Ekonomi, Politika & Finans Araştırmaları Dergisi, 2025, 10(2): 596-618
Journal of Research in Economics, Politics & Finance, 2025, 10(2): 596-618
Araştırma Makalesi / Research Article, https://doi.org/10.30784/epfad.1635472

ANALYSIS OF AGRICULTURAL PERFORMANCE OF BRICS COUNTRIES AND TÜRKİYE WITH CRITIC-BASED GREY RELATIONAL ANALYSIS METHOD

BRICS Ülkeleri ve Türkiye'nin Tarımsal Performansının CRITIC Tabanlı Gri İlişkisel Analiz Yöntemi ile Analizi

Ahmet İNKAYA* **& Mahmut MASCA****

Keywords: Agriculture, Multi-Criteria Decision Making Techniques, BRICS Countries

JEL Codes: Q10, C44, P52

Abstract

This study aims to evaluate the agricultural performance of BRICS countries (Brazil, Russia, India, China, and South Africa) and Türkiye using CRITIC (Criteria Importance through Inter-Correlation) and GRA (Grey Relational Analysis) approaches. The following criteria are applied to assess each country's agricultural performance: Livestock Production, Primary (Ton/Population), Crop Production, Primary (Ton/Population), Gross Production Value (constant 2014-2016 thousand US$) (Value/Hectare), Self-sufficiency in Agriculture (Export/Import) (%), Methane (CH4) Emission from Agriculture (Value/Agricultural Land) in million metric tonnes of carbon dioxide equivalents (Mt CO2e), Employment in Agriculture (as a percentage of total employment), and Fertilizer Consumption (kilograms per hectare of arable land), Arable Land (% of land area). The years 2000, 2010, and 2022 are all included in the analysis. According to the GRA approach, South Africa had the worst agricultural performance in all reviewed years. While Russia had the highest rank in 2000, Brazil rose to the top ten years later, in 2010, its rank remained unchanged in 2022. Specifically, the top and bottom-ranked nations remain unchanged from 2010 to 2022. In terms of Türkiye, it ranked fourth in all studied years.

Anahtar Kelimeler: Tarım, Çok Kriterli Karar Verme Teknikleri, BRICS Ülkeleri

JEL Kodları: Q10, C44, P52

Öz

Bu çalışmanın amacı, CRITIC (Kriterler Arası Korelasyon Yoluyla Kriter Önemi) ve GRA (Gri İlişkisel Analiz) yaklaşımlarını kullanarak, BRICS ülkeleri (Brezilya, Rusya, Hindistan, Çin ve Güney Afrika) ve Türkiye'nin tarımsal performansını değerlendirmektir. Her ülkenin tarımsal performansını değerlendirmek için aşağıdaki kriterler uygulanmıştır: Hayvancılık Üretimi, Birincil (Ton/Nüfus), Bitkisel Üretim, Birincil (Ton/Nüfus), Gayri Safi Üretim Değeri (sabit 2014-2016 bin ABD$) (Değer/Hektar), Tarımsal Öz Yeterlilik (İhracat/İthalat) (%), Tarımsal Metan (CH4) Emisyonu (Değer/Tarımsal Arazi) milyon metrik ton karbondioksit eşdeğeri (Mt CO2e), Tarımsal İstihdam (toplam istihdamın yüzdesi olarak) ve Gübre Tüketimi (hektar başına ekilebilir arazi kilogramı), Ekilebilir Arazi (% arazi alanı). Analize 2000, 2010 ve 2022 yılları dahil edilmiştir. GRA yaklaşımına göre, Güney Afrika incelenen tüm yıllarda en kötü tarımsal performansa sahiptir. Rusya 2000 yılında en yüksek sıraya sahipken, Brezilya on yıl sonra 2010'da zirveye yükselmiş, sıralaması 2022'de değişmemiştir. Özellikle, en üst ve en alt sıradaki ülkeler 2010'dan 2022'ye değişmeden kalmıştır. Türkiye, incelenen tüm yıllarda dördüncü sırada yer almıştır.

* Assist. Prof. Dr., Afyon Kocatepe University, Faculty of Economics and Administrative Sciences, Department of Economics, Türkiye, inkaya@aku.edu.tr
** Prof. Dr., Afyon Kocatepe University, Faculty of Economics and Administrative Sciences, Department of Economics, Türkiye, mmasca@aku.edu.tr

Received Date (Makale Geliş Tarihi): 07.02.2025 *Accepted Date (Makale Kabul Tarihi): 05.05.2025*

1. Introduction

Agriculture, which has always made its presence and importance felt due to meeting the nutritional needs of people, is a strategic, political, and economic sector that all countries in the world pay attention to. The industrial sector, which rose to prominence with the start of the international development race and the concept of development after the Second World War, has caused agriculture to be neglected, especially in developing countries. This situation has also brought about disruptions in the development process. The food price crisis of 2007 and the fragility of global food supply chains during the 2019-2021 pandemic reminded us that the agricultural sector is sensitive and critical today, bringing it to the forefront again. The protectionist and nationalist policies implemented in the agricultural sector have shown an increasing trend in this process.

The social and economic changes experienced are exciting to all sectors globally. On the one hand, developments that mainly manifest themselves with concerns about high efficiency require advanced technology. On the other hand, they have begun to shape agricultural and economic policies that may impact climate change, sustainability, food supply security, efficient use of water resources, employment, and price stability. While the world population continues to grow, the need for agricultural products is increasing day by day; in this context, the tendency for water resources to shrink and developments that may limit productivity and production, such as global warming/climate change, are causing concern, and are placing the sector in a critical position to a great extent.

Countries must use natural resources to be self-sufficient in agricultural foreign trade and increase competitiveness. Developed countries have already completed their industrialization processes, while developing countries have entered the industrialization process without completing this process. Rapid and uncontrolled industrialization creates adverse, severe effects on the environment. Policymakers must interpret, analyze, and understand all these problems and development trends. Policymakers must closely follow all these developments on a regional, national, and global scale.

While neo-liberal policies are excluded from the agricultural field in developed countries, developing countries are forced to implement these policies through several international organizations. This situation negatively affects their agricultural competitiveness and performance. Therefore, it would be a more accurate approach to evaluate the agricultural performances of developed and developing countries separately.

Türkiye and the BRICS nations—Brazil, Russia, India, China, and South Africa—share specific economic characteristics. These parallels stem from their positions in the global economy, dynamic economic structures in particular industries, and status as developing nations. In this context, this study will attempt to measure the agricultural performances of developing countries, BRICS countries, and Türkiye, using CRITIC-based GRA analysis. This study is not an analysis measuring the performance of countries' agricultural production but rather presents a holistic approach that addresses the agricultural sector in terms of production, consumption, employment, productivity, and environmental dimensions. Several policy recommendations will be made based on the findings obtained from the analysis.

In previous MCDM analyses (TOPSIS, ARAS, ELECTRE, GRA, etc.), the importance levels of the criteria were determined subjectively by taking expert opinion. Later, objective weighting methods such as CRITIC, Entropy, LOPCOW, Standard Deviation, etc., were developed and combined with MCDM methods. The fact that the objective weighting methods do not require different data in their application, i.e., they use the same decision matrix as in the ranking method, has facilitated the frequent use of these methods together. A distinctive feature of this study is that it uses the CRITIC method, which is one of the objective weighting methods, together with the GRA method used in rankings. The agricultural performance of Türkiye and the BRICS countries was examined using the CRITIC and GRA methodologies. This hybrid model is developed using the CRITIC and GRA approaches. The importance of agricultural performance criteria was assessed using the CRITIC approach. The countries were ranked based on their agricultural performance using the GRA approach.

MCDM methods do not show a causal relationship as in econometric models (Granger causality analysis, time series analysis, panel data analysis). The MCDM methods do not identify the relationship between variables. As a result, it cannot be applied to forecast future events using cause-and-effect relationships. Several policy suggestions can be offered to improve the performance of underperforming nations. It is, therefore, not used for testing hypotheses. These methods enable the ranking of the best-performing solutions according to preset standards.

In MCDM analyses, a single year of data is usually used to determine the ranking of the alternatives subject to the study in the relevant year. In this case, the ranking for the relevant year does not contain information about the past status of the alternatives. For example, in a single-year analysis with 10 alternatives, it is not possible to make a judgment about whether an alternative ranked 5th in the relevant year rose from 10th place or fell from 1st place. The distinctive feature of this study is the use of three data sets for the years 2000, 2010, and 2022 (no data are available after this year) at approximately 10-year intervals to determine how far nations have progressed during that time. In addition, it takes a certain period of time for the agricultural policies implemented in a country to be reflected in the agricultural performance of that country and for their results to fully emerge. The periodic determination of the data used in the study provides the opportunity to observe the developments that may emerge in the relevant period. The originality of this study and its contribution to the literature can be summarized as follows: (i) There are very few studies that conduct agricultural analysis with MCDM methods, but there are no studies that rank countries according to their agricultural performance using a hybrid MCDM method (CRITIC-GRA). (ii) There are no studies that rank BRICS countries according to their agricultural performance. (iii) It is the study that uses the most criteria in agricultural performance analysis. In this respect, it has the potential to inspire future studies. (iv) In the analysis, the agricultural performance of countries is addressed not only according to the amount of production, but also in a multi-faceted macro dimension by considering productivity, agricultural production potential, self-sufficiency, employment, and environmental effects of production. (v) Unlike other studies, not only data from one year but three separate datasets with an interval of approximately 10 years were used. This method provided the opportunity to observe the change in agricultural performance of countries over time from a comparative static analysis perspective.

A review of the literature, an explanation of the data, the stages involved in the CRITIC and GRA methodologies, the results, the sensitivity analysis, and a conclusion are all included in the following chapters.

2. Literature Review

There is no study in the literature that analyzes the agricultural performance of countries using the CRITIC-GRA method. Therefore, after specifying the studies on agricultural performance using other methods, information will be given about the studies that use the CRITIC GRA method in different areas.

The paper was written by Madiyoh et al. (2021) to assess the performance of the agriculture sector in ASEAN nations, pinpoint policy shortcomings, investigate competitive advantages, and direct food and nutrition policies. The TOPSIS approach was used in the study to examine secondary time series data spanning ten ASEAN nations from 1967 to 2016. In 1967, according to the data, Thailand, the Philippines, and Indonesia were the most prosperous nations in terms of agricultural policy performance. However, Malaysia has become a leader in recent years, with its industrial sector using financial investments to drive agricultural success.

Gürlük and Uzel (2016) examined the historical success of agro-environmental and economic policies to ensure food security in Germany, France, the Netherlands, and Türkiye. Using the TOPSIS method, countries were ranked according to sustainability criteria.

The above two studies that can be associated with agricultural performance used TOPSIS, one of the MCDM methods. In these studies, the weights were determined by the authors by preferring the subjective method instead of the objective criterion weight determination methods. Other studies using the CRITIC GRA method in different fields are listed below:

Brodny and Tutak (2023) evaluated EU nations' levels of digital maturity in the 2015 Three Seas Initiative. Using the CRITIC GRA technique, the study calculated the digital maturity indices to assess the degree of adoption of Industry 4.0 technology in various nations. According to the findings, Hungary, Romania, and Bulgaria have the lowest degrees of digital maturity, while the Czech Republic, Lithuania, and Estonia have the highest levels.

Through the Brazilian Antarctic Program, Almeida et al. (2022a) seek to support the Naval Administration in choosing volunteer officers for open positions in Antarctica. In order to rank possible candidates, the CRITIC-GRA-3N method combines the CRITIC method for establishing criteria weights with the GRA with three normalizations. Value-focused thinking is utilized to determine the most appropriate criteria.

Almeida et al. (2022b) focus on assisting a Rio de Janeiro microbusiness in allocating available funds. After defining investment alternatives and evaluation criteria using Value-Focused Thinking (VFT), the CRITIC-GRA-3N method ranks the investment options using the GRA with three normalizations and the CRITIC method for determining criteria weights.

Xu et al. (2020), in their analysis of worldwide ship total loss data from 2013 to 2017, employ GRA and CRITIC techniques to look at the connections between contributory elements such as ocean areas, accident causes, and ship types. Three levels of each contributing component are distinguished, and by mixing these levels, several scenarios are produced.

Geeri et al. (2024) use Computational Fluid Dynamics (CFD) simulations to study how input parameters, like spear locations and pressure levels, affect output parameters, such as outlet velocity, outlet pressure, and tangential force component, to determine how well a Pelton wheel performs. These parameters' contribution to the Pelton wheel's performance was evaluated using several optimization approaches, including GRA, TOPSIS, Taguchi Design of Experiments (DoE), and CRITIC.

Junior et al. (2024) use the CRITIC-GRA-3N approach to rate and choose suppliers and distributors to improve the Supply Chain Management (SCM) of an auto parts dealership in Guaratinguetá-SP. The new approach outperformed the original CRITIC and GRA techniques in terms of consistency and proved straightforward, useful, and efficient in locating and ranking substitute sources.

Liu et al. (2023) address shortcomings in current state-of-health calculation techniques by proposing a thorough battery health evaluation indicator based on actual electric car data. The indicator is created by using GRA with the enhanced CRITIC weighting approach.

Miao et al. (2018) evaluate environmental factors, population exposure, and capacities to determine China's population's susceptibility to geological disasters. An index system was created using the CRITIC and GRA methodologies to assess how vulnerable provincial administrative units are to calamities such as debris flows and landslides.

Nguyen et al. (2020) use a mix of MCDM techniques, such as the CRITIC approach, GM(1,1) grey model first-order one variables, and GRA, to examine the evolution of electric car sales and market share across 14 nations. While the CRITIC technique establishes the objective weights of variables annually, the GM(1,1) model predicts future sales based on historical data.

Qi (2021) presents a new multi-attribute group decision-making (MAGDM) method that combines intuitionistic fuzzy sets (IFSs) and GRA to assess the development potential of cultural and creative industry parks. The CRITIC technique addresses the subjective unpredictability frequently present in these assessments by determining the criteria weights.

Saeheaw (2022) looks into optimizing several parameters in the Nd: YAG laser welding process by integrating the GRA-based Taguchi method with the CRITIC method for objective weighting. Six parameters were optimized to improve weld strength and minimize weld width: beam diameter, laser power, flow rate, welding speed, laser offset, and pulse form.

Based on financial data, Silva et al. (2023) suggest an integrated multi-criteria decision-making (MCDM) model that combines GRA and CRITIC approaches to choose investment portfolios. The model uses ten financial parameters from literature research to assess 190 companies listed on the Brazilian stock exchange.

Singh et al. (2023) use a brass C360 electrode to micro-EDM drill aluminum 6061 and examine how operational parameters like capacitance, voltage, feed rate, and rotation speed affect material removal rate, tool wear, overcut, and taper angle. The best process parameters are found using a novel hybrid optimization technique incorporating Taguchi, GRA, and CRITIC. In order to improve the multi-response results, the experiment used a Taguchi L18 orthogonal array. GRA was used to evaluate the responses, and CRITIC was used to determine the weighting values for each response.

Wei et al. (2020) investigate how probabilistic uncertain linguistic MAGDM problems with unknown attribute weights can be solved using the GRA method. The CRITIC approach objectively determines attribute weights based on expected values.

Zhou et al. (2024) offer a hybrid decision-making model that enhances decision stability and dependability in transport safety engineering by combining CRITIC, GRA, and Gaussian mixture model (GMM) with a multiple restart simulation. In order to improve resilience, the model embeds a simulation, which solves problems that the classical GMM encounters, like uncertain initialization and local optima.

Altıntaş (2021) uses the CRITIC-based GRA method to study the innovation performance of the Black Sea Economic Cooperation Organization member countries. Based on the component values identified in the Global Innovation Index (GII) for 2020, the CRITIC-based GRA was used to assess the innovation performances of the concerned nations.

A study by Çilek et al. (2024) examine the connection between dividend yield and profitability rates of businesses listed on the Borsa Istanbul Dividend 25 index between 2020 and 2022. The objective weighing method, known as the CRITIC method, was used to weight the evaluation criteria. The organizations' grey connection degrees were sorted from largest to smallest using the GRA approach based on their profitability rates.

Keleş (2023) focuses on 42 nations' sustainable transportation over the period 2015-2020 based on eight economic, social, and environmental parameters. Out of 42 countries, Norway, Switzerland, Russia, Romania, and Lithuania ranked in the top five for sustainable transportation. Montenegro came in last, according to the results of the GRA method used to assess the alternatives.

Gök Kısa (2021) uses a GRA approach based on CRITIC to assess the renewable energy (RE) resources in the TR83 region. In order to do this, RE resources in the TR83 region were assessed using the CRITIC-based GRA approach, and their performance was ranked.

Türkoğlu et al. (2023) use CRITIC-based GRA and WASPAS software to assess the logistics performance of G20 nations. As a result, it was obtained within the G20 member countries and used to develop a decision matrix. The CRITIC method was used to calculate the logistics performance variable indices of the countries in question, and the GRA and WASPAS methodologies were used to conduct the ranking analysis.

Baki (2024) compares the innovation performances of BRICS countries with the CRITIC and GRA methods in his study. In the first stage of the application, the importance levels of the criteria are obtained with the CRITIC method. In the second stage, the countries are ranked according to their innovation performance through GRA.

3. Data and Methodology

3.1. Data

In this study, the agricultural performance of Türkiye and BRICS countries was ascertained using an integrated CRITIC-based GRA method. The CRITIC method provides the objective weights of the criteria that will be used in the GRA method to rank the countries. The GRA Method measures each country's agricultural performance and ranks the countries. The dataset has been obtained from the Food and Agriculture Organization (FAO, 2024) and the World Bank (2024) Database. Eight agricultural performance criteria for the years 2000, 2010, and 2022 for each country have been used in the computations to see the changes in performance through the years.

Criteria for determining the country's agricultural performance are as follows: Livestock Production, Primary (Ton/Population), Crops Production, Primary (Ton/Population), Gross Production Value (constant 2014-2016 thousand US$) (Value/Hectare), Self-sufficiency in Agriculture (Export/Import) (%), Methane (CH4) Emission from Agriculture (Mt CO2e), Employment in Agriculture (% of total employment) (modeled ILO estimate), Fertilizer Consumption (kilograms per hectare of arable land), Arable Land (% of land area). The first five criteria have been adapted from Madiyoh et al. (2021). The use of fertilizer consumption as a criterion for measuring agricultural performance was adapted from Gürlük and Uzel (2016). The authors have added the rest of the criteria to make a more robust analysis since there are other indicators of agricultural performance. The data on Methane (CH4) Emissions from Agriculture (Mt CO2e), Employment in Agriculture (% of total employment) (modeled ILO estimate), and Fertilizer Consumption (kilograms per hectare of arable land) have been downloaded from the World Bank database, and others from the FAOSTAT (2024) database. As can be noticed, the criteria chosen in the study represent many aspects of agriculture since they reflect production capacity, consumption capacity, productivity, and environmental effects of agriculture. Thus, this study will not rank the countries according to the amounts of their agricultural production but to agricultural performance, reflecting all aspects of agriculture. The agricultural performance criteria, abbreviations, and directions are listed in Table 1.

Table 1. Criteria, Abbreviations, and Directions

No.	Criteria	Abbreviation	Direction
1	Livestock Production, Primary (Ton/Population)	LPP	Maximum
2	Crop Production, Primary (Ton/Population)	CPP	Maximum
3	Gross Production Value (constant 2014-2016 thousand US$) (Value/Hectare)	GPV	Maximum
4	Employment in Agriculture (% of total employment) (modeled ILO estimate)	EAG	Maximum
5	Self-sufficiency in Agriculture (Export/Import) (%)	SSA	Maximum
6	Fertilizer Consumption (kilograms per hectare of arable land)	FER	Maximum
7	Arable Land (% of land area)	ARL	Maximum
8	Methane (CH4) Emission from Agriculture (Mt CO2e) (Value/Agricultural Land (Hectare))	EMI	Minimum

Source: FAOSTAT (2024), World Bank (2024).

Benefit criteria are those included in Table 1 with the numbers 1, 2, 3, 4, 5, 6, and 7; the higher the performance score, the higher the criterion value. The number 8 stands for the cost criterion, and a higher performance score is associated with a lower criterion value. The definition and direction of all criteria, as well as their linkages with agricultural performance, can be explained as follows. The definitions of the criteria are taken from the FAOSTAT and World Bank websites.

Livestock Production, Primary: Primary livestock products are made from both living and killed animals. Meat, raw fats, offal, and fresh hides and skins are all products of slain animals. Live animal products include milk, eggs, honey, beeswax, and animal-derived fibers. In order to make cross-country comparisons more meaningful, the amount of production divided by population is included in the analysis. In order to ensure food security, improve nutrition, reduce poverty, and spur economic growth, livestock production is a crucial part of global agriculture.

The direction of this criterion should be maximum, which means higher values imply better performance.

Crop Production, Primary: Primary crop production data are the actual yields harvested from fields, orchards, and gardens without having undergone any real processing, apart from cleaning; they do not include harvesting and threshing losses or the portion of the crop that is not collected for whatever reason. Thus, production encompasses both the amounts of the commodity sold in the market and the amounts used or consumed by the producers. An essential part of agriculture, which ensures the world's food security, is crop production. The direction of this criterion should be maximum.

Gross Production Value: The production value is calculated as the monetary amount of agricultural output at the farm gate. The value has been divided into agrarian land to show the agricultural revenues obtained per hectare. The direction of this criterion should be maximum for better performance.

Employment in Agriculture: Individuals of working age are considered employed if they engaged in any activity that produced goods or services for compensation or monetary benefit, regardless of whether they were actively working during the designated period or not, due to factors such as a temporary job absence or alternative work arrangements. This sector incorporates farming, hunting, forestry, and fishing as its primary components. Agriculture is the second greatest source of employment worldwide after services. The direction of this criterion should be maximum.

Self-sufficiency in Agriculture: The capacity of a nation or region to generate enough food and agricultural products to meet its own needs without depending on imports is known as agricultural self-sufficiency. Since it highlights the significance of local agricultural production in guaranteeing a steady supply of food for the populace, this idea is strongly related to food security, sustainability, and economic independence. The direction of this criterion should be maximum.

Fertilizer Consumption: Fertilizer consumption quantifies how much plant nutrition is utilized for each unit of arable land. Fertilizers give plants the vital minerals they require for healthy growth, including potassium, phosphorus, and nitrogen. Crops would fall short of their potential without these nutrients, producing lower yields and lower quality. The direction of this criterion should be maximum.

Arable Land: Land that can be plowed and used for crop cultivation is referred to as arable land. In general, it excludes areas that are densely forested, excessively stony or rocky, poorly drained, or prone to flooding. Arable land is essential to the production of food and agriculture worldwide. It acts as the base for agricultural cultivation, offering the resources required for food production and harvest. The direction of this criterion should be maximum.

Methane (CH_4) Emissions from Agriculture: Tropical forest and other vegetation fires, industrial production, landfills, wastewater treatment facilities, and agricultural operations are the main sources of methane emissions. The global warming potential is typically used to quantify the emissions in carbon dioxide equivalents, allowing for a comparison of the effective contributions of various gases. Compared to one kilogram of carbon dioxide, one kilogram of methane traps 21 times as much heat in the Earth's atmosphere in 100 years.

The Earth's radiative equilibrium is upset when man-made greenhouse gases are added to the atmosphere. The Earth's surface temperature is rising as a result, and this has an impact on global agriculture, climate change, and sea level rise. CO2 emissions come from burning wood and garbage, burning coal, oil, and gas for energy, as well as from industrial activities like making cement. The average rate at which a certain pollutant is released from a particular source, concerning the intensity of a particular activity, is known as emission intensity. Comparing the environmental effects of various fuels or activities is another use for emission intensities. Carbon intensity and emission factor are related words that are frequently used interchangeably. A nation's carbon dioxide emissions are just one measure of its greenhouse gas emissions. Gases like methane and nitrous oxide should be considered for a more comprehensive understanding of a nation's role in climate change. In an agricultural economy, this is especially crucial. There is a lot of curiosity about how carbon dioxide affects the environment. The majority of the greenhouse gases causing climate change and global warming are carbon dioxide (CO2). Methane (CH4), nitrous oxide (N2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulfur hexafluoride (SF6), and all other greenhouse gases can be compared, and their respective and combined contributions to global warming can be calculated by converting them to carbon dioxide (or CO2) equivalents.

3.2. CRITIC Method

Diakoulaki et al. (1995) conducted the first study to document the CRITIC method. This method creates objective weights by compiling actual data for each evaluation criterion. The objective weighting of the CRITIC technique is the most significant aspect, as it is determined by incorporating the inter-criteria correlation and the standard deviation of the criteria rather than the subjective outcomes of the expert opinions (Kargı, 2022: 365).

Some advantages of the CRITIC technique include the following (Zardari et al., 2015); (i) The weights determined consider conflict and contrast intensity, which are incorporated into the decision problem’s structure, (ii) The developed approach can be easily translated into an algorithmic version and is predicated on examining the assessment matrix to extract all of the data contained in the evaluation criteria, (iii) The weights derived from the CRITIC approach were found to capture the information that the criterion in the multi-criteria problem conveys.

The procedures that must be adhered to when employing the CRITIC technique are detailed below (Diakoulaki et al., 1995: 765):

Step 1: To display i alternatives to be ranked and j criteria, a decision matrix of dimension mxn is initially constructed using Equation (1).

$$X = \begin{bmatrix} x_{01} & x_{0j} & \cdots & x_{0n} \\ x_{i1} & x_{ij} & \cdots & x_{in} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{mj} & \cdots & x_{mn} \end{bmatrix};\ i = 0,1,\dots,m \text{ and } j = 1,2,\dots,n \tag{1}$$

Step 2: The normalization process is now carried out using the formulas in Equation (2) for the benefit criterion and Equation (3) for the cost criterion in the decision matrix.

$$r_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}};\ \ i = 0,1,\dots,m \text{ and } j = 1,2,\dots,n \tag{2}$$

$$r_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} \; ; \; i = 0,1, \dots, m \text{ and } j = 1,2, \dots, n \tag{3}$$

Step 3: The degree of relationship between the criteria is determined by calculating the correlation coefficient between the criteria pairs using Equation (4) following the normalization step.

$$\rho_{jk} = \frac{\sum_{i=1}^{m} \left(r_{ij} - \bar{r}_j\right)(r_{ik} - \bar{r}_k)}{\sqrt{\sum_{i=1}^{m} \left(r_{ij} - \bar{r}_j\right)^2 \cdot \sum_{i=1}^{m} (r_{ik} - \bar{r}_k)^2}}; k = 1,2,3, \dots, n \tag{4}$$

Step 4: Each criterion's standard deviation is obtained using Equation (5).

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m} (r_{ij} - \bar{r}_j)^2}{m - 1}} \tag{5}$$

Step 5: At this point, Equation (6) uses the values determined in Equations (4) and (5) to determine the total information values of each criterion.

$$C_j = \sigma_j \sum_{k=1}^{n} (1 - \rho_{jk}) \; (j, k = 1,2, \dots, n) \tag{6}$$

Step 6: Equation (7) is used in the final step to determine the importance weights of each criterion.

$$w_j = \frac{C_j}{\sum_{k=1}^{n} C_j} (j, k = 1,2, \dots, n) \tag{7}$$

3.3. GREY Relational Analysis Method

Grey relational analysis, a method for ranking, classifying, and making decisions, has become one of the subheadings of grey system theory in scientific studies. Julong Dung's 1982 study "Control Problems of Gray Systems" was the first to introduce grey theory in Thailand. With subheadings including grey relational analysis, grey modeling, grey estimation, and grey decision-making, the grey theory is applied in various domains in the literature (Dinçer, 2019: 61).

In comparison to other statistical methods, the grey relational analysis method has the following advantages: it requires a small sample size, yields effective results with uncertain data, does not require any probability distribution of the data, measures the grey relational coefficient, and requires fewer operations (Atan et al., 2020: 63).

The relationship between the series to be compared can be computed numerically using the Grey Relational Analysis method, which can be used to measure the relationship between two series logically and numerically. The relationship degree that is determined as a result of the operations carried out is known as the grey relationship degree (Wang et al., 2004).

The GRA method's application stages are explained below (Wen, 2004; Zhai et al., 2009: 7076).

Step 1: Creating the Decision Matrix

Equations 8 and 9 help create a decision matrix with m alternatives and n criteria.

$$X = \begin{bmatrix} x_1(1) & x_1(2) & x_1(n) \\ x_2(1) & x_2(2) & x_2(n) \\ \vdots & \vdots & \vdots \\ x_m(1) & x_m(2) & x_m(n) \end{bmatrix} \tag{8}$$

$$x_i = (x_i(j), \dots x_i(n)), i = 1,2, \dots, n \tag{9}$$

$x_i(j)$ shows the value of the i^{th} alternative (i =1 .... m) according to the j^{th} criterion (j = 1.........n).

Step 2: Generation of Reference Sequence and Comparison Matrix

At this stage, reference series are determined according to minimum or maximum values. If the criterion requires benefit/maximization, the reference series value of the relevant criterion is the maximum of the alternative series; if it involves cost/minimization, the minimum value of the appropriate criterion. The purpose of creating the reference series is to determine the closest alternatives to the reference series, which are determined by the minimum and maximum values according to the study. The determined reference series is placed in the decision matrix's first row, thus creating the comparison matrix.

$$x_0 = (x_0(j)), j = 1,2, \dots n \tag{10}$$

The $x_0(j)$ value in Equation 10 shows the best value of the j^{th} criterion among the normalized values to be obtained in the next stage.

Step 3: Normalization of Decision Matrix

Since the series used in decision problems are measured in different units, a normalization process must be performed to make them comparable. In other words, if the series in question are in broad ranges, "normalization" must be applied by pulling them to smaller ranges. In the normalization process, three different equations are used depending on whether the benefit, cost, or optimal value is preferred.

If the higher is the better (benefit situation), the normalization process is done using Equation 11.

$$x_i^* = \frac{x_i(j) - \min_j x_i(j)}{\max_j x_i(j) - \min_j x_i(j)} \tag{11}$$

If the lower is the better (cost situation), the normalization process is formulated using Equation 12.

$$x_i^* = \frac{\max_j x_i(j) - x_i(j)}{\max_j x_i(j) - \min_j x_i(j)} \tag{12}$$

Equation 13 is utilized in the study to conduct a normalization process based on the researcher's optimal value rather than cost and benefit scenarios.

$$x_i^* = \frac{|x_i(j) - x_{0b}(j)|}{\max_j x_i(j) - x_{0b}(j)} \tag{13}$$

The $x_{0b}(j)$ value is the optimal value determined by the researcher and shows the target value of the jth criterion.

The optimal value can take values in the range, $\min_j x_i(j) \leq x_{0b} \leq \max_j x_i(j)$.

After the normalization process, all values obtained will be between 0 and 1. The normalization matrix created after the operations is shown in Equation 14. x_i^* represents the normalization matrix.

$$x_i^* = \begin{bmatrix} x_1^*(1) & x_1^*(2) & x_1^*(n) \\ x_2^*(1) & x_2^*(2) & x_2^*(n) \\ \vdots & \vdots & \vdots \\ x_m^*(1) & x_m^*(2) & x_m^*(n) \end{bmatrix} \tag{14}$$

Step 4: Creating the Absolute Value Matrix

The value of the absolute difference between the normalized values of the reference series and the values of the normalized decision matrix is shown in Equation 15.

$$\Delta_{0i}(j) = |x_0^*(j) - x_1^*(j)| = \begin{bmatrix} \Delta_{01}(1) & \Delta_{01}(2) & \Delta_{01}(n) \\ \Delta_{02}(1) & \Delta_{02}(2) & \Delta_{02}(n) \\ \vdots & \vdots & \vdots \\ \Delta_{0m}(1) & \Delta_{0m}(2) & \Delta_{0m}(n) \end{bmatrix} \tag{15}$$

Step 5: Creating the Grey Relational Coefficient Matrix

The values in the grey relational coefficient matrix are obtained using Equations 16 and 17.

$$\gamma_{0i}(j) = \frac{\Delta\min + \zeta\Delta\max}{\Delta_{0i}(j) + \zeta\Delta\max} \tag{16}$$

$$\Delta\max = \max_i \max_j \Delta_{0i}(j) \text{ and } \Delta\min = \min_i \min_j \Delta_{0i}(j) \tag{17}$$

The ζ parameter in Equation 11 is the distinguishing coefficient between 0 and 1. The reason for using the ζ parameter is the necessity of regulating the difference between Δ_{0i} and Δmax. In this context, the ζ parameter eliminates the possibility of Δmax being the most extreme value in the data series. It has been observed in the literature that the ζ parameter generally takes a value of 0.5.

Step 6: Grey Relational Grade

Grey relational grades are calculated using two different formulas for cases where the criteria have equal weights and different weights.

If all criteria have equal weight, it can be calculated with Equation 18, and if the criteria have different weights, it can be calculated with Equation 19.

$$\Gamma_{0i} = \frac{1}{n}\sum_{j=1}^{n} \gamma_{0i}(j), i = 1, \dots, m \tag{18}$$

$$\Gamma_{0i} = \sum_{j=1}^{n} [w_i(j)\gamma_{0i}(j)], i = 1, \dots, m \tag{19}$$

After calculating the grey relational grades, a ranking is made among the series according to their similarity to the reference series. The alternative with the highest grey relational grade is accepted as the best alternative.

4. Findings

The CRITIC approach established the criteria weights in this section. After that, the GRA technique was used to rank the BRICS countries and Türkiye based on their agricultural performance in 2000, 2010, and 2022. Every calculation about the GRA and CRITIC methodologies was completed using the Excel application. FAOSTAT and the World Bank databases provided the data used in this section.

The empirical results reported herein should be considered in the light of some limitations. It is possible to create a more comprehensive scale by increasing the criteria that can be used to measure agricultural performance. For example, criteria related to agricultural support programs implemented in countries, indicators related to agricultural modernization and machine use, indicators related to irrigation opportunities, indicators related to agricultural planning, indicators related to digitalization in agriculture, etc. However, the limited data on these issues limits the scope of the study. It is possible to apply many methods to determine the importance levels of the criteria used. One of these methods was selected in the study and its calculation steps were mentioned. Although the results of several other methods were also examined during the sensitivity analysis, the calculation steps related to each method were not included. In addition, although there are many MCDM methods other than GRA in the ranking of countries, only one of them and its calculation steps were presented. MCDM methods make a ranking among alternatives for a certain period according to certain criteria. This method does not create a trend for the future, but it is possible to make policy recommendations to the relevant countries according to the ranking results. Again, with this method, it is not possible to determine, for example, how much a certain increase in fertilizer use will increase crop production or agricultural revenue. For such analyses, it will be necessary to use different econometric methods.

4.1. Results of the CRITIC Method

Using the CRITIC Method, the importance of the criteria is objectively determined when comparing the performance levels of agriculture across countries. According to the CRITIC method calculations, the highest score represents the most important criterion's percentage weight for each year. These weights are used in the GRA method to determine each country's rank in the related year. The decision matrix used in calculations for both the CRITIC method and the GRA method is the same and is presented in the appendix. Tables related to the other stages of the calculations are not included in the text due to the large amount of space they take up. However, they will be sent if requested by the reader. The weights obtained by the CRITIC method for the years 2000, 2010, and 2022 are shown in Table 2.

Table 2. Importance Level of Criteria by the CRITIC Method

Criteria	2000 Value	Rank	Criteria	2010 Value	Rank	Criteria	2022 Value	Rank
EAG	0.1424	1	EMI	0.1538	1	EMI	0.1519	1
EMI	0.1420	2	EAG	0.1333	2	GVP	0.1493	2
LPP	0.1328	3	LPP	0.1327	3	ARL	0.1295	3
GVP	0.1278	4	GVP	0.1290	4	EAG	0.1295	4
ARL	0.1256	5	ARL	0.1267	5	LLP	0.1250	5
FER	0.1136	6	FER	0.1120	6	FER	0.1128	6
CPP	0.1097	7	CPP	0.1083	7	SSA	0.1019	7
SSA	0.1061	8	SSA	0.1043	8	CPP	0.1000	8

Note: ARL: Arable land (% of land area), CPP: Crops Production, Primary (Ton/Population), EAG: Employment in agriculture (% of total employment) (modeled ILO estimate), EMI: Methane (CH4) Emission from Agriculture (Mt CO2e) (Value/Agricultural Land Hectare), FER: Fertilizer consumption (kilograms per hectare of arable land), GPV: Gross Production Value (constant 2014-2016 thousand US$) (Value/Hectare), LPP: Livestock Production, Primary (Ton/Population), SSA: Self-sufficiency in Agriculture (Export/Import) (%).

According to Table 2, the most important criterion is employment in agriculture in 2000, with a rate of 14,24%, but emissions from agriculture in 2010 and 2022 rates of 15.38% and 15,19%, respectively. Self-sufficiency in agriculture is the least important criterion, with rates of 10,61% in 2000, 10,43% in 2010, and Crop production at 10% in 2022.

4.2. Results of Grey Relational Analysis Method

This study examined the value of data spanning almost a decade to determine the progress made by countries throughout the reviewed time. The data covers the years 2000, 2010, and 2022. The scores and rankings of the countries by the GRA Method on agricultural performance for the related years can be seen in Table 3. The CRITIC method calculated the criteria weights used in the GRA method. So, the results come from the CRITIC-based GRA model, an integrated MCDM model recently used in academic research.

Table 3. Scores and Rankings of Counties by Grey Relational Analysis Method

Countries	2000 Values	Rank	Countries	2010 Values	Rank	Countries	2022 Values	Rank
Russia	0.5880	1	Brazil	0.6118	1	Brazil	0.6400	1
India	0.5767	2	Russia	0.5869	2	Russia	0.5778	2
Brazil	0.5762	3	India	0.5567	3	India	0.5727	3
Türkiye	0.5291	4	Türkiye	0.5102	4	Türkiye	0.5478	4
China	0.5229	5	China	0.5042	5	China	0.4984	5
S. Africa	0.4679	6	S. Africa	0.4603	6	S. Africa	0.4617	6

Table 3 shows that Russia had the best agricultural performance, and South Africa had the worst in 2000. Ten years later, in 2010, Brazil came to the first rank and South Africa to the last. In 2022, the rank did not change. Namely, the first- and last-ranked countries are the same as in 2010. As for Türkiye, it was in the fourth rank in all studied years. The countries' position changes throughout the years can also be observed from the table. In 2000, Russia was the country with the highest agricultural performance. However, it decreased to the second rank in 2010 and 2022. Brazil's position attracted attention since it was in the third rank in 2000, but increased rapidly to the first rank in 2010 and stayed at the top in 2022. India had the second rank in 2000 but decreased to third in 2020 and stayed at the same rank in 2022. South Africa and China had similar ranks. China had the fifth rank, and South Africa followed it with the sixth rank in all the years reviewed.

This study can be compared with Madiyoh et al. (2021), which we were inspired. Madiyoh et al. (2021) analyzed the agricultural performance of ten ASEAN countries using the TOPSIS method, using the criteria of total agricultural production value of the land, self-sufficiency of animal products, self-sufficiency of crop products, rural population rate, greenhouse gas emissions from agriculture, and value of foreign trade in agricultural products. In our study, the employment in agriculture criterion was used instead of the rural population rate, and methane (CH4) emissions from the agriculture criterion were used instead of greenhouse gas emissions from agriculture. In our study, in addition to the above criteria, the arable land criterion was used to measure agricultural production potential, and fertilizer consumption criterion was used to measure productivity. While the analysis in question was carried out for ASEAN countries with the TOPSIS method, our study was carried out with the CRITIC-GRA method for BRICS and Türkiye. While the criterion weights were determined subjectively by the authors in Madiyoh et al. (2021), in our study, the criterion weights were determined with the CRITIC method, which is one of the objective criterion weight determination methods. While no sensitivity analysis was conducted in Madiyoh et al. (2021), a sensitivity analysis was conducted in our study.

4.3. Sensitivity Analysis and Examination of GRA Results

The MCDM method’s outcomes heavily rely on the criteria' weight coefficient values, or the proportional weights given to each criterion. Generally, the results of MCDM approaches should be followed by an investigation of their sensitivity to these changes, since sometimes, a minor change in the weight coefficients of the criterion causes the final selections to alter. A sensitivity analysis was conducted to determine how the ranking of alternatives would shift if the weights assigned to the criterion were altered (Pamučar and Ćirović, 2015).

The sensitivity analysis of the GRA method was carried out using different criterion weights obtained from different objective weighting methods. For this purpose, in addition to the CRITIC method, the Entropy, LOPCOW (Logarithmic Percentage Change-driven Objective Weighting), and standard deviation methods were used. Finally, a situation in which each criterion was equally weighted was also included in the analysis. The criterion weights obtained using these methods for the years 2000, 2010, and 2022 are given in Table 4.

Table 4. Criterion Weights Obtained by Different Weighting Methods, 2000, 2010, 2022

	CRITIC	ENTROPY	LOPCOW	STD DEV	EQUAL
2000					
LPP	0,1328	0,0666	0,0960	0,1204	0,1250
CPP	0,1097	0,0756	0,0678	0,1004	0,1250
GPV	0,1278	0,1471	0,1237	0,1323	0,1250
EAG	0,1424	0,0875	0,1025	0,1262	0,1250
SSA	0,1061	0,0993	0,1769	0,1296	0,1250
FER	0,1136	0,1721	0,1221	0,1381	0,1250
ARL	0,1256	0,1907	0,0670	0,1268	0,1250
EMI	0,1420	0,1610	0,2440	0,1261	0,1250
2010					
	CRITIC	**ENTROPY**	**LOPCOW**	**STD DEV**	**EQUAL**
LPP	0,1327	0,0398	0,1285	0,1087	0,1250
CPP	0,1083	0,1345	0,0347	0,1124	0,1250
GPV	0,1290	0,1105	0,1506	0,1347	0,1250
EAG	0,1333	0,0818	0,1319	0,1201	0,1250
SSA	0,1043	0,2194	0,0731	0,1340	0,1250
FER	0,1120	0,1490	0,1294	0,1354	0,1250
ARL	0,1267	0,1365	0,0698	0,1263	0,1250
EMI	0,1538	0,1285	0,2819	0,1283	0,1250
2022					
	CRITIC	**ENTROPY**	**LOPCOW**	**STD DEV**	**EQUAL**
LPP	0,1250	0,0401	0,1396	0,1091	0,1250
CPP	0,1000	0,1024	0,0547	0,1163	0,1250
GPV	0,1493	0,1117	0,1603	0,1339	0,1250
EAG	0,1295	0,0828	0,1330	0,1201	0,1250
SSA	0,1019	0,2750	0,0427	0,1275	0,1250
FER	0,1128	0,1185	0,1548	0,1323	0,1250
ARL	0,1295	0,1419	0,0575	0,1299	0,1250
EMI	0,1519	0,1277	0,2573	0,1310	0,1250

When the criteria weights are determined using various objective weight determination methods, the differences among these methods are significant. In 2000, the EAG (Employment in Agriculture) criterion ranked first with 14.24% using the CRITIC method, the ARL (Arable Land) was at 19.07% using the Entropy method, the EMI (Methane (CH4) Emissions from Agriculture) accounted for 24.4% with the LOPCOW method, and the FER (Fertilizer Consumption) had 13.81% according to the Standard Deviation method. In the equal-weight method, each criterion was assigned a weight of 12.5%.

In 2010, the EMI (Methane (CH4) Emissions from Agriculture) criterion ranked first with 15.38% using the CRITIC method, followed by SSA (Self-sufficiency in Agriculture) at 21.94% with the Entropy method, EMI (Methane (CH4) Emissions from Agriculture) at 28.19% with the LOPCOW method, and FER (Fertilizer Consumption) at 13.54% using the Standard Deviation method. In the Equal-weight method, each criterion was allocated a weight of 12.5%.

In 2022, the EMI (Methane (CH4) Emissions from Agriculture) criterion was ranked first with 15.19% using the CRITIC method, SSA (Self-sufficiency in Agriculture) with 27.5% in the Entropy method, EMI (Methane (CH4) Emissions from Agriculture) with 25.73% in the LOPCOW method, and GPV (Gross Production Value) with 13.39% in the Standard Deviation method. In the equal-weight method, each criterion was assigned a weight of 12.5%.

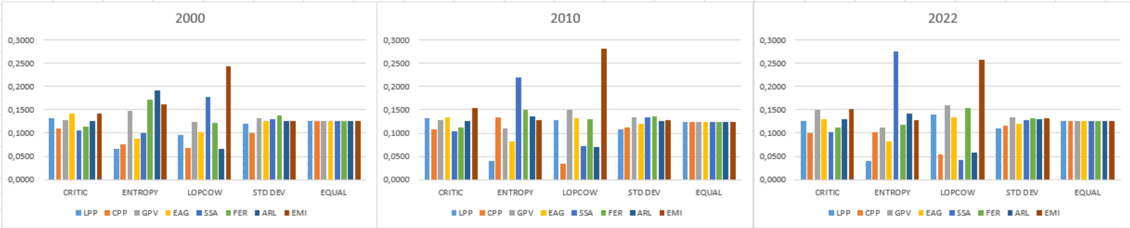

Figure 1. Criteria Weights by Different Methods (2000, 2010, 2022)

The weight values derived from the CRITIC method, the Standard Deviation method, and the equal-weight approach are quite similar, as shown in Figure 1; however, the weights derived from the Entropy and LOPCOW approaches differ. When the weights obtained with the LOPCOW method are examined, it is noteworthy that the EMI criterion differs significantly from the weights of other criteria in the three periods examined. In the Entropy method, it is seen that the weight of the SSA criterion differs from the weights of other criteria in 2010 and 2022.

Countries were ranked by integrating the criteria weights obtained with the CRITIC, Entropy, LOPCOW, Standard Deviation, and Equal-weight methods with the GRA method. The sensitivity analysis results on how the GRA method responds to changes in the criteria weights are given in Table 5.

Table 5. GRA Method Sensitivity Analysis Results

			2000		
	CRI_GRA	**ENT_GRA**	**LOP_GRA**	**STD_GRA**	**EQU_GRA**
Brasil	3	3	2	2	1
Russia	1	1	1	1	2
India	2	2	6	3	3
China	5	5	5	5	5
S. Africa	6	6	4	6	6
Türkiye	4	4	3	4	4
			2010		
	CRI_GRA	**ENT_GRA**	**LOP_GRA**	**STD_GRA**	**EQU_GRA**
Brasil	1	1	2	1	1
Russia	2	2	1	2	2
India	3	3	6	3	3
China	5	5	4	4	5
S. Africa	6	6	5	6	6
Türkiye	4	4	3	5	4
			2022		
	CRI_GRA	**ENT_GRA**	**LOP_GRA**	**STD_GRA**	**EQU_GRA**
Brasil	1	1	2	1	1
Russia	2	3	1	2	2
India	3	2	4	3	3
China	5	5	5	5	5
S. Africa	6	6	6	6	6
Türkiye	4	4	3	4	4

When Table 5 is examined, it is seen that the rankings obtained from the CRITIC-GRA method in the relevant years are largely similar to the results obtained from the Entropy-GRA method. In addition, the results of the Standard Deviation-GRA method and the Equal Weights-

GRA method are almost the same. It is noteworthy that the results of the LOPCOW-GRA method differ from the other methods. The weight rankings obtained with the LOPCOW method also differed from the other methods. Namely, according to the LOPCOW method, Methane (CH4) Emissions from Agriculture were determined as the most important criterion by far from the other criteria in the relevant three years. This situation seems to have caused the results of the LOPCOW-GRA method to differ from the results of the other methods. Therefore, it is possible to say that the GRA method is sensitive to changes in the criterion weights.

5. Conclusion

Brazil, Russia, India, China, and South Africa are the five leading emerging economies of the BRICS international economic alliance. Due to their similar economic potential, these nations hope to unite and have a bigger voice in the global economy. These nations are regarded as major actors because of their size, quick development, and strategic significance in the global economy.

This study used the CRITIC-based GRA approach to examine the agricultural performance of the BRICS countries and Türkiye. The CRITIC approach was used to establish the criteria's importance, and the countries were ranked based on their agricultural performance in 2000, 2010, and 2022. The reason for choosing three different years is to monitor the changing trend of the agricultural performance of the countries over time. This is a multifaceted agricultural performance analysis that covers a wide range of agricultural topics, including production, consumption, employment, agricultural potential, productivity, self-sufficiency, and the environment, rather than comparing nations based on the production of particular items.

If an expert had been consulted to define the criteria weights, this study might have been finished without the use of the CRITIC approach. However, this scenario may have been questioned because subjectivity would have been involved. A hybrid strategy known as the CRITIC-GRA model was created to lessen the possible criticisms that can be aimed at this issue. The CRITIC method is one of the objective weight determination strategies that has been widely used in recent years.

According to the CRITIC technique, employment in agriculture is the most significant factor in 2000 and agricultural emissions in 2010 and 2022, while self-sufficiency in agriculture in 2000 and 2010 and crop production in 2022 are the least significant criteria. According to the GRA Method, Russia ranked first in 2000 for agricultural performance. However, Brazil topped the list in both 2010 and 2022. South Africa was ranked lowest in all studied years. Regarding Türkiye, it had the fourth rank in 2000 and stayed at the same rate in 2010 and 2022.

Brazil's success can be attributed to its agricultural policies, which have been in effect since the 1990s. Brazil is among the nations that have made great strides in exporting and producing agricultural goods. An information technology-focused division of the Brazilian Agricultural Research Agency has created a range of computerized systems for use in fundamental research and agro-industrial applications since 1991. Despite a decline in Brazil's agricultural labor market, the advancements in agro-industrial technological systems with Agriculture 4.0 have increased the demand for more specialized personnel. As part of Agriculture 4.0, artificial neural networks are used in Brazil to estimate soybean harvest and determine the ideal planting area size. Brazilian programs known as "BovChain" use big data and cloud computing to control socio-environmental aspects. These apps connect buyers, investors, slaughterhouses, and farmers. The real-time monitoring of herds and commercial transactions within a shared digital market facilitates accountability and environmental management of agricultural and animal production chains. In terms of precision agriculture, Brazil has also advanced significantly. In this context, applications have been developed in smart irrigation, pesticide optimization, satellite surveillance, and computational visualization of crops and animals. A Brazilian platform named "Agrosmart" is another example that stands out in this context. Its goals are to improve product performance and lessen its influence on the environment (Aydınbaş, 2024: 526).

The following can be said about South Africa having the lowest performance. This country has one of the largest agricultural lands in the world, with 96 million hectares of agricultural land. However, extraordinary heatwaves and the absence of rain at critical times affect not only summer planting areas, but also the livestock industry in the country. The recurrence of drought effects in the country continues to exist as a long-term risk factor for the agricultural sector (Meza et al., 2021)

The agricultural performance of low-performing nations will improve if they implement measures to lower agricultural emissions and boost productivity, self-sufficiency, per capita consumption of agricultural products, agricultural production, and arable land.

Declaration of Research and Publication Ethics
This study, which does not require ethics committee approval and/or legal/specific permission, complies with the research and publication ethics.

Researcher’s Contribution Rate Statement
The authors declare that they have contributed equally to the article.

Declaration of Researcher’s Conflict of Interest
There are no potential conflicts of interest in this study.

References

Almeida, I.D.P., Hermogenes, L.R.S., Costa, I.P.A., Moreira, M.A.L., Gomes, C.F.S., Santos, M., … Gomes, I.J.A. (2022a). Assisting in the choice to fill a vacancy to compose the PROANTAR team: Applying VFT and the CRITIC-GRA-3N methodology. *Procedia Computer Science*, 214, 478-486. doi:10.1016/j.procs.2022.11.202

Almeida, I.D.P., Hermogenes, L.R.S., Costa, I.P.A., Moreira, M.A.L., Gomes, C.F.S., Santos, M., … Gomes, I.J.A. (2022b). Structuring and mathematical modeling for investment choice: a multi-method approach from value-focused thinking and CRITIC-GRA-3N method. *Procedia Computer Science*, 214, 469-477. doi:10.1016/j.procs.2022.11.201

Altıntaş, F.F. (2021). Karadeniz ekonomik işbirliği örgütüne üye ülkelerin inovasyon performanslarının CRITIC tabanlı GRI ilişkisel analiz yöntemi ile incelenmesi. *Karadeniz Araştırmaları,* 18(71), 547-570. Retrieved from https://dergipark.org.tr/tr/pub/karadearas

Atan, M. and Altan, Ş. (2020). *Örnek uygulamalarla çok kriterli karar verme yöntemleri*. Ankara: Gazi Kitabevi.

Aydınbaş, G. (2024). Tarımsal verimlilik ile ilişkili faktörlerin tespiti: BRICS-T ülkeleri örneği. *Türk Tarım ve Doğa Bilimleri Dergisi,* 11(2), 524–535. doi:10.30910/turkjans.1401633

Baki, R. (2024). Comparison of innovation performances of BRICS countries through CRITIC and GRA methods. *Gaziantep University Journal of Social Sciences,* 23(4), 1561-1570. doi:10.21547/jss.1368192

Brodny, J. and Tutak, M. (2023). Assessing the level of digital maturity in the Three Seas Initiative countries. *Technological Forecasting and Social Change,* 190, 122462. doi:10.1016/j.techfore.2023.122462

Çilek, A., and Şeyranlıoğlu, O. (2024). Temettü verimi ile karlılık oranları arasındaki ilişki: Borsa İstanbul temettü 25 endeksinde bir inceleme. *Journal of Economics and Administrative Sciences*, 25(1), 166-182. doi:10.37880/cumuiibf.1381845

Deng, J.L. (1982). Control-Problems of Grey Systems. *Systems & Control Letters*, 1, 288-294, https://doi.org/10.1016/S0167-6911(82)80025-X

Diakoulaki, D., Mavrotas, G. and Papayannakis, L. (1995). Determining objective weights in multiple criteria problems: The CRITIC method. *Computers & Operations Research*, 22(7), 763–770. https://doi.org/10.1016/0305-0548(94)00059-H

Dinçer, S.E. (2019). *Çok kriterli karar alma*. Ankara: Gece Akademi.

FAO. (2024). *Food and agriculture data*. Retrieved from https://www.fao.org/faostat/en/#data

FAOSTAT. (2024). Retrieved from http//fao.org/faostat/en/#home

Geeri, S., Kolakoti, A., Samuel, O.D., Abbas, M., Aigba, P.A., Ajimotokan, H.A., … Mujtaba, M.A. (2024). Investigation of flow behavior in the nozzle of a Pelton wheel: Effects and analysis of influencing parameters. *Heliyon,* 10(8), e28986. doi:10.1016/j.heliyon.2024.e28986

Gök Kısa, A.C. (2021). TR83 bölgesinde yenilenebilir enerji kaynaklarının CRITIC tabanlı gri ilişkisel analiz yaklaşımı ile değerlendirilmesi. *Pamukkale University Journal of Engineering Sciences,* 27, 542-548. doi:10.5505/pajes.2021.99389

Gürlük, S. and Uzel, G. (2016). An evaluation of agri-environmental indicators through a multi-criteria decision-making tool in Germany, France, the Netherlands, and Türkiye. *Polish Journal of Environmental Studies*, 25(4), 1523-1528. Retrieved from https://www.pjoes.com/

Junior, E.L.P., Morreira, M.AL., Gomes, C.F.S., Santos, M., Costa, A.P.A., Chagas, S.S.S., … Kojima, E.H. (2023). Supply Chain Management (SCM): An analysis based on the CRITIC-GRA-3N method in the selection of auto parts suppliers for an auto parts dealer in the city of Guaratinguetâ. *Procedia Computer Science*, 221, 402-409. doi:10.1016/j.procs.2023.07.055

Kargı, V. S. A. (2022). Determining digital readiness levels of the OECD countries with CRITIC-based ARAS method. *Akademik Yaklaşımlar Dergisi*, 13(2), 363-376. https://doi.org/10.54688/ayd.1111357

Keleş, N. (2023). CRITIC tabanli gri ilişkisel analiz yöntemiyle OECD ülkelerinin sürdürülebilir taşimacilik performanslarinin değerlendirilmesi. *Süleyman Demirel Üniversitesi Vizyoner Dergisi,* 14(38), 544-563. doi:10.21076/vizyoner.1142333 (in Turkish)

Liu, P., Liu, C., Wang, Z., Wang, Q., Han, J. and Zhou, Y. (2023). A data-driven comprehensive battery SOH evaluation and prediction method based on improved CRITIC-GRA and Att-BiGRU. *Sustainability,* 15, 15084. doi:10.3390/su152015084

Madiyoh, A., Turan, Ö. and Gürlük, S. (2021). Agriculture policy scores of selected countries through the technique for order of preference (TOPSIS) method. *Rural Sustainability Research,* 45, 7-12. doi:10.2478/plua-2021-0002

Meza, I., Eyshi Rezaei, E., Siebert, S., Ghazaryan, G., Nouri, H., Dubovyk, O., Gerdener, … Hagenlocher, M. (2021). Drought risk for agricultural systems in South Africa: Drivers, spatial patterns, and implications for drought risk management. *Science of The Total Environment*, 799, 149505. https://doi.org/10.1016/j.scitotenv.2021.149505

Miao, C., Teng, J., Wang, J., & Zhou, P. (2018). Population vulnerability assessment of geological disasters in China using CRITIC–GRA methods. *Arabian Journal of Geosciences*, 11, 1-12. https://doi.org/10.1007/s12517-018-3598-z

Nguyen, T.K.L., Le, H., Ngo, V. and Hoang, B. (2020). CRITIC method and grey system theory in the study of global electric ears. *World Electric Vehicle Journal*, 11, 79, 1-15. doi:10.3390/wevj11040079

Pamučar, D. and Ćirović, G. (2015). The selection of transport and handling resources in logistics centers using multi-attributive border approximation area comparison (MABAC). *Expert Systems with Applications,* 42(6), 3016-3028. doi:10.1016/j.eswa.2014.11.057

Qi, Q.S. (2021). GRA and CRITIC method for intuitionistic fuzzy multiattribute group decision making and application to development potentiality evaluation of cultural and creative garden. *Mathematical Problems in Engineering,* 9957505. doi:10.1155/2021/9957505

Saeheaw, T. (2022). Application of integrated CRITIC and GRA-based Taguchi method for multiple quality characteristics optimization in laser-welded blanks, *Heliyon*, 8(11), e11349. doi:10.1016/j.heliyon.2022.e11349

Silva, N.F., Santos, M., Gomes, C.F.S. and Andrade, L.P. (2023). An integrated CRITIC and grey relational analysis approach for investment portfolio selection. *Decision Analytics Journal*, 8, 100285. doi:10.1016/j.dajour.2023.100285

Singh, R.K., Tiwari, S. K., Srivastava, S.C. and Kumar, B. (2023). Hybrid Taguchi-GRA-CRITIC optimization method for multi-response optimization of micro-EDM drilling process parameters. *Technical Gazette,* 30(3), 804-814. doi:10.17559/TV-20220601114015

Türkoğlu, M. and Duran, G. (2023). G20 ülkelerinin lojistik performanslarının CRITIC tabanlı GIA ve WASPAS uygulaması ile değerlendirilmesi. *Hukuk ve İktisat Araştırmaları Dergisi,* 15(1), 50-72. doi:10.53881/hiad.1247196

Wang, R.T, Ho, C.T, Feng, C.M. and Yang, Y.K. (2004). A comparative analysis of the operational performance of Taiwan's major airports. *Journal of Air Transport Management,* 10(5), 353-360. doi:10.1016/j.jairtraman.2004.05.005

Wei, G., Lei, F., Lin, R., Wang, R., Wu, J. and Wei, C. (2020). Algorithms for probabilistic uncertain linguistic multiple attribute group decision making based on the GRA and CRITIC method: application to location planning of electric vehicle charging stations. *Economic Research-Ekonomska Istraživanja,* 33, 828-846. doi:10.1080/1331677X.2020.1734851

Wen, K.L. (2004). The grey system analysis and its application in gas breakdown and var compensator finding. *International Journal of Computational Cognition*, 2(1), 21-44. Retrieved from https://citeseerx.ist.psu.edu/

World Bank. (2024). [Dataset]. http://data.worldbank.org

Xu, T., Liu, X. and Zhang, Z. (2020). Simplified likelihood estimation of ship total loss using GRA and CRITIC methods. *Transportation Planning and Technology*, 43(2), 223-236. doi:10.1080/03081060.2020.1717147

Zardari, N.H., Ahmed, K., Shirazi, S.M. and Yusop, Z.B. (2015). *Weighting methods and their effects on multi-criteria decision making model outcomes in water resources management*. USA: Springer Press.

Zhai, L.Y., Khoo, L.P. and Zhong, Z.W. (2009). Design concept evaluation in product development using rough sets and grey relation analysis. *Expert systems with Applications*, 36(3), 7072-7079. https://doi.org/10.1016/j.eswa.2008.08.068

Zhou, Z., Zhang, Y., Zhang, Y., Hou, B., Mei, Y., Wu, P., … Chen, F. (2024). Advanced CRITIC–GRA–GMM model with multiple restart simulation for assuaging decision uncertainty: An application to transport safety engineering for OECD members. *Advanced Engineering Informatics*, 60, 102373. doi:10.1016/j.aei.2024.102373

APPENDIX

Decision Matrix, 2000

Country/Criteria	EMI	LPP	CPP	GPV	EAG	SSA	FER	ARL
Brasil	1,40064E-06	0,227021771	2,7767537	0,533830289	15	286,30	144,5168104	5,437573431
Russia	3,56876E-07	0,270182882	0,8731284	0,322427497	14	25,40	287,4484879	7,592419179
India	2,75452E-06	0,081768868	0,6978594	1,173913524	60	195,45	103,7861182	54,12704873
China	1,2388E-06	0,083685714	0,9377889	1,900355335	50	126,44	11,41717722	12,69706
S.Africa	2,60892E-07	0,099416829	1,037276	0,181136306	21	141,36	53,5983203	11,3857999
Türkiye	7,26303E-07	0,187712512	1,5600961	1,42661627	37	103,72	87,66943675	30,95773294

EMI: Methane (CH4) Emission from Agriculture (Mt CO2e) (Value/Agricultural Land Hectare), **LPP**: Livestock Production, Primary (Ton/Population), **CPP**: Crops Production, Primary (Ton/Population), **GPV**: Gross Production Value (constant 2014-2016 thousand US$) (Value/Hectare), **EAG**: Employment in agriculture (% of total employment) (modeled ILO estimate), **SSA**: Self-sufficiency in Agriculture (Export/Import) (%), **FER**: Fertilizer consumption (kilograms per hectare of arable land), **ARL**: Arable land (% of land area)

Decision Matrix, 2010

Country/Criteria	EMI	LPP	CPP	GPV	EAG	SSA	FER	ARL
Brasil	1,78274E-06	0,308261142	4,8733455	0,807546945	11	647,81	202,7967653	6,150291811
Russia	3,06273E-07	0,29631289	0,893888	0,369003313	8	18,45	425,2393478	7,428098287
India	2,96537E-06	0,107990323	0,7030008	1,602930285	51	216,72	179,0358769	52,80826318
China	1,23078E-06	0,116549254	1,1216851	2,579383919	37	49,52	15,72450246	12,81035593
S.Africa	2,93113E-07	0,132548035	0,8284638	0,239619779	17	116,60	53,77802601	10,33146757
Türkiye	7,40798E-07	0,232383583	1,4255284	1,860068697	24	116,57	98,3756547	27,7847797

EMI: Methane (CH4) Emission from Agriculture (Mt CO2e) (Value/Agricultural Land Hectare), **LPP**: Livestock Production, Primary (Ton/Population), **CPP**: Crops Production, Primary (Ton/Population), **GPV**: Gross Production Value (constant 2014-2016 thousand US$) (Value/Hectare), **EAG**: Employment in agriculture (% of total employment) (modeled ILO estimate), **SSA**: Self-sufficiency in Agriculture (Export/Import) (%), **FER**: Fertilizer consumption (kilograms per hectare of arable land), **ARL**: Arable land (% of land area).

Decision Matrix, 2022

Country/Criteria	EMI	LPP	CPP	GPV	EAG	SSA	FER	ARL
Brasil	2,00542E-06	0,783180765	10,011142	1,101242886	9	962,22	363,0017726	6,657229958
Russia	2,86319E-07	0,721576295	3,793978	0,592582624	6	90,45	397,6634511	7,428098287
India	3,14181E-06	0,334382394	1,7162437	2,390578085	43	151,07	193,2275591	51,9468813
China	1,22334E-06	0,276034043	2,6855376	3,264454707	23	31,19	28,21271034	11,50847311
S.Africa	2,57419E-07	0,324990817	1,8306842	0,310874913	19	167,48	91,46647417	9,892093744
Türkiye	1,38506E-06	0,710496587	3,0269593	3,085078738	17	106,60	114,5730415	26,23858218

EMI: Methane (CH4) Emission from Agriculture (Mt CO2e) (Value/Agricultural Land Hectare), **LPP**: Livestock Production, Primary (Ton/Population), **CPP**: Crops Production, Primary (Ton/Population), **GPV**: Gross Production Value (constant 2014-2016 thousand US$) (Value/Hectare), **EAG**: Employment in agriculture (% of total employment) (modeled ILO estimate), **SSA**: Self-sufficiency in Agriculture (Export/Import) (%), **FER**: Fertilizer consumption (kilograms per hectare of arable land), **ARL**: Arable land (% of land area).