Doi : https://doi.org/10.46465/endustrimuhendisligi.1087736

Sultana, S., Hossain, M. M., & Haque, M. N. (2023). Estimating the potato farming efficiency: A comparative study between stochastic frontier analysis and data envelopment analysis. *PLOS ONE, 18*(4), e0284391. Doi : https://doi.org/10.1371/journal.pone.0284391

Suroso, A. I. (2022). The effect of logistics performance index indicators on palm oil and palm-based products export: The case of Indonesia and Malaysia. *Economies, 10*(10), 261. Doi : https://doi.org/10.3390/economies10100261

Şişman, Z., & Tekiner-Mogulkoc, H. (2022). Using Malmquist TFP index for evaluating agricultural productivity: Agriculture of Türkiye NUTS2 regions. *Sigma Journal of Engineering and Natural Sciences, 40*(3), 513–528.

Telleria, R., & Aw-Hassan, A. (2011). Agricultural productivity in the WANA region. *The Journal of Comparative Asian Development, 10*(1), 157–185. Doi : https://doi.org/10.1080/15339114.2011.578490

Tunca, H., & Deliktaş, E. (2015). OECD ülkelerinde tarımsal etkinlik ölçümü: Dinamik veri zarflama analizi. *Ege Akademik Bakış, 15*(2), 217–224.

Ward, F. A., & Michelsen, A. (2002). The economic value of water in agriculture: Concepts and policy applications. *Water Policy, 4*(5), 423–446. Doi : https://doi.org/10.1016/S1366-7017(02)00039-9

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. Cambridge University Press.

Yin, R. R., Guo, Q., Yang, J. N., & Liu, J. G. (2018). Inter-layer similarity-based eigenvector centrality measures for temporal networks. *Physica A: Statistical Mechanics and Its Applications, 512*, 165–173. Doi : https://doi.org/10.1016/j.physa.2018.08.018

Yu, J. K., & Ma, J. Q. (2020). Social network analysis as a tool for the analysis of the international trade network of aquatic products. *Aquaculture International, 28*(3), 1195–1211. Doi : https://doi.org/10.1007/s10499-020-00520-5