

Target Market Selection in Agricultural Machinery Exports with BWM Based WASPAS Method

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ABSTRACT

The selection of export target market is not only based on marketing-mix elements its also effected by internal factors such as market share, expected profits or long-term strategy and external economic, political and environmental factor. Target-market selection is a strategically critical decision for companies, and this decision-making process can be conducted more systematically and objectively using multi-criteria decision-making (MCDM) techniques. In this context, MCDM methods offer an analytical approach that enables the selection of the most suitable alternative based on multiple criteria. In this study, an integrated MCDM model is proposed for companies to analyze their target markets. The empirical setting comprises 89 agricultural machinery enterprises exporting from Konya. Within the decision process, the importance weights of nine criteria were determined using the Best–Worst Method, revealing that Current Market Volume, Economic Structure and Future Expectations, and Agricultural Land and Climate are the most critical criteria in that order. Potential target-market alternatives were then evaluated using the WASPAS (Weighted Aggregated Sum Product Assessment) method. According to the analysis results, Russia emerged as the most suitable target market for the study region.

Keywords: Agricultural Machinery Exports, Best-Worst Method, Target Market Selection, WASPAS Method.

INTRODUCTION

Agricultural sustainability and global food security have long been the focus of international attention for a long time with rapid population growth, epidemics, regional conflicts, [climate change](#) and [decreasing water resources](#), all of which jointly threaten agricultural productivity (Çiftci & Oğuz, 2025; Kabato et al., 2025; Saboori et al., 2024; Rabbi et al., 2023; Wijerathna-Yapa et al., 2022; Muluneh, 2021). [Inspite of many technological advances](#), the agricultural sector still remains sensitive to climate change, which continues to endanger productivity, [reduce rural incomes](#), and [exacerbate poverty](#) (Örs et al., 2024). To address these challenges, agricultural mechanization, which increases productivity and lower costs as well as

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environmental sustainability has become a strategic requirement in both production and trade (Pandey and Mishra, 2024; Daum, 2023; Liao et al., 2022).

Demand for mechanization is increasing due to farm consolidation, urbanization, improved access to finance, and technological progress (Sasmal and Sasmal, 2016). Mechanization optimizes production planning, improves product quality, and increases labor productivity, helping to address labor shortages and an aging workforce. When combined with environmentally friendly technologies, it conserves natural resources and delivers higher productivity with lower energy consumption (Liao et al., 2022; Emami et al., 2018).

As the agriculture's status an economically and strategically essential sector in both developed and developing countries equally impacts agricultural mechanization. Because of agricultural mechanization increases production efficiency and serves as a key driver of competitiveness in agriculture. High production capacity has created a strong global demand for advanced machinery; while developed countries leverage mechanization to become technology exporters, developing countries are increasingly dependent on imported equipment to modernize their agricultural systems (Kirui, 2019). European and North American manufacturers continue to expand exports of tractors, tillage and irrigation machinery, and digital agricultural technologies to Asia, Africa, and Latin America. Precision agricultural machinery, which mostly used in developed countries, has recently become widespread worldwide, accelerating this transformation (Oğuz et al., 2017). Meanwhile Industry 4.0 and Agriculture 4.0 applications are rapidly increasing global demand for smart agricultural technologies and further intensifying competition (Öztürk and Çelik, 2024).

Currently, global oversupply narrowing profit margins, and diminishing public support are putting downward pressure on the sector. Furthermore, high interest rates and rising machinery prices are limiting investment in new equipment and increasing reliance on used machinery (Agrievolution, 2025). Global foreign trade data still clearly demonstrates the enormous economic potential of agricultural mechanization on an international scale. In 2024, under HS 8432 (soil cultivation machinery) totaled \$9.36 bn in imports and \$9.65 bn in exports; HS 8433 (harvesting/threshing machinery) recorded \$26.76 bn in imports and \$27.25 bn in exports; HS 8434 (milking/dairy equipment) saw \$2.30 bn in imports and \$2.32 bn in exports; and HS 8701 (tractors) posted \$70.60 bn in imports versus \$74.17 bn in exports (ITC Trademap, 2025). Exports in this high-potential sector are crucial for both national trade balances and manufacturers, yet competition remains intense. The US, China, Germany, France and Italy lead, while Türkiye currently holds limited market influence.

Evaluation of Türkiye's position in the global agricultural mechanization market reveals the country's increasing technological capacity and competitiveness. Exports rose from \$56 million in 2001, when the sector ran a deficit, to over \$1.5 billion in 2023, with consistent trade surpluses. Türkiye's global export ranking improved from 31st (0.3% share) in 2001 to 17th (1.5%) in 2023 (TARMAKBIR, 2024). Türkiye's 2024 data show: HS 8432 (soil processing) \$212.6m exports vs. \$177.7m imports; HS 8433 (harvesting/threshing) \$135.3m exports vs. \$276.5m imports; HS 8434 (dairy equipment) \$75.1m exports vs. \$27.8m imports; HS 8701 (tractors) \$1.20bn exports vs. \$1.65 bn imports (ITC Trademap, 2025). Türkiye has a surplus in tillage and dairy equipment, while it has a deficit in harvesting machinery and tractors, particularly in high-technology segments where imports are nearly double those of exports.

Literature Review and Research Gap

Research in the literature emphasizes that agricultural mechanization increases efficiency, reduces costs and promotes environmental sustainability (Daum, 2023; Pandey and Mishra, 2024). In Kirui (2019)'s analysis of eleven African countries found that the adoption of mechanization and the resulting productivity depended heavily on household characteristics, farm size, and market accessibility. In parallel, several studies have applied multi-criteria decision-making (MCDM) techniques in agricultural and trade-related contexts. A fuzzy AHP and COPRAS for product markets (Atlı, 2024); fuzzy VIKOR for tractor selection (Ateş, 2024); SWARA for machinery maintenance prioritization (Mishra and Satapathy, 2023); CRITIC-Entropy and GRA-TOPSIS for equipment choice (Lu et al., 2022); and FAHP-WR-DEA for regional distribution (Houshyar et al., 2020). Regionally, studies such as Jiangxue et al. (2024) link mechanization in China (2002–2021) to export growth and food security, while Iqbal et al. (2015) assess Pakistan's mechanization competitiveness. However, Türkiye's high-technology export potential has not yet been adequately explored. While previous structuring agreement system and MCDM applications have been examined, no study has yet been conducted combining expert-based criteria weighting with a hybrid BWM-WASPAS approach to assess Türkiye's agricultural machinery export potential. This study contributes to the literature by combining mechanization, export market enhancement, and multi-criteria assessment into a single, integrated approach. To enhance Türkiye's export competitiveness, strategic target-market selection is critical. Hyper-competition in global trade makes identifying and prioritizing markets a complex, multi-factor decision (Zhang et al., 2007). Accordingly, the primary purpose of this study is to

determine the most promising international target markets using MCDM techniques in the field of agricultural mechanization in Türkiye.

This study specifically aims to answer the following research questions:

(1) Which international markets offer the highest potential for Türkiye's agricultural mechanization sector?

(2) How can MCDM methods support evidence-based target market selection in this context?

MATERIALS AND METHODS

The study employed primary data collected through a survey method. The data, obtained directly by the researcher, pertain to companies that exported in 2024. Face-to-face voluntary surveys were conducted with agricultural machinery exporters located in Konya, and the results were analyzed using the BWM and WASPAS methods to determine target market selection. Konya was selected as the research area because, among the 1,394 companies in Türkiye registered under NACE code 28.30 (Agricultural and Forestry Machinery Manufacturing), 410 are located in Konya. İzmir follows with 115 companies. This data show that Konya is one of Türkiye's leading production centers for agricultural machinery manufacturing (TARMAKBİR, 2024). The sample size was determined using a simple random probability sampling method, taking into account the finite population correction factor as suggested by Newbold (1995).

$$n = \frac{N \times p \times (1 - p)}{(N - 1) \times \sigma_{p^x}^2 + p \times (1 - p)} \quad (1)$$

In the formula:

n = Sample volume,

N = Number of companies exporting agricultural machinery in the main mass (410),

$\sigma_{p^x}^2$ = Variance,

$p = 0.50$

Equality (1) was used to calculate the required sample size as 78, based on a 5% margin of error and 95% confidence level. However, data was collected from 89 agricultural machinery exporters.

To identify the factors that influence the determination of target markets in agricultural machinery exports, the opinions of subject matter experts working at universities, public institutions, and relevant organizations, as well as agricultural machinery exporting companies, were sought. The nine criteria identified as effective in this process are: C1: Agricultural Land and Climate, C2: Product Types, C3: Economic Structure and Future Expectations, C4:

Population and Rural Area Ratio, C5: Distance and Transportation Cost, C6: Taxes and Customs Regulations, C7: Current Market Volume, C8: Trade Risks and C9: Payment Methods.

Nine criteria were identified based on expert consensus and prior studies in international trade, agricultural literature, and MCDM applications (Bagai and Wilson, 2006; Özpınar and Çay 2018; Korobeynikov, et.al, 2020; Parvin, et.al, 2022; Yan, et.al, 2024; Kolisnichenko, 2025; FAO, n.d.). Each criterion was conceptually defined as follows:

C1: Refers to the suitability of a country's agricultural area, climatic conditions, and production potential for the use of agricultural machinery.

C2: The diversity of crops grown in the target market affects the type and amount of machinery needed.

C3: Assesses the economic stability, growth rate, and agricultural investment trends in the importing country.

C4: Indicates the country's population, and the proportion of rural population and agricultural land engaged in agricultural activities.

C5: Refers to the operational costs in logistics activities between importing and exporting countries.

C6: Addresses trade policies, import duties, tariffs and non-tariff barriers that directly affect the profitability of exports.

C7: Expresses the state of demand and competition level which also effected by the current economic situation, agricultural land and government incentives.

C8: Encompasses financial, political and operational uncertainties arising from political instability, exchange rate volatility, inflation and regulatory uncertainty, which increase transaction costs and hinder exporters' market selection.

C9: It vary from advence payment (the importer assumes the most risk), to letter of credit (the parties' transactions are secured through banks) determine the degree of risk sharing.

These criteria were evaluated in 5-point scale for the world's top ten importing countries: USA, Italy, Iraq, Russia, France, Azerbaijan, Germany, Uzbekistan, Algeria, and Bulgaria.

BWM Method

The BWM is an effective MCDM tool applicable in areas such as economics, health, engineering, and agriculture. It helps determine the relative importance of criteria based on expert judgments, requiring fewer comparisons and offering more consistent results than many traditional MCDM approaches (Rezaei et al., 2016). In BWM, the decision-maker identifies the

most and least important criteria, conducts pairwise comparisons, calculates the weights, and determines the most appropriate alternative (Rezaei, 2015).

The steps of the method developed by Rezaei are as follows;

Step 1. A set of criteria is defined:

The criteria $c_1, c_2, \dots, c_n$ affecting the decision problem are determined.

Step 2. The best and worst criteria are determined:

The decision-maker selects one or more criteria as the best and worst among criteria. At this point, only the criteria themselves are identified without any comparison, focusing on selection rather than on their values.

Step 3. The importance of the best criterion compared to other criteria is determined:

At this stage, the superiority of the best criterion over the others is evaluated using the 1–9 scale provided in Table 1, where 1 reflects equal importance and 9 indicates a strong dominance of the best criterion. This evaluation results in a preference vector extending from the best criterion to the others, as expressed in Equation 2.

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn}) \quad (2)$$

Here, a_{Bj} in the vector A_B represents the preference of the best criterion B among the evaluation criteria (C_1 – C_9) with respect to criterion j . Also, $a_{BB} = 1$. This means that the most important criterion will be compared with itself.

Table 1. Comparison scale between criteria in the BWM.

Scale	Value Definition
1	Equally important
3	Moderately important
5	Strongly important
7	Very strongly important
9	Extremely important
2,4,6,8	Intermediate values

Step 4. The importance of other criteria is determined according to the worst criterion:

In this step, decision makers are asked to determine their preference levels according to the 1–9 evaluation scale to determine the preference rate of all other criteria according to the worst criterion (Rezaei, 2015). This time, the superiority of other criteria over the worst criterion is determined and the A_W vector in Equation 3 is created.

$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW})^T \quad (3)$$

Here, a_{jW} in the vector A_W represents the preference of each evaluation criterion (C_1 – C_9) with respect to the worst criterion W and $a_{WW} = 1$. This means that the worst criterion will be compared with itself.

At this stage, expert pairwise comparison data were aggregated using the geometric mean method, which preserves proportional consistency and minimizes the impact of outliers (Rezaei, 2015). The combined matrix was then used in Step 5 for weight calculation.

Step 5. The most appropriate weight is determined:

In this step, the most appropriate weight for the criteria is determined as $(w_1^*, w_2^*, \dots, w_n^*)$ by BWM. To derive the optimal weights pairwise comparison ratios between best criterion B and each criterion j (a_{Bj}), and between each criterion j (a_{jW}) and the worst criterion W , are employed as follows:

$$W_B / W_j = a_{Bj}, W_j / W_W = a_{jW} \quad j = 1, 2, \dots, n$$

The objective is to minimize the maximum absolute deviation ξ from these consistency conditions:

$$\left| \frac{W_B}{W_j} - a_{Bj} \right| < \xi, \quad \left| \frac{W_j}{W_W} - a_{jW} \right| < \xi$$

Considering the total-sum condition and the non-negativity condition of the weights, the BWM is finally formulated as the following linear optimization model:

$$\min \xi \quad (4)$$

$$\text{Subject to} = \begin{cases} |w_B - w_j a_{Bj}| \leq \xi & j = 1, 2, \dots, n \\ |w_W a_{jW} - w_j| \leq \xi & j = 1, 2, \dots, n \\ \sum_j w_j = 1, w_j \geq 0, \quad \xi \geq 0 \end{cases} \quad (5)$$

The final weights w_j obtained from the optimization model represent the relative importance of the evaluation criteria (C_1 – C_9) based on expert judgments. ξ is the maximum deviation measuring the degree of consistency. Once the model is solved, the optimal weight vector $(w_1^*, w_2^*, \dots, w_n^*)$ and the consistency index ξ^* are obtained, ensuring that the results are mathematically robust and internally consistent (Rezaei, 2015).

In the present study, the weighting process in Step 5 reflects the relative importance assigned to each criterion by agricultural machinery exporters operating in Konya. Each firm performed

pairwise comparisons of the criteria according to the BWM scale, identifying the most and least important factors affecting their target-market decisions. The resulting individual weight vectors were computed using the BWM linear optimization model, and the final criterion weights were obtained by calculating the geometric mean of all firms' responses to ensure a representative and consistent weighting structure.

WASPAS Method

The WASPAS method was developed by Zavadskas et al. (2012). It is a method obtained by combining the Weighted Sum Model (WSM) and Weighted Product Model (WPM) from the MCMD models. The WASPAS method consists of the following 6 steps (Chakraborty and Zavadskas, 2014; Zavadskas et al., 2012). After obtaining the weights of the criteria through the BWM, the WASPAS method is applied to evaluate and rank the alternatives. Let the decision matrix be defined as:

Step 1. Creation of the Decision Matrix:

The decision matrix consists of m alternatives and n criteria, as shown in Equation (6). Here, $i=1,2,\dots,m$ denotes the alternatives and $j=1,2,\dots,n$ denotes the criteria. x_{ij} represents the performance value of the i th alternative with respect to the j th criterion.

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & & x_{mn} \end{bmatrix} \quad (6)$$

Step 2. Creating the Normalized Decision Matrix:

Each criterion in the decision matrix is normalized to ensure comparability among different scales. Depending on the problem, criteria can be either benefit-oriented or cost-oriented. For benefit criteria, normalization is performed by dividing each value by the maximum value of that criterion (Equation 7). For cost criteria, normalization is performed by dividing the minimum value of that criterion by each value (Equation 8).

$$\bar{x}_{(ij)} = \frac{x_{(ij)}}{\max_i x_{(ij)}}, j \in J_{benefit} \quad (i=1,2,\dots,m; j=1,2,\dots,n) \quad (7)$$

$$\bar{x}_{(ij)} = \frac{\min_i x_{(ij)}}{x_{(ij)}}, j \in J_{cost} \quad (i=1,2,\dots,m; j=1,2,\dots,n) \quad (8)$$

The $\bar{x}_{(ij)}$, $i=1,2,\dots,m; j=1,2,\dots,n$ value here is the normalized version of the x_{ij} value.

Step 3. In the WSM, the total relative importance of each alternative is calculated by multiplying the normalized performance values with their corresponding criterion weights and summing the results, as shown in Equation (9)

$$Q_i^{(1)} = \sum_{j=1}^n \bar{x}_{ij} * w_j, (i = 1, 2, \dots, m) \quad (9)$$

where w_j is the weight of criterion j .

Step 4. In the WPM, the relative importance of the i th alternative is calculated by multiplying the normalized performance values of all criteria, each raised to the power of its corresponding weight, as shown in Equation (10).

$$Q_i^{(2)} = \prod_{j=1}^n (\bar{x}_{ij})^{w_j}, (i = 1, 2, \dots, m) \quad (10)$$

Step 5. Finding the Common Generalized Criterion Value:

The overall relative importance (aggregated performance score) of the alternatives is obtained by combining the WSM and WPM results through a general formula, as presented in Equation (11).

$$Q_i = \lambda Q_i^{(1)} + (1 - \lambda) Q_i^{(2)}, (i = 1, 2, \dots, m) \quad (11)$$

The alternative with the highest Q_i value is considered the best alternative. The λ value is a parameter of the WASPAS method and takes values $0 \leq \lambda \leq 1$. Here, the λ value is determined by the decision maker. This value is usually chosen as 0.5. However, regarding how to choose the λ value, Zavadskas et al. (2012) propose a method in Equation (12) for calculating the optimal λ value.

$$\lambda = \frac{\sigma^2(Q_i^{(2)})}{\sigma^2(Q_i^{(1)}) + \sigma^2(Q_i^{(2)})} \quad (12)$$

RESULTS AND DISCUSSION

Criteria weights for determining the target market in agricultural machinery exports were calculated using the BWM method, while market evaluation and ranking were performed via the WASPAS method. A common ranking of criteria was obtained by taking the geometric mean of companies' responses. The most important criterion was identified as 'C7', and the least important as 'C5'. Python was used for weight calculations, with Microsoft Excel supporting the analysis.

Obtaining Criteria Weights with BWM

Step 1. 9 criteria identified, including C1, C2, C3, C4, C5, C6, C7, C8, and C9. Data from 89 agricultural machinery exporters were used to rank the best and worst criteria. The integrated ranking, based on the geometric mean, showed C7 as the most important and C5 as the least important criterion.

Step 2. The priority rankings of the criterion determined as the best, compared to other criteria, were created based on the evaluations of each agricultural machinery exporting company. For example, Table 2 shows the answers given by any agricultural machinery exporting company participating in the survey.

Table 2. Pairwise Comparisons with the Criterion Evaluated as the Best.

Finding the A_B vector									
Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
Preference Ratios Relative to the Best Criterion (C7)	4	2	3	5	9	7	1	6	8

Step 3. The priority rankings of the worst criterion relative to others were obtained based on the evaluations of each agricultural machinery exporter. As an example, Table 3 shows the responses of a participating company, while Table 4 presents the calculated importance levels of the criteria for that company.

Table 3. Pairwise Comparisons with the Criterion Evaluated as the Worst.

Finding the A_W vector									
Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
Preference Ratios over the Worst Criterion (C5)	6	5	7	4	1	2	8	9	3

Table 4. Weight values and consistency ratio from an agricultural machinery exporter's survey responses.

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
w_j	0,101	0,203	0,135	0,0813	0,0195	0,0581	0,2816	0,0677	0,0508
$\xi = 0,1251$									

Step 4. Based on the evaluations of 89 agricultural machinery exporters, the weight values of each criterion were calculated. Final importance levels were obtained by averaging these values, as shown in Table 5.

Table 5. Weight values and consistency ratio from all agricultural machinery exporters' responses.

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
w_j	0,112	0,105	0,135	0,071	0,0265	0,0740	0,295	0,106	0,072
$\xi = 0,1242$									

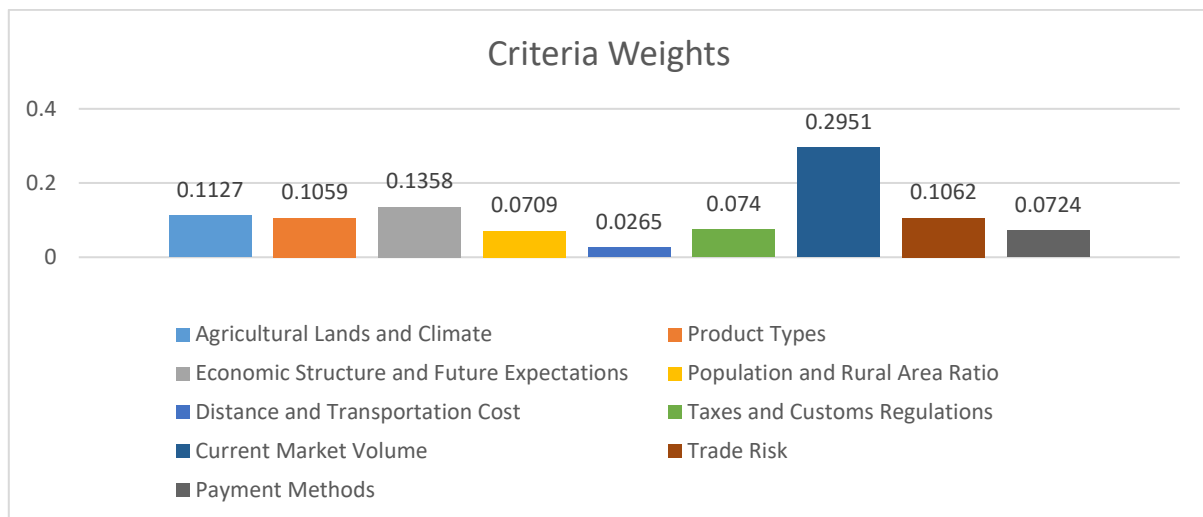


Figure 1. Criteria weights and ranking positions.

As shown in Figure 1, the importance weights of the nine criteria are ranked as follows: $C7 > C3 > C1 > C8 > C2 > C6 > C9 > C4 > C5$. The total of all weight values equals 1, indicating the relative importance of each criterion in the overall evaluation.

The leading criterion is $C7$ (29.51 %), reflecting immediate demand. Next is $C3$ (13.58 %), indicating market sustainability. $C1$ (11.27 %) follow, since machine suitability depends on local conditions. $C8$ (10.62 %) accounts for political, legal, and economic uncertainty, while $C2$ (10.59 %) assesses portfolio alignment with local production needs. $C6$ (7.40 %) affect entry costs; $C9$ (7.20 %) ensure financial security via diverse payment methods $C4$ (7.00 %) indicates labour and market density. Finally, $C5$ (2.00 %) are deemphasized for exporters. In international trade, Incoterms allocate responsibilities, risks and costs between seller and buyer. For agricultural machinery, Ex Works (EXW) is most common: the exporter makes goods available at their premises, and the importer assumes all transport, insurance and delivery obligations. Under EXW, distance and freight costs bear minimal weight in exporters' market assessments.

Selecting the Most Appropriate Target Market with the WASPAS Method

Step 1. In the first step of the WASPAS method, the decision matrix is created. In this context, $C1$, $C2$, $C3$, $C4$, $C7$, and $C8$ are defined as benefit criteria, while $C5$, $C6$, and $C9$ are defined as cost criteria. The decision matrix was constructed by calculating the arithmetic mean of the evaluations provided by 89 agricultural machinery exporting firms for these nine criteria ($C1$ – $C9$), and it is presented in Table 6.

Table 6. Decision Matrix.

Target Market Selection									
Alternative/ Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
USA	3,977	4,772	3,778	3,579	2,187	2,982	4,176	4,176	4,772
Italy	3,380	4,375	3,380	3,381	3,778	3,181	3,778	3,778	4,573
Iraq	3,181	2,982	2,386	3,977	4,573	3,579	3,579	2,585	3,381
Russia	4,573	4,772	3,380	4,176	3,977	2,784	4,573	2,784	2,784
France	3,579	4,375	3,778	2,982	4,176	3,380	4,176	3,977	4,375
Azerbaijan	3,977	4,176	2,982	3,579	4,375	3,778	3,579	3,579	4,176
Germany	3,181	3,778	3,579	2,982	3,778	3,181	3,778	3,977	4,573
Uzbekistan	4,375	3,579	3,181	4,176	3,977	3,181	4,573	2,585	2,784
Algeria	3,381	2,982	2,982	4,176	3,977	2,982	3,181	3,181	3,778
Bulgaria	3,778	3,977	3,181	3,778	4,573	3,778	3,977	3,977	4,375
Max	4,573	4,772	3,778	4,176	4,573	3,380	4,573	4,176	4,772
Min	3,181	2,982	2,386	2,982	2,187	2,784	3,181	2,585	2,784

Step 2. The benefit criteria in Equation (7) and the cost criteria in Equation (8) were used for the normalization process performed to convert the criteria values of the alternatives to a fixed unit. The normalized decision matrix is shown in Table 7.

Table 7. Normalized decision matrix according to WASPAS method.

Target Market Selection									
Alternative/ Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
USA	0,869	1,000	1,000	0,857	1,000	0,933	0,913	1,000	0,583
Italy	0,739	0,916	0,894	0,809	0,578	0,875	0,826	0,904	0,608
Iraq	0,695	0,625	0,631	0,952	0,478	0,777	0,782	0,619	0,823
Russia	1,000	1,000	0,894	1,000	0,550	1,000	1,000	0,666	1,000
France	0,782	0,916	1,000	0,714	0,523	0,823	0,913	0,952	0,636
Azerbaijan	0,869	0,875	0,789	0,857	0,5	0,736	0,782	0,857	0,666
Germany	0,695	0,791	0,947	0,714	0,578	0,875	0,826	0,952	0,608
Uzbekistan	0,956	0,75	0,842	1,000	0,550	0,875	1,000	0,619	1,000
Algeria	0,739	0,625	0,789	1,000	0,550	0,933	0,695	0,761	0,736
Bulgaria	0,826	0,833	0,842	0,904	0,478	0,736	0,869	0,952	0,636

Step 3: By using WSM and WPM, the value of $Q_i^{(1)}$ is obtained based on Equation (9), and the value of $Q_i^{(2)}$ is obtained based on Equation (10), as presented in Table 8.

Table 8. Q1 and Q2 values of Alternatives.

Target Market	$Q_i^{(1)}$	$Q_i^{(2)}$
USA	0,913	0,906
Italy	0,823	0,818
Iraq	0,724	0,717
Russia	0,937	0,928
France	0,863	0,854
Azerbaijan	0,796	0,792
Germany	0,811	0,803
Uzbekistan	0,885	0,873
Algeria	0,751	0,744
Bulgaria	0,831	0,824

Step 5. The total relative importance of the alternatives calculated based on the WSM and WPM methods, the Q_i value with the formula in Equation (11), is presented in Table 9.

Table 9. Q_i rankings of alternatives.

Target Market	Q_i					Arrangement
	$\lambda = 0.1$	$\lambda = 0.3$	$\lambda = 0.5$	$\lambda = 0.7$	$\lambda = 0.9$	
USA	0,907	0,909	0,911	0,911	0,913	2
Italy	0,818	0,819	0,821	0,821	0,822	6
Iraq	0,718	0,719	0,721	0,722	0,723	10
Russia	0,929	0,932	0,933	0,935	0,936	1
France	0,855	0,857	0,858	0,861	0,862	4
Azerbaijan	0,793	0,794	0,795	0,796	0,796	8
Germany	0,804	0,805	0,807	0,808	0,809	7
Uzbekistan	0,874	0,876	0,879	0,881	0,883	3
Algeria	0,745	0,746	0,747	0,748	0,751	9
Bulgaria	0,825	0,826	0,827	0,829	0,831	5

To examine the robustness of the WASPAS model, the λ parameter was tested at 0.1, 0.3, 0.5, 0.7 and 0.9 levels. As shown in Table 9, the ranking order of the alternatives remained unchanged across these scenarios, confirming the model's stability.

The data obtained from the survey conducted on companies exporting agricultural machinery in the study area were analyzed using the WASPAS method. As a result, the order of preference among the alternatives in target market selection was determined as Russia > USA > Uzbekistan > France > Bulgaria > Italy > Germany > Azerbaijan > Algeria > Iraq (Figure 2).

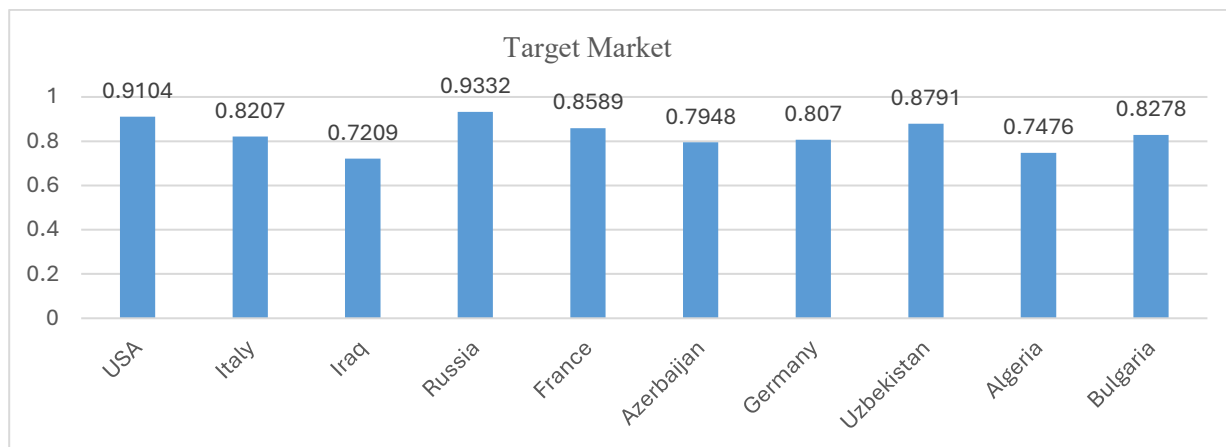


Figure 2. Country ranking according to WASPAS method.

This ranking shows that apart from major agricultural markets such as Russia, USA, Turkish agricultural sector's historical connections with Uzbekistan and Azerbaijan, and logistical advantages make these two countries attractive target markets due to their demand potential, customs advantages, and existing trade relations. In the context of Western embargoes following the Russia-Ukraine conflict, Türkiye's political stance has contributed to its growing significance as a supplier of Russian imports (Republic of Türkiye Ministry of Trade, 2024).

Countries in EU such as France, Bulgaria, Italy, Germany are attractive destination even with strong domestic producers. Türkiye can leverage its geographic proximity, low logistical cost advantage, and Customs Union framework to compete with low tech Chinese and Indian producers in the medium-technology segments through quality and after-sale service. Nevertheless, stringent quality control and compliance with technical specifications are necessary according to EU certification standards (European Commission, 2025).

Jiangxue et al. (2024), increasing mechanization between 2011 and 2020 loosened up exports through higher standardization, greater harvesting efficiency, and lower logistics costs. The need for supportive policies and incentive mechanisms was also stressed. Iqbal et al (2015) similarly reported that even while there are gains to foreign exchange due to the production of tractors locally, there are structural barriers among small farms in Pakistan. The proposals included cooperative ownership, expansion of the technical training programme, and stronger assistance to domestic manufacturers in meeting global quality standards.

CONCLUSIONS

Russia and Central Asia were found to be priority markets. This is due to close political, cultural and logistical relationships, as well as post-war demand gap in Russia. Türkiye can provide competitive price-performance due to the benefits of the Customs Union, nearness of logistics,

flexibility of the medium-technology industry and favourable exchange rate within the EU. To take benefit of these opportunities, the firms should develop country-specific export strategies and ensure full compliance to CE, emission, safety and environmental standards through university–industry R&D and obtain relevant certifications. There should be strong customer after sales support, availability of necessary spare-parts and technical assistance. Also, the enhancement of awareness and digitalization, especially utilizing the blockchain-based platform for Ministry of Trade export programs (fairs, branding, overseas office), will ease access to institutions. Finally, raising R&D investments and designing specific incentives for harvesting machinery and tractor production would lower import dependence, broaden domestic technology capacity and put Türkiye in a stronger position in global agricultural machinery exports. Theoretically, the study applies hybrid MCDM in international trade and agricultural marketing. From a management perspective, it provides useful information for policy makers and exporters. However, the findings are limited to the Konya, and expert-based weighting and ranking may entail subjective bias. Research may examine any limitation using larger data from other regions or even a cross-country investigation, the future research may. Furthermore, we suggest using fuzzy or Pythagorean fuzzy MCDM techniques rather than classical ones to address the uncertainty of experts. The results may become more robust and generalizable through sensitivity and comparative analyses using different techniques.

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