

Article

Analyzing Nitrogen Fertilizer Markets in the Context of Agricultural Sustainability: Informed Target Market Selection with Multi-Criteria Decision-Making

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Abstract

Nitrogen fertilization is essential for balancing yield stability and supporting agricultural intensification, particularly in nations where cropland expansion is constrained. The pivotal role of nitrogen fertilizers in sustainable agriculture also renders them a strategically traded commodity. Consequently, trade-oriented analyses of fertilizer markets represent a vital dimension of sustainability research, as they influence input accessibility, production stability, and global food security. This study aims to develop an integrated and structured multi-criteria decision-making (MCDM) framework to identify emerging markets for nitrogen fertilizer exporters, accounting for the multi-dimensional impacts of global change. The analysis focuses on AMIS countries, which constitute the core of global agricultural production and trade. The decision model incorporates a diverse set of agricultural, demographic, and trade-related criteria, including import value, trade balance, agricultural nitrogen use, fertilizer use per unit of cropland, cropland availability, food vulnerability, and urbanization rate. Criterion weights are established using the CRITIC method—accounting for both contrast intensity and inter-criteria correlations—while alternative markets are ranked via the Fuzzy TOPSIS method. The results indicate that India, the United States, and China achieved the highest overall scores, with closeness coefficients of 0.5945, 0.5197, and 0.5098, respectively. The most influential criteria are food vulnerability (0.2035), urbanization (0.1865), and cropland area (0.1407). The findings identify high-potential markets characterized by structurally sustained fertilizer demand, driven by land constraints, demographic pressures, and the necessity for agricultural intensification.

Keywords: international market selection; fertilizer market; multi-criteria model; sustainable agriculture; global food security



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1. Introduction

Feeding the growing world population has long been a central global concern. Rising population, climate change, and multifaceted crises—such as pandemics and geopolitical conflicts—represent major challenges exacerbating global food insecurity and vulnerability. Recent global assessments highlight the severity of these challenges; the United Nations (UN) projects that the world's population will reach 10.3 billion in the mid-2080s, a significant increase from 8.2 billion in 2025 [1], driving higher food demand. Furthermore, the Food Security Information Network (FSIN) and the Global Network Against

Food Crises (GNAFC) reported that 281.6 million people across 59 food-crisis countries faced acute food insecurity in 2023 [2]. Parallel to demographic growth, urbanization also plays a pivotal role in the escalating food demand through its impact on land-use alterations. Urbanization, together with industrial development, exerts significant pressure on cropland availability by encroaching upon high-quality cultivated land [3]. According to World Bank projections, urbanization will continue to rise, with approximately 68% of the global population residing in urban areas by 2050 [1]. Simultaneously, global urban land area is expected to increase by an average of 112% [4], expanding to 3.6 million square kilometers by 2100 [5]. Notably, over 60% of the world's irrigated farmland is situated in the immediate vicinity of urban centers [6], underscoring the intensified pressure for conversion and fragmentation of productive cropland, particularly in Asia, Africa, and South America [4]. Consequently, cropland areas continue to decline, especially in rapidly urbanizing nations [7–10]. Empirical studies indicate that approximately 50–63% of new urban expansion is expected to occur on existing croplands, potentially resulting in a 1–4% decline in global food production [11].

In the current era, characterized by rapid urbanization, climate change and geopolitical upheaval, expanding agricultural output through land conversion has become increasingly constrained. Consequently, productivity gains achieved through input-intensive farming practices have become the primary mechanism for meeting rising food demand [12,13]. Agricultural productivity research underscores the growing significance of fertilizers as key determinants of yield performance [12,14,15]. Within this framework, modern agricultural inputs—specifically fertilizers—play a central role, as they directly influence production stability and resource-use efficiency. Nitrogen-based fertilizers (N-fertilizers) in particular constitute a critical production input embedded in modern food systems. The use of N-fertilizers remains one of the most vital practices in contemporary agriculture [16] and has become increasingly essential for sustaining productivity under conditions of land scarcity and escalating demand. Given their critical role, the demand for N-fertilizers is projected to rise under the collective pressures of urbanization, global population growth, and declining arable land. Therefore, N-fertilizers can be regarded as one of the most tactical trade commodities for ensuring global food security. Accordingly, generating systematic, comparative, and data-driven insights into countries where demographic trends and agricultural practices sustain expanding demand is important for the initial screening of potential N-fertilizer markets, irrespective of a specific exporting origin. However, existing literature generally examines the fertilizer industry from either a production or an agricultural-use perspective, leaving a gap in trade-oriented strategic analysis. Research concerning N-fertilizer trade operations and export-oriented target market selection remains remarkably limited. Existing studies primarily concentrate on conventional trade metrics, often neglecting the profound impact of global structural shifts. Specifically, there is a lack of data-driven frameworks that concurrently account for urbanization pressures, cropland constraints, and food vulnerability alongside commercial trade dynamics. Consequently, a comprehensive assessment of the N-fertilizer trade necessitates an integrated evaluation of both market-based factors and broader structural drivers.

Addressing this gap, this research aims to provide an exporter-independent, first-stage screening and prioritization of potential N-fertilizer markets by jointly assessing destination-country trade conditions and the structural drivers of agricultural demand. Rather than identifying the optimal market for a particular exporting country or firm, the framework evaluates the general structural attractiveness of alternative destination markets. Rather than presenting MCDM as a novel methodology in itself, the study extends existing target-market selection research by developing a fertilizer-specific decision framework that integrates conventional trade indicators with agricultural use, fertilizer-use

intensity, cropland availability, food vulnerability, and urbanization. This multidimensional structure enables countries to be evaluated not only according to their current commercial attractiveness but also according to the longer-term agricultural and demographic conditions shaping N-fertilizer demand. By combining objective CRITIC weighting with Fuzzy TOPSIS and incorporating long-term market observations, the framework provides a systematic basis for distinguishing structurally sustained fertilizer markets from markets whose attractiveness is primarily driven by short-term trade conditions.

The study contributes to the literature in three main respects. First, it extends the application of target-market selection models to the N-fertilizer sector by addressing a product-specific trade problem with direct implications for agricultural productivity and food security. Second, it integrates conventional trade indicators with agricultural, demographic, land-use, and food-vulnerability variables, thereby broadening the assessment of market potential beyond current import performance. Third, it combines objective CRITIC weighting with Fuzzy TOPSIS and long-term market observations to account for both the informational structure of the criteria and the uncertainty associated with changing market conditions. These contributions are conceptual and application-oriented rather than based on the methodological novelty of MCDM itself.

Furthermore, the research contributes to sectoral development by supporting data-driven marketing strategies and providing strategic insights for exporting countries and enterprises. Identifying high-potential markets can help refine international marketing strategies, reduce market-entry uncertainty, and enhance long-term competitiveness amid intensifying global food-security pressures.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature on MCDM techniques applied to target market selection, alongside prior studies on fertilizer markets. Section 3 provides a detailed exposition of the dataset, the selected criteria, and the procedural steps of the CRITIC and Fuzzy TOPSIS methods used for weighting and ranking the nitrogen fertilizer markets. Section 4 presents the resulting criteria weights and market rankings, followed by a comprehensive discussion of the high-potential markets identified. Finally, Section 5 offers a summary of the overall findings, outlines strategic implications for policymakers and exporters, and suggests directions for future research.

2. Literature Review

Target market selection is a multidimensional challenge influenced by economic, logistical, political, and social variables, requiring decision-makers to evaluate multiple and often conflicting criteria simultaneously. In this context, the rapid increase in publications using MCDM across industrial and other application areas highlights the relevance of these methods for complex decision-making problems involving competing objectives and constraints [17]. In the existing literature, research in this domain is typically categorized by either methodological frameworks—ranging from AHP and TOPSIS to entropy and hybrid systems—or by specific industrial contexts. Due to its efficacy in structuring hierarchical decisions, AHP has seen extensive adoption. For instance, Aghdaie et al. (2013) utilized a Fuzzy AHP-COPRAS-G model to examine entry barriers in the Iranian furniture sector, while Sener (2014) and Aghdaie and Alimardani (2015) applied AHP and hybrid AHP-TOPSIS models, respectively, to identify strategic expansion opportunities in the porcelain and furniture industries [18–20].

The application of these methods extends into customer segmentation and diverse industrial sectors. Güçdemir and Selim (2015) merged AHP with segmental clustering to categorize OEM customers, whereas Khalili and Khalilpour (2016) leveraged TOPSIS for risk-based classification [21,22]. Subsequent sector-specific evaluations expanded upon

these frameworks by incorporating Ghorabae et al. (2017), who applied the CODAS technique to the footwear industry, and Oey et al. (2018), who integrated goal programming with AHP for the metal products sector [23,24]. In an agricultural context, Ünal and Çetin (2019) employed a hybrid AHP-TOPSIS model to identify prime fertilizer markets in India and Brazil, demonstrating a recurring scholarly emphasis on economic and logistical feasibility [25].

Recent years have witnessed a shift toward advanced computational and objective data-driven approaches. The integration of machine learning for retail satisfaction classification [26] and the use of hybrid systems like TOPSIS-GRA-ANP for the hosiery industry [27] reflect this trend. Furthermore, researchers such as Ray et al. (2021) and Vanegas-Lopez et al. (2021) integrated MCDM tools with data mining to enhance export entry strategies in the retail and textile sectors [28,29]. While Çelik and Akmermer (2022) underscored product-specific preferences in seafood markets using Fuzzy AHP-TOPSIS, Duong and Thao (2021) shifted toward objective entropy-based weighting to evaluate agricultural segments [30,31].

The most contemporary literature highlights a transition toward increasingly sophisticated hybrid models to navigate the complexities of modern trade. Recent contributions include the use of TOPSIS for transportation demand [32], proximity–distance models for insurance classification [33], and complex integrations such as AHP-VIKOR-TOPSIS for the fiberboard industry [34]. Furthermore, the emergence of the Comparative Alternative Market Assessment (CAPMA) method has provided specialized insights into commodity markets like hazelnuts and figs [35,36]. Öztürkçü (2025) introduced an entropy-ARAS-CAPMA framework for the dried apricot trade [37]. Recent studies have continued to explore export market dynamics; for instance, Meral et al. (2025) utilized a hybrid Entropy-TOPSIS framework to assess potential international markets for Turkey’s dried apricot exports [38]. In a similar vein, Akmermer and Şentürk (2026) investigated the expansion of wood pellet markets by employing a combination of the CRITIC and ARAS methodologies [39]. Collectively, these advancements signify a clear methodological evolution toward more integrated and robust decision-making architectures in global trade analysis.

3. Materials and Methods

This research adopts a structured and systematic methodological framework for the exporter-independent screening and prioritization of potential N-fertilizer destination markets. The methodology is designed to ensure analytical transparency and replicability while considering the multiple dimensions—such as market attractiveness, vulnerability-related risks, and external supply dependence—that characterize international markets. This framework facilitates the simultaneous integration of heterogeneous indicators capturing demand intensity, trade potential, and structural fragilities within a unified decision matrix.

In the present decision problem, the decision-maker is conceptualized as a generic N-fertilizer exporter rather than a specific exporting country or fertilizer-producing firm. The decision objective is to comparatively assess the structural attractiveness of alternative destination markets and identify countries warranting further exporter-specific evaluation. Accordingly, the model focuses on destination-country characteristics and does not incorporate origin-specific or firm-specific factors. Geographic distance, freight costs, bilateral tariffs, sanctions, trade agreements, port and logistics conditions, payment risk, existing distribution channels, product-registration requirements, and geopolitical relationships are therefore outside the scope of the present analysis. Consequently, the resulting rankings represent a first-stage market screening rather than definitive market-entry recommendations for a particular exporter. The comprehensive research workflow is illustrated in Figure 1.

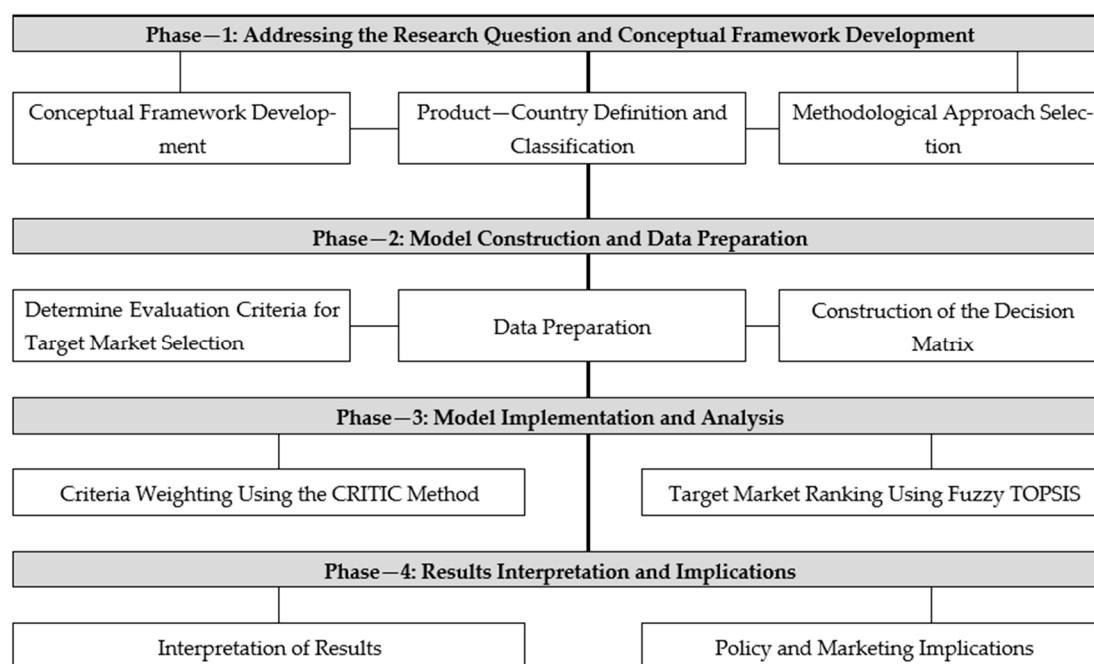


Figure 1. Research methodology. The authors used (ChatGPT, GPT-5, OpenAI) to support the ideation and initial draft of Figure 1.

3.1. Product Classification for Nitrogen Fertilizers in International Trade

To ensure consistency in data selection and cross-country comparability, the product classification for nitrogen fertilizers is explicitly defined in Table 1. This empirical research utilizes the Harmonized System (HS) chapters as the basis for product classification. The HS, an international nomenclature published by the World Customs Organization (WCO), enables participating countries to categorize traded goods on a standardized basis for customs and statistical purposes. At the international level, the HS nomenclature operates as a hierarchical six-digit coding system. The specific nitrogen fertilizer products analyzed in this study, along with their corresponding HS codes, are detailed in Table 1. All trade data utilized in this research were compiled based on these codes.

Table 1. Harmonization codes of N-fertilizer product group.

HS Codes	Mineral or Chemical Nitrogenous Fertilizers (3210)
310210	Urea, whether in aqueous solution or not (excl. that in tablets or similar forms, or in packages)
310221	Ammonium sulphate (excl. that in tablets or similar forms, or in packages with a gross weight)
310230	Ammonium nitrate, whether in aqueous solution or not (excl. that in tablets or similar forms)
310240	Mixtures of ammonium nitrate with calcium carbonate or other inorg. non-fertilizing substances
310280	Mixtures of urea and ammonium nitrate in aqueous or ammoniacal solution
310290	Mineral or chemical nitrogen fertilizers (excl. urea; ammonium sulphate; ammonium nitrate)
310260	Double salts and mixtures of calcium nitrate and ammonium nitrate
310229	Double salts and mixtures of ammonium sulphate and ammonium nitrate
310250	Sodium nitrate (excl. that in tablets or similar forms, or in packages with a gross weight)

3.2. Selection of Countries as Decision Alternatives

The decision alternatives in the proposed screening framework consist of the Agricultural Market Information System (AMIS) participant countries, which are evaluated as potential N-fertilizer destination markets. These countries were selected due to their dominant roles in global agricultural production, consumption, and trade, as well as their influence on international food markets and input-demand dynamics. AMIS is composed of G20 members plus Spain and eight additional major countries exporting and importing

agricultural commodities. Collectively, the AMIS countries shown in Table 2 account for approximately 80–90% of global production, consumption, and trade of the targeted crops.

Table 2. List of AMIS countries grouped according to their importance for research purposes.

Advanced Economies/Developed Agricultural Markets		
• United States • Canada • Australia	• Japan • Republic of Korea • France	• Germany • United Kingdom • Italy
Countries with large-scale, high-input, technology-intensive agriculture. This group consists of markets where demand for fertilizer is permanent in the medium–long term, due to high productivity and input intensity.		
Major Emerging Agricultural Producers		
• China • India	• Brazil • Russia	• Argentina • Indonesia
Countries with high cultivated areas and absolute fertilizer consumption The countries with the highest volumetric impact on global fertilizer demand are in this group.		
Middle-Income, Rapidly Urbanizing Economies		
• Mexico • Türkiye	• Thailand • Vietnam	• Philippines
Countries experiencing rapid urbanization, increasing food demand, and high levels of intensification pressure. These countries are important for considering the relationship between urbanization and fertilizer demand.		
Food-Import-Dependent & Vulnerability-Exposed Countries		
• Egypt • Nigeria		
Countries experiencing high food vulnerability and with import-dependent agricultural systems. In these countries, agricultural production is highly dependent on imported fertilizers due to limited domestic input capacity. Thus, trade balance and food vulnerability indicators are particularly important for assessing fertilizer market potential.		
Resource-Based Economies with Agricultural Dependence		
• Saudi Arabia		
Countries experiencing limited but critical agricultural production. Food security is politically important. The fertilizer market is largely import-dependent, and there is policy-driven demand.		

Furthermore, AMIS nations increasingly shape international food markets and input demand trends. Fertilizer demand within these countries is structurally embedded in large-scale agricultural systems and global supply–demand balances, making them critical case studies for N-fertilizer market analysis.

3.3. Determination of Criteria

The structural attractiveness of potential N-fertilizer destination markets is influenced not only by conventional trade conditions but also by broader agricultural, demographic, and socioeconomic changes. To ensure effective decision-making, it is imperative to develop a comprehensive understanding of multiple dimensions, including market attractiveness, vulnerability-related risks, and external supply dependence. Within the context of international N-fertilizer trade, these dimensions reflect both demand-side pressures and trade-related dynamics. Accordingly, this research incorporates a set of criteria designed to jointly capture agricultural use, land availability, demand intensity, trade exposure, and structural fragility within potential target markets. These criteria are selected based on their theoretical relevance in the agricultural economics and trade literature, as well as

their empirical suitability for cross-country comparison within the AMIS group. Table 3 presents the operational definitions of each criterion and their classification as benefit-type or cost-type variables within the CRITIC–Fuzzy TOPSIS framework.

Table 3. List of evaluation criteria used in the research.

	ID	Criteria	Description	Type of Criteria
Market Attractiveness	C1	Agricultural use	Refers to the use for crops, livestock, forestry, fisheries and aquaculture, excluding use for animal feed. This indicator reflects the aggregate demand for nutrients in crop production.	Benefit
	C2	Cropland area (ha)	Refers to the total land area dedicated to crop production at a given point in time, typically measured in hectares (ha). This includes arable land and land under permanent crops used for the cultivation of food and other crops.	Benefit
	C3	Use per area of cropland (kg N/ha)	Refers to the amount of fertilizer nutrients (specifically nitrogen in this study) applied per hectare of cropland area. It represents the intensity of fertilizer use in agricultural production and allows cross-country comparability for fertilizer demand. Use per area of cropland is calculated as:	Benefit
			$U_{(i,c,y)} = \frac{F_{(i,c,y)}}{Area_{(c,y)}}$ $U_{(i,c,y)}$: Use per area of cropland of fertilizer nutrient i in country c and year y (in kg/ha): $F_{(i,c,y)}$ Total agricultural use of fertilizer nutrient i in country c and year y (in tonnes) [40]	Benefit
External Supply Dependence	C4	Import value (ton)	Refers to the total physical value of a specific product that a country imports from foreign partners. Import value should be added to decision criteria when analyzing market size and import dependency.	Benefit
	C5	Trade balance (USD thousand)	Refers to the difference between the value of a country's exports and imports of goods over a specified period, typically one year. It is a key indicator of a country's external trade performance and international competitiveness. $Trade\ Balance = Export\ Value - Import\ Value$ Negative trade balance (trade deficit) reflects a net importer position for countries. Therefore, negative trade balance is taken into account.	Benefit
Vulnerability-related risks	C6	Food vulnerability	Refers to a composite indicator grounded in the FAO definition of food security, capturing a country's exposure to and resilience against climate change. The food vulnerability index integrates four core dimensions of food security: food production, food demand, nutrition and rural population. Indicators include projected change in cereal yields, projected population growth, food import dependency, rural population, agriculture capacity, and child malnutrition (University of Notre Dame Global Adaptation Initiative (ND-GAIN)) [41]. Although high food vulnerability indicates a latent need for productivity-enhancing inputs, it is treated as a cost attribute used to mitigate risk. A high vulnerability rate often indicates a lack of agricultural investment and over-reliance on imported food. In consideration of the aim of research, lower vulnerability values are preferred, as they represent more robust, production-oriented markets that offer a more secure and sustainable environment for fertilizer exporters.	Cost
	C7	Urbanization rate	Refers to the proportion of a country's population residing in urban areas and captures the demographic and spatial transformation associated with population concentration in cities. $Urbanization\ Rate\ (\%) = \left(\frac{Urban\ Population}{Total\ Population} \right) \times 100$ Urbanization is categorized as a cost criterion in this study within the specific context of AMIS countries, which were selected because of their major role in global agricultural production, consumption, and trade. Although urbanization may increase aggregate food demand, the present analysis focuses on its potential effect on the agricultural production base that sustains nitrogen-fertilizer demand. In agricultural economies, increasing urbanization may lead to the conversion of cropland into residential, industrial, and infrastructural uses and may also contribute to a structural shift in labor away from agriculture. Such changes can reduce the physical base available for crop production. Since nitrogen-fertilizer demand is closely linked to the scale and continuity of agricultural production, a contraction in the agricultural production base may also constrain long-term fertilizer-use capacity. Therefore, higher urbanization rates are treated as a cost criterion, reflecting the potential land-use pressure of urban expansion on agricultural production and fertilizer-market potential rather than the food-demand effect of urban population growth.	Cost

The data for each criterion utilized in this study are obtained from internationally recognized and publicly accessible databases to ensure transparency, reliability, and cross-country comparability. Indicators related to agriculture and land use—including ‘*cropland area*,’ ‘*agricultural use*,’ and ‘*use per area of cropland*’—are sourced from the Food and Agriculture Organization of the United Nations Corporate Statistical Database (FAOSTAT) [40]. Trade values used in the analysis are reported in current nominal USD. Consequently, their variation over the 2005–2024 period may reflect both changes in underlying trade activity and changes in prices, exchange rates, and broader market conditions. This issue is particularly relevant to fertilizer markets, which experienced substantial price and energy-

market fluctuations during the observation period. Accordingly, nominal trade-value indicators are interpreted as measures of observed market conditions rather than pure measures of changes in physical trade flows. Demographic and structural data, including the ‘urbanization rate’ (defined as urban population as a percentage of the total population), are retrieved from the World Bank’s World Development Indicators (WDI) [42]. Finally, the ‘food vulnerability’ indicator is derived from food security assessment datasets provided by the FSIN, GNAFC, and FAO, which provide composite measures reflecting national exposure to food security risks, supply shocks, and structural fragility [40,43].

3.4. Research Methods

The CRITIC–Fuzzy TOPSIS framework was selected to address two complementary requirements of the present decision problem. First, the evaluation criteria originate from heterogeneous agricultural, trade, demographic, and vulnerability-related indicators, and their relative importance is intended to be determined objectively from the data rather than through expert judgment. CRITIC is therefore used because it incorporates both the variability of each criterion and its correlation with the remaining criteria when deriving weights. Second, the country evaluations are based on long-term observations that exhibit temporal variation. Fuzzy TOPSIS allows this variability to be represented through fuzzy numbers and ranks alternative markets according to their relative proximity to the ideal market profile. Thus, CRITIC provides an objective weighting structure, while Fuzzy TOPSIS provides a suitable ranking mechanism for multidimensional and temporally variable market data.

To ensure methodological transparency, the relationship between the 20-year observations, the CRITIC weighting procedure, and the fuzzy representation is clarified as follows. The original dataset consists of annual observations for 27 country alternatives, seven evaluation criteria, and the 2005–2024 period. For each country–criterion combination, the 20 annual observations were summarized using the minimum, median, and maximum values.

Two related but methodologically distinct decision matrices were subsequently constructed. First, the median value of the 20-year series for each country–criterion combination was used as a single crisp representative value. The conventional CRITIC method was applied exclusively to this median-based crisp matrix. After normalization, the standard deviation of each criterion and the correlations among criteria were calculated across the 27 country alternatives, and these statistics were used to derive the seven objective criterion weights.

Second, the same 20-year observations were represented by triangular fuzzy numbers using the minimum, median, and maximum values for each country–criterion combination. The criterion weights previously obtained from the crisp CRITIC analysis were then incorporated into the Fuzzy TOPSIS procedure to rank the alternative markets.

3.4.1. The CRITIC Method

The CRITIC method has been proposed to objectively determine the weights of the criteria of MCDM problems. The CRITIC method was introduced to the literature in 1995 by Diakoulaki et al. [44]. The CRITIC method is a weighting method performed by using the standard deviations of the criteria and the correlation between the criteria.

The steps of the CRITIC method are as follows.

Step 1. The decision matrix is created.

In the decision matrix expressed by Equation (1), the index i represents the alternatives and the index j represents the criteria, while x_{ij} represents the performance value of the i th alternative in terms of the j th criterion.

$$X = [X_{ij}]_{m \times n} = \begin{bmatrix} x_{11} & \dots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \dots & x_{mn} \end{bmatrix} \quad (i = 1, 2, \dots, m \text{ and } j = 1, 2, \dots, n) \quad (1)$$

Step 2. The decision matrix is normalized by Equation (2).

$$x_{ij}^* = \frac{x_{ij} - \min x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \quad (\text{benefit criteria})$$

$$(i = 1, 2, \dots, m \text{ and } j = 1, 2, \dots, n) \quad (2)$$

$$x_{ij}^* = \frac{\max x_{ij} - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \quad (\text{cost criteria})$$

Step 3. In this step, the standard deviation of the criterion and its correlation between other criteria are included. Then, the weight is calculated by Equation (3).

$$w_j = \frac{C_j}{\sum_{j=1}^n C_j} \quad (3)$$

C_j shows the quantity of information contained in the j th criterion, determined as:

$$C_j = \sigma_j \sum_{j=1}^n (1 - r_{ij}) \quad (4)$$

This method assigns greater weight to criteria with higher standard deviations and lower correlation coefficients with other criteria. In other words, a higher value of C_j indicates that the criterion provides a greater amount of unique information, thereby signifying its higher relative importance for the decision problem.

3.4.2. Fuzzy TOPSIS Method

TOPSIS, which was developed by Hwang and Yoon, 1981 [45], is a technique that is mostly used by researchers in performance evaluation studies. The most important feature of the TOPSIS method is choosing the alternative that has the shortest distance from the positive ideal solution and the farthest from the negative ideal solution [46]. Briefly, the positive ideal solution comprises all the best values obtainable with the criteria, whereas the negative ideal solution constitutes all the worst values obtainable with the criteria [47]. In the TOPSIS method, the ratings of alternatives are precise numbers; however, due to the vagueness of the decision data, precise numbers are unavailable to model real-life decision problems [48].

The usefulness of using the fuzzy approach is to appoint the relative importance of attributes analyzing fuzzy numbers instead of crisp numbers [49]. The steps of Fuzzy TOPSIS are as follows [50–52]:

Step 1. Creating the data matrix

Firstly, ratings are calculated by using Equation (5):

$$\tilde{X}_{ij} = \frac{1}{s} [\tilde{x}_{ij}^1 \oplus \tilde{x}_{ij}^2 \oplus \dots \oplus \tilde{x}_{ij}^s] \quad (5)$$

where $\tilde{x}_{ij}^s$ is the performance rating value obtained by the s -th decision-maker. The fuzzy evaluation matrix is created using Equation (6):

$$D = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1j} & \cdots & \tilde{x}_{1n} \\ \vdots & & \vdots & & \vdots \\ \tilde{x}_{i1} & \cdots & \tilde{x}_{ij} & \cdots & \tilde{x}_{in} \\ \vdots & & \vdots & & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mj} & \cdots & \tilde{x}_{mn} \end{bmatrix} \quad (6)$$

where $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$.

Step 2. Normalizing the evaluation matrix

The normalized fuzzy matrix is $\tilde{R} = [\tilde{r}_{ij}]_{m \times n}$. B represents benefit criteria and C presents cost criteria.

$$\begin{aligned} r_{ij} &= \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right), \quad j \in B \\ r_{ij} &= \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right), \quad j \in C \\ c_j^* &= \max_i c_{ij}, \quad \text{if } j \in B \\ a_j^- &= \min_i a_{ij}, \quad \text{if } j \in C \end{aligned} \quad (7)$$

After normalization, the fuzzy elements take values between $[0, 1]$.

Step 3. Calculating the weighted normalized fuzzy decision matrix

The weighted normalized decision matrix is $\tilde{V} = [\tilde{v}_{ij}]_{m \times n}$;

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes w_j, \quad (8)$$

$$i = 1, 2, \dots, m, \text{ and } j = 1, 2, \dots, n$$

Step 4. Calculating the positive and negative ideal solutions

The Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) can be given as:

$$\begin{aligned} A^* &= (\tilde{v}_1^*, \tilde{v}_2^*, \dots, \tilde{v}_n^*) \\ A^- &= (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-) \end{aligned} \quad (9)$$

where $\tilde{v}_j^* = (1, 1, 1)$, $\tilde{v}_j^- = (0, 0, 0)$ and $j = 1, 2, \dots, n$.

Step 5. Calculating the distances from FPIS and FNIS

Using Equations (10) and (11), the distances from the FPIS and FNIS are calculated.

$$d_i^* = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^*), \quad i = 1, 2, \dots, m \quad (10)$$

$$d_i^- = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^-), \quad i = 1, 2, \dots, m \quad (11)$$

The distance between two triangular fuzzy numbers $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$ is calculated by Equation (12):

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3} [(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2]} \quad (12)$$

Step 6. Computing the closeness coefficients

The closeness coefficients of each alternative are computed by Equation (13):

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-}, i = 1, 2, \dots, m \quad (13)$$

If the CC_i value of the alternative is close to 1, then the alternative is the best choice.

4. Results

This section establishes a hybrid decision-support framework by integrating the CRITIC and Fuzzy TOPSIS methodologies discussed previously. The evaluation model is structured around seven distinct criteria. Specifically, C1 through C5 are classified as benefit criteria, where higher performance levels are desirable. In contrast, C6 and C7 are designated as cost (non-beneficial) criteria, where lower numerical values are prioritized for the ranking process.

Upon establishing the decision matrix and its subsequent normalization—as detailed in the initial stages of the CRITIC methodology—the standard deviation for each criterion is derived from its respective vectors in Table 4. This statistical measure captures the inherent variability in and diversity of the data across the evaluated alternatives. For a thorough overview of the raw and normalized datasets, readers may refer to Tables S1 and S2 in the Supplementary Materials.

Table 4. Standard deviations.

C1	C2	C3	C4	C5	C6	C7
0.2195	0.2866	0.2096	0.2388	0.2220	0.2677	0.2938

A higher standard deviation signifies a greater contrast intensity among the alternatives for a given criterion, thereby warranting a more significant objective weight. Conversely, a lower standard deviation suggests that the values are relatively homogeneous, indicating that the criterion offers less distinctive information and should be assigned a diminished priority.

In this case study, the highest value of standard deviation is obtained for urbanization, and hence, a higher priority is assigned to this criterion in the decision-making process, followed by cropland area. Then, the correlation matrix and information measure of each criterion are calculated using Equation (2).

The correlation matrix is derived by evaluating the inter-criteria relationships, where the information measure (C_j) quantifies the degree of redundancy or divergence between each criterion and the rest of the set. A higher C_j value indicates that a criterion provides more unique information (lower redundancy), thereby increasing its significance in the final decision-making framework. Based on the results presented in Table 5, criterion C6 (food vulnerability) achieved the highest informational content, followed by C7 (urbanization) and C2 (cropland area).

In the final stage of the weighting process, the objective weight for each criterion is determined according to Equation (3). As illustrated in Table 4, food vulnerability emerged as the most significant factor with a weight of 0.2035 followed by urbanization (0.1865) and cropland area (0.1407). The thorough list of weights for the remaining criteria is documented in Table 5.

The CRITIC method derives objective weights by evaluating two fundamental dimensions: contrast intensity and inter-criteria correlation. While contrast intensity is quantified through standard deviation values, the correlation between criteria is assessed using the information measure of each attribute. Detailed calculations regarding the inter-criteria correlation coefficients are documented in Table S3 of the Supplementary Material.

Table 5. Weights of the criteria.

	σ_j	S_j	C_j	w_j
C1	0.2195	4.5332	0.9948	0.1043
C2	0.2866	4.6821	1.3419	0.1407
C3	0.2096	5.6571	1.1860	0.1244
C4	0.2388	4.5077	1.0764	0.1129
C5	0.2220	5.4902	1.2187	0.1278
C6	0.2677	7.2506	1.9408	0.2035
C7	0.2938	6.0539	1.7788	0.1865

Once the criteria weights are established, the procedure shifts to the final evaluation stage, where the alternatives are ranked using the TOPSIS technique. This transition ensures that the objective importance of each indicator is directly integrated into the performance assessment of the alternatives.

To reach the values of 20 years, the representative indicator of country i on indicator j presented with the triangular fuzzy number $(g_{ij}^l, g_{ij}^m, g_{ij}^u)$ is defined as:

$$g_{ij}^l = \min\{b_{ij}|e = 2005, 2006, \dots, 2024\}, \quad (14)$$

$$g_{ij}^m = \tilde{x} \{b_{ij}|e = 2005, 2006, \dots, 2024\} \quad (15)$$

and

$$g_{ij}^u = \max\{b_{ij}(e)|e = 2005, 2006, \dots, 2024\} \quad (16)$$

The median is preferred over the arithmetic mean as the central representative value to reduce sensitivity to extreme fluctuations and outliers in the 20-year time series. This choice is particularly relevant for nominal trade-value indicators, which may be affected by temporary price, exchange-rate, and commodity-market shocks. Nevertheless, because the lower and upper bounds of the triangular fuzzy numbers are based on the observed minimum and maximum values, this approach does not completely eliminate the influence of exceptional price conditions. Following the application of the triangular fuzzy number approach, the fuzzy weights for each criterion are detailed in Table 6. The complete dataset, including the expanded results for all indicators, is available in Table S4 of the Supplementary Material.

The normalized fuzzy decision matrix and the subsequent weighted normalized matrix are derived using Equations (7) and (8). Detailed computations for both matrices are provided in Tables S5 and S6 of the Supplementary Material. In addition, the fuzzy positive ideal solution (A^*) and the fuzzy negative ideal solution (A^-) are established via Equation (9), serving as benchmark points to evaluate the relative performance of each alternative. The specific A^* and A^- values for each criterion are summarized in Table 7 (Supplementary Material, Table S7).

Table 6. Decision matrix.

Countries	C1			C2			C7		
	l	m	u	l	m	u	l	m	u
Argentina	477,061	826,807	1,767,478	32,794.4	40,507.1	44,167.0	90.1234	91.4449	92.2742
Australia	835,018	1,262,419	2,150,334	23,530.0	31,035.0	32,307.0	85.6191	86.8000	87.6021
Brazil	2,200,284	3,727,501	6,775,062	58,682.0	62,588.0	63,518.0	82.9839	85.5634	87.8959
Canada	1,371,962	2,480,743	3,116,000	37,463.7	38,489.0	40,114.0	79.9761	81.2289	82.7003
China	24,562,312	28,423,537	31,140,379	128,362.0	132,803.2	136,204.6	42.9900	56.5400	65.8947
Egypt	1,086,800	1,246,200	1,372,900	3478.0	3723.1	4058.0	42.4486	42.7306	42.9730
France	1,733,621	2,129,239	2,402,000	17,926.8	19,307.0	19,488.2	77.0963	77.5987	78.8000
Germany	1,007,364	1,620,101	1,822,791	11,860.0	12,048.0	12,145.0	80.1745	80.6366	82.0211
India	11,712,729	16,885,250	20,456,400	168,048.0	169,331.5	169,891.0	29.0945	32.3881	35.3789
Indonesia	2,309,142	2,931,051	3,669,339	35632.6	40,503.1	44,122.2	46.2374	52.8361	58.7510
Italy	498,605	596,656	866,469	9048.0	9427.8	10,529.0	67.5897	69.4806	69.6100
Japan	337,600	374,800	478,818	4297.0	4528.0	4714.0	85.9574	91.3041	92.1902
Kazakhstan	16,300	63,071	105,264	28,598.5	29,518.3	29,880.0	54.1167	55.8315	62.0725
Mexico	939,477	1,305,013	1,491,239	22,129.0	25,303.5	26,145.0	81.1617	81.5612	81.9685
Nigeria	70,115	215,038	591,628	41,845.7	42,304.7	44,226.2	76.4749	77.0823	79.7539
Philippines	401,297	594,383	799,021	9855.0	10,983.5	11,222.6	47.5656	55.3279	62.9756
Rep. of Korea	209,484	222,667	417,304	1512.0	1694.5	1836.0	41.3298	50.6971	55.4521
Russia	838,270	1,250,055	2,210,573	123,368.0	123,442.0	123,956.0	73.1614	74.2268	75.1119
Saudi Arabia	149,000	195,500	264,991	3605.2	3675.5	3778.8	80.9776	82.8693	84.5554
South Africa	327,000	424,562	618,738	12,413.0	12,413.0	13,680.0	59.8242	63.1724	63.6918
Spain	739,757	975,969	1,101,895	16,606.5	17,160.4	17,957.0	77.2207	79.1826	80.3152
Thailand	1,053,556	1,466,610	2,684,041	21,467.0	22,026.0	22,471.9	38.1302	46.6330	61.8689
Türkiye	1,133,068	1,510,214	2,052,685	23,099.0	23,908.5	26,606.0	63.3302	85.4096	89.3443
Ukraine	345,280	989,280	1,769,865	33,333.0	33,665.0	33,777.0	67.8136	69.1071	69.5316
United Kingdom	862,000	1,015,000	1,125,000	5776.0	6085.2	6310.3	80.4456	81.7300	83.2430
United States of America	10,397,607	11,683,827	12,249,080	154,734.1	159,320.7	171,216.2	79.9975	80.4498	80.6998
Vietnam	726,655	1,550,817	1,764,702	9153.6	10,221.3	11,746.0	27.4286	32.1646	38.4901

Table 7. Positive and negative ideal solutions.

	C1			C2			C7		
	l	m	u	l	m	u	l	m	u
A ⁺	0.0823	0.0952	0.1043	0.1381	0.1391	0.1407	0.1446	0.1590	0.1865
A [−]	0.0001	0.0002	0.0004	0.0012	0.0014	0.0015	0.0554	0.0559	0.0568

In the subsequent phase, the distances from each alternative to the fuzzy positive (A⁺) and negative (A[−]) ideal solutions are determined. The proximity to the ideal best solution is quantified using the Vertex Method (Euclidean distance), as defined in Equation (10), while the distance to the ideal worst solution is computed via Equation (11). Alternatives exhibiting minimal distance to A⁺ are considered most favorable. Finally, the closeness coefficient (performance score) for each alternative is derived through Equation (13). According to this metric, the alternative achieving the highest score represents the optimal choice. The thorough performance scores and corresponding distance measurements are detailed in Table 8.

Based on the calculated performance scores, India emerges as the highest-ranked market in the exporter-independent structural screening, followed by the United States and China. These rankings indicate comparatively favorable destination-market conditions under the selected country-level criteria and should not be interpreted as definitive market-entry recommendations for a particular exporting country or firm.

Table 8. Performance scores.

	d_i^*	d_i^-	CC_i
Argentina	0.3690	0.1290	0.2591
Australia	0.3706	0.1286	0.2576
Brazil	0.3363	0.1780	0.3461
Canada	0.3432	0.1920	0.3587
China	0.2635	0.2741	0.5098
Egypt	0.3799	0.1564	0.2917
France	0.3555	0.1589	0.3089
Germany	0.3628	0.2453	0.4034
India	0.2462	0.3610	0.5945
Indonesia	0.3544	0.1569	0.3068
Italy	0.3695	0.1449	0.2817
Japan	0.3825	0.1819	0.3223
Kazakhstan	0.3647	0.1330	0.2673
Mexico	0.3563	0.2089	0.3697
Nigeria	0.3629	0.1330	0.2682
Philippines	0.3973	0.1625	0.2903
Republic of Korea	0.3861	0.1560	0.2877
Russia	0.3222	0.2059	0.3898
Saudi Arabia	0.4088	0.0994	0.1955
South Africa	0.3818	0.1244	0.2458
Spain	0.3725	0.1354	0.2666
Thailand	0.3525	0.1591	0.3110
Türkiye	0.3644	0.1331	0.2676
Ukraine	0.3661	0.1183	0.2442
United Kingdom	0.3682	0.2187	0.3726
United States of America	0.2659	0.2877	0.5197
Vietnam	0.3567	0.2193	0.3807

In the last step of the application, scenario analysis is performed to investigate the impact of variations in criteria weights on the final ranking as a way of confirming the robustness of the suggested methodology. Indeed, these analyses are necessary to evaluate the stability of results in MCDM, which is characterized by its inherent uncertainties [53]. Since the determination of weights in MCDM is usually based on subjective approaches, such as AHP and ANP, conducting a sensitivity analysis is important to confirm the robustness of the results and the correctness of interpreting the data.

While the baseline model relies on data-driven CRITIC weights, the sensitivity analysis deliberately introduces controlled variations in criteria weights to evaluate how shifts in strategic priorities and indicator importance impact the final market rankings. These seven scenarios represent distinct weighting schemes designed to test the responsiveness and stability of the ranking framework under alternative policy and trade contexts.

The findings in Table 9 indicate strong stability at the top of the ranking, as India, the United States, and China remain within the top three positions across all seven scenarios. However, the quantitative robustness assessment shows greater sensitivity among several middle- and lower-ranked alternatives. Therefore, robustness is strongest for the leading alternatives rather than uniform across the full ranking.

Table 9. Sensitivity analysis.

Scenarios	1		2					6		7	
Weights	w ₁	0.1043	w ₁	0.2035				w ₁	0.143	w ₁	0.1043
	w ₂	0.1407	w ₂	0.1407				w ₂	0.143	w ₂	0.1407
	w ₃	0.1244	w ₃	0.1244				w ₃	0.143	w ₃	0.2035
	w ₄	0.1129	w ₄	0.1129				w ₄	0.143	w ₄	0.1129
	w ₅	0.1278	w ₅	0.1278				w ₅	0.143	w ₅	0.1278
	w ₆	0.2035	w ₆	0.1043				w ₆	0.143	w ₆	0.1244
	w ₇	0.1865	w ₇	0.1865				w ₇	0.143	w ₇	0.1865
	CC _j	Ranking	CC _j	Ranking	.	.	.	CC _j	Ranking	CC _j	Ranking
Argentina	0.2591	23	0.2074	21	.	.	.	0.2563	21	0.2728	18
Australia	0.2576	24	0.2106	20	.	.	.	0.2608	19	0.2771	17
Brazil	0.3461	10	0.3157	6	.	.	.	0.3733	4	0.3715	8
Canada	0.3587	9	0.2287	14	.	.	.	0.2943	13	0.2670	21
China	0.5098	3	0.6413	2	.	.	.	0.5687	2	0.5433	2
Egypt	0.2917	15	0.2673	10	.	.	.	0.2807	16	0.3665	11
France	0.3089	13	0.2229	16	.	.	.	0.2822	15	0.2645	23
Germany	0.4034	4	0.2422	12	.	.	.	0.3228	7	0.2857	16
India	0.5945	1	0.6802	1	.	.	.	0.6502	1	0.7057	1
Indonesia	0.3068	14	0.2894	7	.	.	.	0.3205	8	0.3990	6
Italy	0.2817	18	0.1925	24	.	.	.	0.2431	25	0.2406	25
Japan	0.3223	11	0.1936	25	.	.	.	0.2595	20	0.2351	27
Kazakhstan	0.2673	21	0.2283	13	.	.	.	0.2647	18	0.3178	12
Mexico	0.3697	8	0.2246	18	.	.	.	0.2969	12	0.2671	20
Nigeria	0.2682	19	0.2216	15	.	.	.	0.2710	17	0.2981	14
Philippines	0.2903	16	0.2718	9	.	.	.	0.3106	9	0.4055	5
Republic of Korea	0.2877	17	0.2625	11	.	.	.	0.2913	14	0.3690	9
Russia	0.3898	5	0.3205	5	.	.	.	0.3664	5	0.3743	7
Saudi Arabia	0.1955	27	0.1644	27	.	.	.	0.2044	27	0.2611	24
South Africa	0.2458	25	0.2135	19	.	.	.	0.2525	23	0.3057	13
Spain	0.2666	22	0.1866	26	.	.	.	0.2377	26	0.2373	26
Thailand	0.3110	12	0.2792	8	.	.	.	0.3044	10	0.3668	10
Türkiye	0.2676	20	0.2075	22	.	.	.	0.2556	22	0.2644	22
Ukraine	0.2442	26	0.2033	23	.	.	.	0.2439	24	0.2862	15
United Kingdom	0.3726	7	0.2265	17	.	.	.	0.3010	11	0.2687	19
United States of America	0.5197	2	0.5118	3	.	.	.	0.5558	3	0.5176	3
Vietnam	0.3807	6	0.3481	4	.	.	.	0.3452	6	0.4312	4

For a more intuitive understanding of the distributions, Figure 2 presents the graphical representation of the calculated values.

To quantitatively assess ranking robustness, Spearman rank correlations, maximum absolute rank changes, and top-three stability were calculated by comparing each alternative weighting scenario with the baseline CRITIC-weighted ranking. As shown in Table 10, the Spearman rank correlation coefficients ranged from 0.4695 to 0.9799 across Scenarios 2–7. Scenarios 3 and 4 exhibited particularly high agreement with the baseline ranking ($\rho = 0.9799$), whereas Scenario 7 produced the greatest overall ranking variation ($\rho = 0.4695$). The maximum absolute rank change ranged from 5 to 16 positions, indicating that some middle- and lower-ranked alternatives were sensitive to changes in criterion importance. Nevertheless, India, the United States, and China remained within the top three positions under all seven scenarios, corresponding to a top-three stability rate of 100%. These findings indicate that robustness is strongest for the leading alternatives, while the relative positions of several middle- and lower-ranked countries are more sensitive to alternative weighting structures.

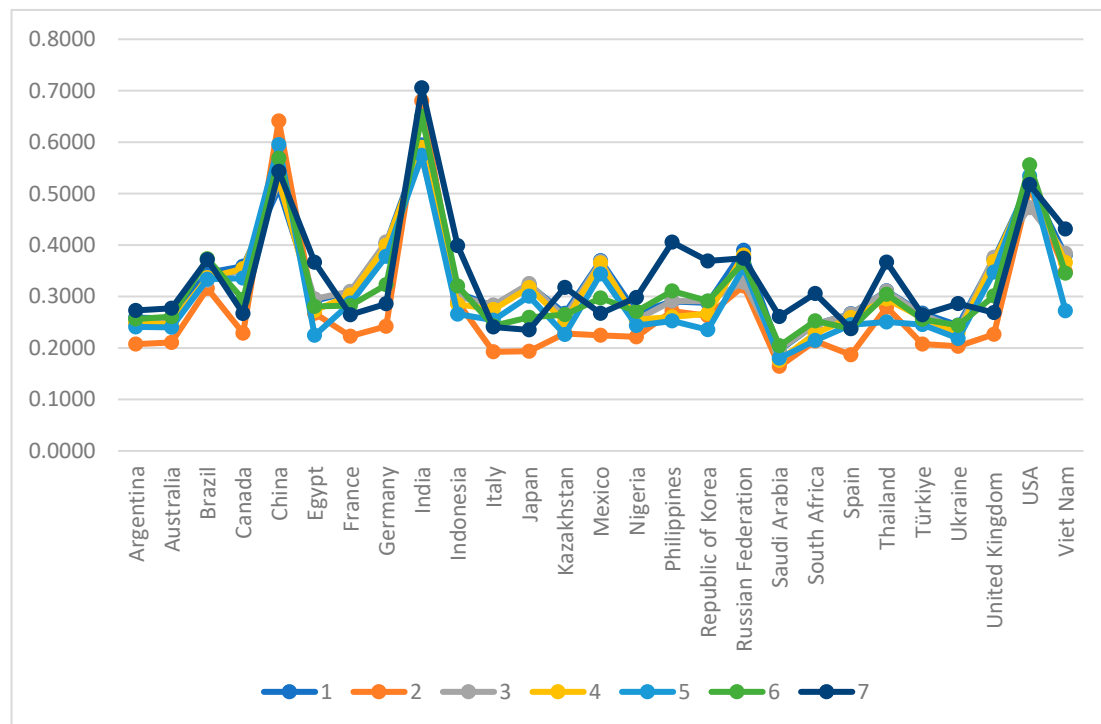


Figure 2. Sensitivity analysis.

Table 10. Quantitative robustness assessment of country rankings across sensitivity scenarios.

Scenario	Spearman Rank Correlation (ρ)	Maximum Absolute Rank Change	Country with Maximum Rank Change	Top-3 Stability (%)
Scenario 1 (Baseline)	1.000	0	–	100.0
Scenario 2	0.7277	14	Japan	100.0
Scenario 3	0.9799	6	Russia	100.0
Scenario 4	0.9799	5	Philippines	100.0
Scenario 5	0.9267	9	Egypt	100.0
Scenario 6	0.8785	9	Japan	100.0
Scenario 7	0.4695	16	Japan	100.0

Note: Scenario 1 represents the baseline ranking obtained using the original CRITIC weights. Spearman rank correlations and maximum absolute rank changes for Scenarios 2–7 were calculated relative to the baseline ranking. Top-three stability represents the percentage of the three highest-ranked baseline alternatives that remained within the top three positions in each scenario.

5. Discussion and Conclusions

5.1. Study Objectives and Overview

This study developed and implemented a structured and systematic methodological framework to identify and prioritize potential target markets for nitrogen fertilizer exporters. The methodology was designed to ensure analytical transparency and replicability while capturing the multidimensional nature of international fertilizer trade and agricultural demand dynamics. The analysis was executed in four integrated stages, utilizing an MCDM approach to identify optimal export destinations. By integrating seven pivotal indicators—agricultural nitrogen use, cropland area, fertilizer use per unit of cropland, import value, trade balance, food vulnerability, and urbanization—this research provided a robust basis for evaluating 27 AMIS member countries through the objective CRITIC weighting and Fuzzy TOPSIS ranking techniques.

5.2. Evaluation of Findings and Results

The empirical results derived from the CRITIC method reveal that food vulnerability holds the highest significance ($w_j = 0.2035$), indicating that it carries the greatest objective information within the decision matrix. This is closely followed by urbanization ($w_j = 0.1865$) and cropland area ($w_j = 0.1407$). The high information intensity (CC_j) values for food vulnerability (1.9408) and urbanization (1.7788) suggest that these criteria exhibit significant conflict and contrast with other indicators, marking them as the primary drivers in market differentiation.

The Fuzzy TOPSIS ranking (Table 7) identifies India as the most optimal export destination ($CC_j = 0.5945$), primarily due to its proximity to the fuzzy positive ideal solution. Following India, the United States ($CC_j = 0.5197$) and China ($CC_j = 0.5098$) are ranked as the second and third priority markets, respectively. Notably, these three nations are the only alternatives to exceed a performance score of 0.50, significantly outperforming others. The leading positions of India, China, and the United States reflect their combined performance across several dimensions rather than superiority in any single criterion. Their large agricultural production bases, substantial nitrogen-fertilizer use and import-market scale, together with their relative performance on land- and vulnerability-related indicators, contribute to their comparatively favorable structural profiles under the selected criteria. Conversely, cost criteria such as urbanization may partially offset these advantages, illustrating the multidimensional nature of the resulting rankings. Conversely, countries such as Saudi Arabia and Ukraine were positioned at the lower end of the ranking, reflecting a higher proximity to the negative ideal solution under the selected criteria. The robustness of these rankings was further validated through a comprehensive sensitivity analysis involving seven distinct scenarios, ensuring reliability amidst decision-making uncertainties.

5.3. Theoretical Contributions to Literature

The contribution of this study is primarily conceptual and application-oriented rather than being based on the novelty of MCDM itself. Previous studies have demonstrated the usefulness of MCDM techniques for export market selection, including applications in agricultural and commodity markets. Building on this literature, the present research extends the conventional target-market selection perspective by conceptualizing nitrogen-fertilizer demand as the outcome of both market conditions and broader structural pressures affecting agricultural production.

Accordingly, the proposed framework simultaneously incorporates three interconnected dimensions: market attractiveness, external supply dependence, and structural vulnerability. In addition to conventional indicators such as import value and trade balance, the model incorporates agricultural nitrogen use, fertilizer-use intensity, cropland availability, food vulnerability, and urbanization. This structure connects international market selection with agricultural intensification, land-use constraints, and food-security conditions, thereby providing a broader explanation of why fertilizer demand may remain structurally important in particular markets.

A further contribution is the use of an objective weighting procedure together with a long-term fuzzy representation of market conditions. CRITIC determines criterion weights from the information contained in the data, while the Fuzzy TOPSIS framework incorporates temporal variability in the evaluation of alternative markets. Thus, the study complements previous MCDM-based export market selection research by offering a nitrogen-fertilizer-specific decision-support framework focused on structurally sustained market potential rather than solely on contemporaneous trade attractiveness.

5.4. Managerial and Policy Implications

Beyond its theoretical novelty, the findings offer strategic insights for fertilizer producers and trade policymakers.

- For Managerial Decision-Makers: India, the United States, and China emerge as the highest-ranked markets in the exporter-independent structural screening and may therefore be considered priority candidates for further exporter-specific assessment. Their rankings reflect comparatively favorable conditions under the agricultural, trade, demographic, and vulnerability-related criteria included in the model. However, actual market-entry decisions should additionally consider exporter-specific factors such as transportation costs, tariffs, regulatory requirements, logistics, distribution networks, and geopolitical conditions.
- For Policymakers: The relatively high weight assigned to food vulnerability indicates that structural fragility is an important consideration when assessing potential fertilizer markets. Accordingly, market-oriented assessments should consider not only fertilizer demand potential but also the broader economic and institutional conditions affecting market stability. Land-Use Monitoring: The impact of urbanization serves as a critical signal for exporters to monitor land-use policies; rapid urban expansion may necessitate a shift toward high-efficiency, specialized nitrogen products to compensate for shrinking cultivable areas.

5.5. Contributions to Global Agricultural Sustainability

The sustainability relevance of this study should be interpreted primarily in terms of agricultural production continuity, input accessibility, and food-system resilience rather than as a direct assessment of the environmental sustainability of nitrogen-fertilizer use. Nitrogen fertilizers remain a critical input for sustaining agricultural productivity, particularly in countries where production is constrained by land availability, demographic pressures, and structural vulnerability. From this perspective, identifying markets in which fertilizer demand is likely to remain structurally important can contribute to more informed planning of fertilizer supply and international trade.

This perspective is also related to Sustainable Development Goal 2 (Zero Hunger), as stable access to productivity-enhancing agricultural inputs is an important component of maintaining food-production capacity. However, the present framework does not directly evaluate environmental dimensions such as nitrogen-use efficiency, nutrient losses, greenhouse-gas emissions, or pollution risks. Therefore, the sustainability contribution of the study is limited to the production and food-system dimensions of agricultural sustainability.

At the same time, the environmental consequences of excessive or inefficient nitrogen-fertilizer use should not be overlooked. Future research could extend the proposed framework by incorporating environmental indicators, including nitrogen-use efficiency, emissions intensity, nutrient-loss risks, and other measures of environmental performance, thereby enabling a broader assessment that integrates market attractiveness with environmental sustainability.

5.6. Limitations and Future Research Directions

Despite its contributions, this study is subject to several limitations that should be considered when interpreting the findings. First, the analysis is restricted to 27 AMIS countries, and the selection of evaluation criteria is partly constrained by the availability of comprehensive and harmonized cross-country datasets. Although AMIS countries represent a substantial share of global agricultural production, consumption, and trade, the resulting rankings should not be generalized to all potential N-fertilizer markets.

Future research could extend the geographical coverage of the framework and incorporate additional indicators as comparable international data become available.

A second limitation concerns the temporal comparability of trade indicators expressed in nominal monetary values. The study covers the 2005–2024 period, during which international fertilizer markets experienced substantial fluctuations associated with commodity and energy prices, inflation, exchange-rate movements, and major global disruptions. Consequently, variations in nominal trade values may reflect price effects in addition to changes in underlying trade activity. Although the use of the median as the central value of the triangular fuzzy representation reduces sensitivity to extreme observations, the minimum and maximum values may still capture temporary price spikes or exceptional market conditions. Therefore, the trade-related indicators should not be interpreted solely as measures of structural changes in physical fertilizer trade. Future research could improve temporal comparability by employing constant-price trade values, appropriate fertilizer-price deflators, quantity-based net import measures, or shorter and rolling observation periods.

A third limitation concerns the exporter-independent nature of the proposed framework. The analysis evaluates the structural attractiveness of destination markets using country-level indicators and does not adopt the perspective of a specific exporting country or fertilizer-producing firm. Consequently, bilateral and firm-specific determinants of actual export feasibility—including geographic distance, freight costs, bilateral tariffs, trade agreements, sanctions, logistics and port conditions, payment risk, established distribution channels, product-registration requirements, and geopolitical relationships—are not incorporated into the present model. The resulting rankings should therefore be interpreted as a first-stage strategic screening of structurally attractive markets rather than as definitive market-entry recommendations for a particular exporter. Future research could extend the framework through a second-stage exporter-specific assessment incorporating bilateral trade costs, regulatory barriers, logistical conditions, and firm-level capabilities.

Finally, future studies may extend the current framework by examining broader indicator combinations and alternative criterion orientations under different decision objectives. In particular, the roles of urbanization and food vulnerability may be reassessed alongside alternative measures of agricultural scale, fertilizer-use intensity, import demand, and external dependence. Furthermore, environmental indicators such as nitrogen-use efficiency, nutrient losses, and emissions intensity could be integrated into future applications to provide a more comprehensive assessment combining market attractiveness, trade feasibility, and environmental sustainability.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su182110709/s1>, Table S1: Decision Matrix; Table S2: Normalized Matrix; Table S3: Correlation Matrix; Table S4: Decision Matrix; Table S5: Normalized Matrix; Table S6: Weighted Normalized Matrix; Table S7: Positive and Negative Ideal Solutions; Table S8: Scenario Analysis.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

MCDM	Multi-Criteria Decision-Making
AMIS	Agricultural Market Information System
UN	United Nations
FSIN	Food Security Information Network
GNAFC	Global Network Against Food Crises
FAO	Food and Agricultural Organization
AHP	Analytic Hierarchy Process
HS	Harmonized System
WCO	World Customs Organization
CRITIC	Criteria Importance Through Intercriteria Correlation
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
FPIS	Fuzzy Positive Ideal Solutions
FNIS	Fuzzy Negative Ideal Solutions
WDI	World Development Indicators
ND-GAIN	Notre Dame Global Adaptation Initiative

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