KSÜ Tarım ve Doğa Derg 29 (3), 732-755, 2026
KSU J. Agric Nat 29 (3), 732-755, 2026
DOI:10.18016/ksutarimdoga.vi.1727037

Multi-Criteria Decision-Making for Tractor Selection in Agricultural Mechanization

Alkan DURMUŞ[1] ✍, Abdurrahman İSKENDER[2],
[1]Dokuz Eylül Üniversitesi Hastanesi, [2] Sivas Cumhuriyet Üniversitesi, Yıldızeli Meslek Yüksekokulu, İzmir
[1]https://orcid.org/0000-0000-0000-0000, [2]https://orcid.org/ 0000-0001-8055-7869
✉: alkan.durmus@deu.edu.tr

ABSTRACT

This study aims to determine the most suitable tractor brand for farmers operating in the Aegean Region of Türkiye. In light of rising cost pressures and the need for enhanced agricultural productivity, the study emphasizes the necessity of objective and scientific approaches in tractor selection processes. To address uncertainties in decision-making, fuzzy multi-criteria decision-making techniques were employed. Specifically, the Fuzzy Simplified Best-Worst Method was used to calculate the weights of the evaluation criteria, while the Fuzzy Combined Compromise Solution method was applied to rank 14 tractor brands based on 18 defined criteria. Expert evaluations were obtained from a panel of five experienced decision-makers. The analysis revealed that the most critical main criterion was economic factors (0.366), whereas brand and image (0.122) were considered the least important. Among the sub-criteria, purchase cost (0.1352), operating cost (0.1296), and maneuverability (0.1293) were the most influential. New Holland was identified as the most preferred tractor brand with the highest score. The consistency of these findings was confirmed through sensitivity analysis. The findings of the study indicate that economic factors are the most influential main criterion in tractor selection, with purchase and operating costs emerging as the most critical sub-criteria. Based on the evaluation conducted using the F-CoCoSo method, the New Holland brand received the highest score and was identified as the most appropriate alternative by the decision-makers. Sensitivity analyses revealed that New Holland consistently ranked first across all weighting scenarios, thereby confirming the robustness and reliability of the model. These results demonstrate that the integrated use of the F-SBWM and F-CoCoSo methods offers a systematic and consistent evaluation framework for addressing complex multi-criteria decision-making problems such as tractor selection. The integration of F-SBWM and F-CoCoSo methods offers a systematic and reliable framework for tractor selection. The results indicate that scientific decision-making tools in agricultural machinery selection significantly improve resource efficiency and agricultural productivity.

Agricultural Mechanization

Research Article

Article History
Received : 25.06.2025
Accepted : 02.10.2025

Keywords
Agricultural Mechanization
F-CoCoSo,
Fuzzy Multi-Criteria Decision-Making,
F-SBWM ,
Tractor Selection

Tarımsal Mekanizasyonda Traktör Seçimi için Çok Kriterli Karar Verme

ÖZET

Bu çalışma, Ege Bölgesi'nde faaliyet gösteren çiftçiler için en uygun traktör markasının belirlenmesini amaçlamaktadır. Artan maliyet baskıları ve tarımsal verimlilik gereksinimi doğrultusunda, traktör tercihlerinde objektif ve bilimsel yöntemlere duyulan ihtiyaç bu çalışmanın temelini oluşturmaktadır. Çalışmada karar verme sürecindeki belirsizlikleri gidermek amacıyla bulanık çok kriterli karar verme yöntemleri kullanılmıştır. Öncelikle Fuzzy Simplified Best-Worst Method yöntemi ile kriter ağırlıkları belirlenmiş, ardından Fuzzy Combined Compromise Solution yöntemi ile 14 traktör markası 18 kritere göre değerlendirilmiştir. Uzman görüşleri 5 kişilik deneyimli bir panel aracılığıyla toplanmıştır. Analiz sonucunda en önemli ana kriterin ekonomik faktörler (0,366), en az

Tarımsal Mekanizasyon

Araştırma Makalesi

Makale Tarihçesi
Geliş Tarihi : 25.06.2025
Kabul Tarihi : 02.10.2025

Anahtar Kelimeler
Tarımsal Mekanizasyon
F-CoCoSo
Bulanık Çok Kriterli Karar Verme
F-SBWM
Traktör Seçimi

önemli kriterin ise marka ve imaj (0,122) olduğu belirlenmiştir. Alt kriterler arasında satın alma maliyeti (0,1352), işletme maliyeti (0,1296) ve hareket kabiliyeti (0,1293) öne çıkmıştır. Alternatifler arasında en yüksek skora sahip marka New Holland olmuştur. Sonuçlar, duyarlılık analizleriyle de doğrulanmıştır. Çalışmada elde edilen bulgular, traktör seçiminde en belirleyici ana kriterin ekonomik faktörler olduğunu ve özellikle satın alma ile işletme maliyetlerinin ön plana çıktığını göstermektedir. F-CoCoSo yöntemiyle yapılan değerlendirme sonucunda, New Holland markası en yüksek skoru alarak karar vericiler tarafından en uygun alternatif olarak belirlenmiştir. Duyarlılık analizleri, farklı ağırlık senaryolarında dahi New Holland'ın tüm varyasyonlarda birinci sırada yer aldığını ortaya koyarak, modelin istikrarını ve güvenilirliğini teyit etmiştir. Bu sonuçlar, F-SBWM ve F-CoCoSo yöntemlerinin entegre kullanımının traktör seçimi gibi çok kriterli karar problemlerinde karar vericilere sistematik ve tutarlı bir değerlendirme yaklaşımı sunduğunu göstermektedir. F-SBWM ve F-CoCoSo yöntemlerinin entegre kullanımıyla yapılan analiz, traktör seçimi sürecinde karar vericilere sistematik bir yaklaşım sunmaktadır. Bulgular, tarım makineleri tercihlerinde bilimsel yöntemlerin kullanılmasının, kaynakların etkin kullanımına ve tarımsal verimliliğin artırılmasına katkı sağlayacağını göstermektedir.

Atıf İçin : Durmuş, A, Iskender , A. (2026). Tarımsal Mekanizasyonda Traktör Seçimi için Çok Kriterli Karar Verme. *KSÜ Tarım ve Doğa Derg 29* (2), 732-755. DOI: 10.18016/ksutarimdoga.vi.1727037.

To Cite: Durmuş, A, Iskender , A. (2026). Multi-Criteria Decision-Making for Tractor Selection in Agricultural Mechanization. *KSU J. Agric Nat 28* (*), 000-000. DOI: 10.18016/ksutarimdoga.vi.1727037.

INTRODUCTION

Mechanization is a fundamental aspect of modern agriculture, playing a crucial role in enhancing productivity, reducing labor dependency, and optimizing resource utilization. The selection of agricultural machinery is a complex and critical decision-making process, as the choice of equipment must be strategically aligned with the specific type of production to maximize efficiency and effectiveness (Nedeljković et al., 2024). The integration of modern machinery in agricultural practices not only increases crop yields but also improves working conditions, facilitates the implementation of advanced production techniques, and enhances economic sustainability (Altuntaş, 2020). However, due to varying agricultural landscapes and operational requirements, selecting the appropriate machinery remains a challenging yet essential task for farmers (Nedeljković et al., 2024).

Agricultural mechanization significantly contributes to overcoming technical and climatic limitations, enabling the expansion of cultivated land while ensuring higher agricultural efficiency. Modern mechanical technologies support the application of research-driven innovations across various agricultural domains, making mechanization indispensable for sustainable food production (Amini & Asoodar, 2016). Among agricultural machinery, tractors serve as the backbone of mechanized farming, providing the necessary power for key operations such as plowing, planting, fertilizing, cultivating, and harvesting (Goering et al., 2003; Renius, 2020).

Tractors not only increase farm productivity but also contribute to the economic and social stability of rural communities by facilitating access to essential resources and improving farm operations (Ateş, 2024). In addition to their agricultural applications, tractors are widely used in horticultural farming, construction, and mining industries (Mileusnić et al., 2019). The increasing cultivation of vegetables and fruits has led to the rising demand for compact and high-performance horticultural tractors, particularly in regions where precision agriculture is expanding (Ekinci & Çarman, 2017).

Tractors are classified based on their functionality and application, including two-wheel drive (2WD), four-wheel drive (4WD), track-type (crawler), row-crop, utility, compact, garden, industrial, and specialty tractors, such as orchard and high-clearance models (Renius, 2020). Additionally, autonomous and smart tractors, equipped with GPS, AI-driven automation, and remote monitoring capabilities, are emerging as a game-changer in precision agriculture, optimizing farm operations with minimal human intervention.

The selection of agricultural machinery, particularly tractors, is a crucial investment for farmers, as poor decisions can result in significant financial losses and operational inefficiencies (Li et al., 2023). Given the high capital cost associated with tractor procurement, farmers must carefully evaluate available options using advanced decision-making techniques to select the most suitable model based on their specific farm requirements. Insufficient information during the purchasing process can reduce farm productivity and pose risks to broader economic stability (Durczak et al., 2020).

Farmers' demand for tractors is influenced by economic, operational, social, and policy-related factors. Government subsidies and credit availability play a crucial role in supporting purchasing decisions, while farm size and production scale directly impact efficiency requirements, making mechanization essential for larger farms (Hua, 2015). The labor-saving benefits of tractors further drive demand, as mechanization reduces manual labor in large-scale farming (Hua, 2015). Moreover, technological advancements, such as GPS-guided tractors and smart farming systems, have increased interest in adopting high-tech machinery (Ding et al., 2011).

Several socio-demographic factors also influence tractor adoption. Farmers with higher education levels are more likely to invest in mechanization, recognizing its long-term benefits (Fan & Pardey, 1997). Additionally, age and gender impact adoption trends, with younger farmers being more inclined to use technologically advanced tractors (Li & Niu, 2011). Government policies, including subsidies, tax incentives, and training programs, further encourage tractor adoption, ensuring that modern machinery is accessible to a broader range of farmers (Reganold et al., 2011; Bjornlund et al., 2009). Ultimately, financial support, labor efficiency, technological innovation, and policy interventions collectively shape the demand for tractors in agriculture (Huffman & Evenson, 1992).

In Turkey, the adoption of tractors has been steadily increasing, reflecting the growing importance of mechanization in agriculture. According to Türkiye İstatistik Kurumu (TÜİK) data, the tractor market has experienced significant growth, particularly for lower-horsepower models, which are preferred by small and fragmented agricultural enterprises (Altuntaş, 2020). The projected growth rate for 0–5 HP single-axle tractors is 15.83%, while over 70 HP dual-axle tractors are expected to grow at a rate of 7.95% in the coming years.

However, financial constraints continue to be a major barrier to efficient tractor utilization in Turkey, as many small-scale farmers struggle with high acquisition and maintenance costs. Additionally, it has been observed that tractors are often not used efficiently throughout their economic lifespan, leading to higher operational expenses and reduced long-term benefits (Altuntaş & Demirtola, 2004; Özgüven et al., 2010). Addressing these challenges requires a structured approach to tractor selection, incorporating economic feasibility, operational efficiency, and policy-driven incentives to optimize decision-making for farmers.

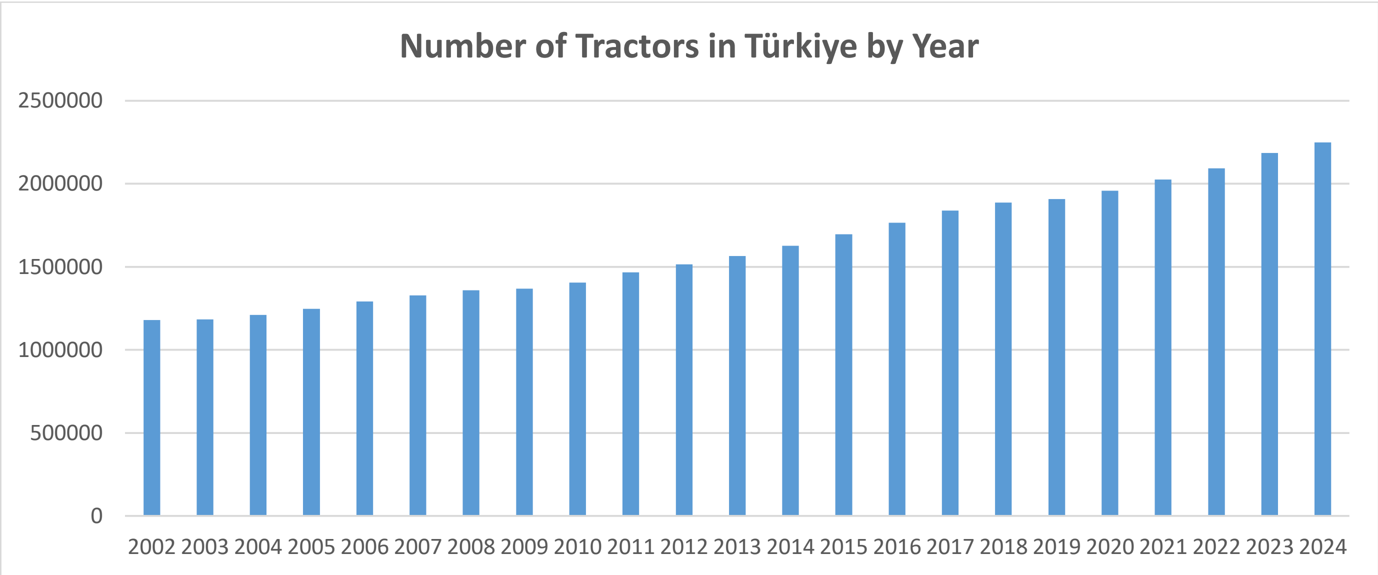


Figure 1. Number of Tractors in Türkiye by Year
Şekil 1. Türkiye'de Yıllara Göre Traktör Sayıları

The number of tractors in Turkey has shown a steady and consistent increase over the years, reflecting the growing importance of mechanization in agriculture. While the number of tractors in Turkey was 1,180,127 in 2002, this number had nearly doubled to 2,259,696 by 2024 (Fig.1). This upward trend reflects the growing demand for modern agricultural equipment, driven by factors such as technological advances, economic policies, government incentives, and improved financial accessibility. The increase in tractor numbers can be attributed to precision agriculture innovations, increased government subsidies, and evolving agricultural productivity needs that are encouraging farmers to invest in more efficient and high-performance machinery.

Selecting the right agricultural machinery, particularly tractors, has become a complex decision-making process due to the presence of multiple, often conflicting criteria. Multi-Criteria Decision Making (MCDM) methods provide a structured and systematic approach to improving the accuracy and efficiency of these decisions. These techniques evaluate economic, operational, technological, and social factors, ensuring a comprehensive and objective assessment of farmers' choices. By breaking down complex issues into smaller, more manageable components, MCDM methodologies enhance analytical clarity and allow farmers and policymakers to make well-informed, evidence-based decisions that align with their specific agricultural needs (Ersen, 2024; Işık, 2023).

Tey and Brindal (2012) identified seven key categories influencing farmers' decision-making in agricultural investments, particularly in mechanization. These include socio-economic factors such as age, education level, and farming experience; agro-ecological factors including land ownership, farm size, and soil quality; and institutional factors such as farm location and access to agricultural subsidies. Additionally, informational factors like the use of consultants and extension services, farmer perception regarding the profitability of new technologies, and behavioral factors such as willingness to adopt variable-rate technology significantly impact decision-making. Moreover, technological factors, including yield mapping systems, computer usage, and irrigation infrastructure, play a crucial role in shaping adoption trends. Their study underscores the critical role of economic, informational, and environmental conditions in the adoption of precision agriculture technologies, directly influencing farmers' purchasing decisions and their selection of efficient and cost-effective tractors (Tey & Brindal, 2012).

In this context, the primary aim of this study is to determine the most appropriate tractor brand for a farmer operating in the Aegean Region by employing a combined fuzzy multi-criteria decision-making approach. To this end, a hierarchical evaluation structure consisting of four main criteria and eighteen sub-criteria was established based on expert opinions. The Fuzzy Simplified Best-Worst Method (F-SBWM) was used to derive the weights of the criteria, while the Fuzzy Combined Compromise Solution (F-CoCoSo) method was applied to rank the tractor alternatives. Furthermore, a sensitivity analysis was conducted to verify the robustness of the obtained results under different weighting scenarios. By integrating expert-driven evaluation with fuzzy logic-based decision modeling, the study aims to contribute both to the methodological literature and to the practical needs of farmers in selecting cost-effective and functionally suitable tractors.

LITERATURE REVIEW

Tractor selection plays a fundamental role in agricultural mechanization, impacting productivity, efficiency, and sustainability. Over the years, numerous studies have explored different evaluation criteria, performance optimizations, maintenance strategies, decision-making methodologies, and sustainability factors to enhance tractor selection processes.

Early research focused on the technical specifications and power output of tractors to ensure efficient mechanization. Gürsoy et al. (2021) analyzed tractor selection based on power output, highlighting its significance in matching tractor capacity with farm requirements. Similarly, Shorkpor and Asakereh (2021) examined tractor selection in the Saral region of Dyvandara district, concluding that the BMI 285 model was the most suitable medium-range tractor based on driving wheel configuration, gearbox type, PTO (RPM), number of cylinders, and power (hp). These studies underscored the importance of technical parameters in tractor selection, emphasizing that selecting an inappropriate model could lead to inefficiencies and financial losses (Li et al., 2023).

As agricultural mechanization advanced, researchers explored performance optimization and propulsion system enhancements. Zhu et al. (2021) introduced a mechanical-electronic-hydraulic powertrain system, improving energy efficiency in tractors, while Xia et al. (2020) proposed a hydro-mechanical continuously variable transmission to optimize power transmission. Additionally, Baek et al. (2022) investigated gear transmission systems, focusing on reducing maintenance costs and improving durability. These studies contributed to the development of technologically advanced tractor models capable of enhancing fuel efficiency, reducing wear and tear, and improving overall operational performance.

Another key area of research has been the maintenance and operational aspects of tractors. Mishra and Satapathy (2023) conducted a farm-based survey to assess the maintenance needs of tractor attachments, utilizing the SWARA (Step-wise Weight Assessment Ratio Analysis) method. Similarly, Lalremruata et al. (2019) studied the impact of tractor noise on operators, considering factors such as engine type, powertrain, rated engine speed, weight, and number of gears. Furthermore, Okoko and Ajav (2019) analyzed plowing techniques, revealing that speed and tillage depth significantly affect tractor performance and fuel consumption.

Beyond operational efficiency, studies have also addressed the safety and environmental impact of tractors. Fargnoli and Lombardi (2019) examined safety risks associated with tractor usage, identifying high injury rates among farmers due to unsafe operating conditions. Hou et al. (2022) evaluated tractor emissions across different districts of Beijing, highlighting the need for sustainable engine technologies to reduce environmental pollution. Mutlu (2020) further analyzed the most widely sold tractor models, providing insights into market trends and consumer preferences.

In recent years, researchers have increasingly applied Multi-Criteria Decision-Making (MCDM) methods to optimize tractor selection by integrating both qualitative and quantitative evaluation criteria. Saaty (1980) pioneered the Analytic Hierarchy Process (AHP), a structured decision-making tool that has since been widely used in agricultural machinery selection. Hoose et al. (2021) employed AHP and DEA (Data Envelopment Analysis) to rank tractor-trailers for grain transportation, while Lu et al. (2022) utilized TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) to optimize supplier selection for agricultural machinery development. Additionally, Hu et al. (2019) applied ANP (Analytic Network Process) and BSC (Balanced Scorecard) methods to develop a maintenance network for agricultural production, improving resource allocation and equipment longevity.

Recent studies have demonstrated the effectiveness of hybrid MCDM models in tractor selection. Puška et al. (2024) applied a fuzzy-rough MCDM approach, integrating LMAW for criteria weighting and SAW for ranking alternatives, identifying Solis S 26 as the most suitable tractor based on expert evaluations. Reis et al. (2014) developed a multi-criteria decision analysis (MCDA) model for family farmers in Pelotas, Brazil, incorporating operational cost, purchase price, and tractor capacity as key factors. Similarly, Blagojević et al. (2012) employed SAW, TOPSIS, and CP methods to rank four tractor models based on ergonomic characteristics, concluding that while New Holland T6040 ranked highest, Massey Ferguson 5455 Dyna 4 was a better alternative for cost-conscious farmers.

In addition to MCDM techniques, sustainability considerations have gained prominence in tractor selection and mechanization strategies. Yang et al. (2019) proposed a multi-objective disassembly process in harvester production, reducing the carbon footprint using the MDFOA (Multi-Objective Disassembly Line Balancing Fruit Fly Optimization Algorithm) method. Lalghorbani and Jahan (2022) applied MULTIMOORA (Multi-Objective Optimization on the Basis of Ratio Analysis) to enhance combine harvester efficiency, while Han et al. (2020) used the MIP (Multi-Objective Mixed Integer Program) method to improve agricultural mechanization efficiency by optimizing service visits and operational performance.

Several studies have focused on economic and financial aspects of tractor selection. Amini & Asoodar (2016) used AHP to analyze tractor preferences in Iran, finding that maintenance costs were the most critical factor in Ahvaz (49.4%), while price was the top priority in Ghaemshahr (29.6%), with ITM285 and John Deere 6150 emerging as the most preferred models. Economic analysis has also been integrated into investment decision frameworks, with Jacobsen (2000) assessing machinery costs and investments to optimize farm resource allocation. Grisso et al. (2014) further explored tractor selection based on empirical test data, ensuring objective performance evaluations for farmers.

Hybrid MCDM approaches have also been widely explored in machinery selection and supplier evaluation. Kahraman et al. (2003) integrated fuzzy logic with AHP, demonstrating its flexibility in handling uncertainty in supplier selection. Russo and Camanho (2015) reviewed AHP applications in agricultural decision-making, reinforcing its versatility in multi-criteria evaluations. Uma Devi et al. (2012) applied AHP for vendor selection, illustrating how structured decision-making techniques can enhance agricultural procurement.

Overall, the literature highlights the growing complexity of tractor selection, influenced by technological advancements, sustainability concerns, economic feasibility, and structured decision-making approaches. While various methodologies have been employed, there remains a gap in integrating hybrid MCDM models that comprehensively evaluate tractors based on economic, operational, environmental, and sustainability factors. This study aims to address this gap by applying a structured MCDM framework that optimizes tractor selection for agricultural applications, ensuring cost-effectiveness, operational efficiency, and long-term sustainability.

MATERIALS and METHODS

The selection of tractors is a complex decision-making process, influenced by multiple economic, technical, operational, and social factors. This study employs a structured evaluation framework to determine the most relevant tractor selection criteria using Multi-Criteria Decision-Making (MCDM) techniques. The methodology integrates expert evaluations, field studies, and previous research findings, particularly those from Turkey, to ensure a comprehensive and regionally relevant analysis (Sağlam & Çevik, 2012; Sağlam & Çetin, 2017; Civelek & Say, 2018; Karaca et. al., 2023; Berk & Keskin, 2020).

Data collection was conducted through literature reviews, farmer surveys, and expert interviews to identify the most significant factors influencing tractor purchasing decisions. The methodology follows a multi-step approach, including the identification of tractor selection criteria, the application of MCDM models, and the assignment of weights based on expert assessments.

To develop a structured decision-making model, tractor selection criteria were categorized into four key dimensions: economic, technical, operational, and social factors. These criteria were determined based on previous studies, expert input, and regional assessments (Nedeljković et al., 2022; Bai & Sarkis, 2009; Mwikali & Kavale, 2012; Hua, 2015; Sivakumar & Kaliyamoorthy, 2014).

Economic considerations play a crucial role in tractor purchasing decisions, as acquiring agricultural machinery represents a significant financial investment. Farmers prioritize purchase price, fuel consumption, maintenance costs, spare parts availability, and resale value when selecting tractors (Cankurt et al., 2009; Aksoy et al., 2019). The availability of government subsidies, loan options, and financial support mechanisms also directly influences purchasing decisions (Sivakumar & Kaliyamoorthy, 2014).

Research conducted in Kayseri and Şanlıurfa indicates that government incentives and credit access significantly impact farmers' choices, often leading them to select lower-horsepower tractors due to financial constraints (Sağlam & Çevik, 2012; Sağlam & Çetin, 2017). Studies in Kayseri Irrigation Unions further highlight that optimal tractor power and machinery size selection is dependent on farm size, crop type, and financial resources (Sağlam et al., 2018).

Technical aspects are among the most important considerations in tractor selection, as they directly impact operational efficiency and productivity. Farmers assess engine power, fuel efficiency, durability, and traction performance to ensure long-term reliability (Aybek & Boz, 2009; Aybek & Şenel, 2009).

Studies in Turkey's Eastern Mediterranean region reveal that larger farms invest in high-horsepower tractors, with an average preferred engine power of 47.83 kW (Aybek & Şenel, 2009). However, some farmers overestimate power needs, leading to inefficiencies in fuel usage and increased operational costs (Aybek & Şenel, 2009). Soil texture, land slope, and farm fragmentation also affect selection, with heavier soils requiring higher-powered tractors, whereas fragmented land conditions lead farmers to prefer lighter, more maneuverable tractors (Gürsoy et al., 2021).

Other significant technical considerations include hydraulic steering, cooling systems, ergonomic cabin designs, and four-wheel drive capability, which enhance operator comfort and overall machine performance (Sağlam & Çevik, 2012; Sağlam & Çetin, 2017).

The operational efficiency of a tractor is another key decision-making criterion, as it affects productivity, usability, and farm performance. Studies have shown that farm size, annual working hours, and workload intensity significantly influence tractor selection (Civelek & Say, 2018).

Research in Çumra, Konya, suggests that land size per tractor and operational hours determine farmers' preferences for newer, more durable tractor models (Berk & Keskin, 2020). In Kayseri and Konya, the selection of tractor power and machinery size is largely based on the number of workable days, crop type, and machine performance (Sağlam et al., 2018; Civelek & Say, 2018). Farmers cultivating multiple crop types prioritize fuel efficiency and multipurpose functionality in their tractors (Sağlam et al., 2018).

Social influences and institutional factors also play a vital role in tractor purchasing behavior. Studies indicate that regional popularity, word-of-mouth recommendations, and prior experiences with specific brands significantly impact decision-making (Sağlam & Çetin, 2017).

In regions such as Kayseri and Şanlıurfa, farmers often base their tractor selection on advice from neighbors, after-sales service availability, and spare parts access (Sağlam & Çevik, 2012). Government programs and training initiatives that promote awareness of modern mechanization techniques also encourage farmers to adopt more advanced tractor models (Hua, 2015). Research further suggests that education level affects purchasing behavior, with higher-educated farmers more likely to explore diverse brands and technical features before making a final decision (Aksoy et al., 2019).

Decision-Making Framework

To develop a scientifically structured approach for tractor selection, this study utilizes Multi-Criteria Decision-Making methods, which are widely recognized in agricultural machinery selection (Saaty, 1980; Hoose et al., 2021). The research applies AHP (Analytic Hierarchy Process), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), and Fuzzy Logic to enhance decision accuracy and reliability.

The AHP method is used to establish priority rankings among tractor selection criteria, ensuring an objective assessment based on expert evaluations. The TOPSIS method is applied to compare and rank different tractor models, considering multiple performance criteria such as technical specifications, operational efficiency, and financial feasibility. Fuzzy Logic is integrated to handle uncertainties and subjective judgments, making the evaluation process more flexible and adaptable.

The weighting of criteria is determined using expert surveys, statistical analysis, and field data, ensuring a data-driven and scientifically validated selection model. Studies show that structured decision-making models significantly improve agricultural investment planning, leading to better resource allocation and optimized tractor selection (Rozman et al., 2017).

Fuzzy Simplified Best-Worst Method (F-SBWM):

The classical Best-Worst Method (BWM), a multi-criteria decision-making method, was developed by Rezaei (2015). In this method, once the relevant criteria for the decision-making process are identified, the decision-maker selects the most important (best) and the least important (worst) criteria. The best criterion is then compared with all other criteria, and all other criteria are compared with the worst criterion using a scale from 1 to 9. These comparisons are used to construct a linear programming model, and solving this model yields the optimal weights of the criteria. When the number of criteria is high, solving the model typically requires optimization software.

To address the computational complexity of the classical BWM, the Simplified Best-Worst Method (SBWM) was proposed by Amiri et al. (2021). In the proposed method, the determination of criteria weights does not require mathematical programming. The steps for applying the method using fuzzy triangular numbers are explained below (Amiri et al., 2022).

Step 1. The best and worst criteria are identified from the set of criteria $C_i = \{c_1, c_2, c_3, \dots\dots, c_n\}$.

Step 2. Using triangular fuzzy numbers, the preference of the best criterion over all other criteria is determined ($\tilde{a}_{Bj} = (a_{Bj}^l, a_{Bj}^m, a_{Bj}^u)$).

Step 3. Using triangular fuzzy numbers, the preference of all other criteria over the worst criterion is determined $\tilde{a}_{jW} = (a_{jW}^l, a_{jW}^m, a_{jW}^u)$).

Step 4. The fuzzy weights of each criterion ($\tilde{w}_j' = (w_j^l, w_j^m, w_j^u)$) are obtained by using the reference comparisons of the best criterion with other criteria. The weight of the best criterion is calculated using Equation (1), which determines its priority over the remaining criteria.

$$\sum_j \frac{1}{\tilde{a}_{Bj}} \, x \, \widetilde{w}_B' = 1 \Rightarrow \widetilde{w}_B' = \frac{1}{\sum_j \frac{1}{\tilde{a}_{Bj}}} \quad (1)$$

The weights of the remaining criteria are obtained using Equation (2), based on the weight of the best criterion.

$$\widetilde{w}_B' - \tilde{a}_{Bj} x \tilde{w}_j' = 0 \Rightarrow \tilde{w}_j' = \frac{\widetilde{w}_B'}{\tilde{a}_{Bj}}, \qquad \forall j \quad (2)$$

Step 5. The priority of each criterion with respect to the worst criterion is determined using reference comparisons and Equation (3), yielding the fuzzy priority weights ($\tilde{w}_j'' = (w_j^l, w_j^m, w_j^u)$). Subsequently, the weight of the worst criterion is calculated, and the weights of the remaining criteria are derived using Equation (4).

$$\textstyle\sum_j \tilde{a}_{jW} \, x \, \tilde{w}_W'' = 1 \Rightarrow \tilde{w}_W'' = \frac{1}{\sum_j \tilde{a}_{jW}} \quad (3)$$

$$\widetilde{w}_j'' - \tilde{a}_{jW} x \tilde{w}_W'' = 0 \Rightarrow \tilde{w}_j'' = \tilde{a}_{jW} x \tilde{w}_W'', \quad \forall j \quad (4)$$

Step 6. The final weights of the criteria ($\tilde{w}_j^* = (\tilde{w}_1^*, \tilde{w}_2^*, \dots\dots\dots, \tilde{w}_n^*)$), are calculated using Equation (5), based on the weights $\tilde{w}_j' and\ \tilde{w}_j''$ obtained in Steps 4 and 5.

$$\tilde{w}_j^* = \alpha * \tilde{w}_j' + (1-\alpha) * \tilde{w}_j'' \quad (5)$$

In multi-criteria decision-making (MCDM) techniques, the parameter α in the final weight aggregation formula is typically set to 0.5. This reflects an equal consideration of both the best-to-others and others-to-worst comparisons when calculating the final criterion weights.

The reliability of results obtained in MCDM methods largely depends on the consistency of the expert judgments used for pairwise comparisons among criteria. In the Fuzzy Simplified Best-Worst Method (F-SBWM), the consistency ratio (CR) of expert evaluations is calculated to assess the coherence of the comparisons provided. This consistency ratio ensures that the fuzzy comparisons made by the experts do not contradict each other significantly and that the resulting weights are meaningful and robust for decision-making purposes:

$$CR = \sum_j \left|\tilde{w}_j' - \tilde{w}_j''\right|^2 \quad (6)$$

…is calculated using the following formula. If the weights derived from the comparison of the best criterion with the others and the comparison of the other criteria with the worst one yield identical values, the comparisons are considered "perfectly consistent." However, when there are numerous decision criteria, it becomes increasingly difficult for experts to make perfectly consistent pairwise comparisons.

Therefore, the consistency value obtained from Equation (6) is used as an indicator:

the closer this value is to zero, the higher the consistency of the expert comparisons.

This measure ensures the reliability and robustness of the criterion weights calculated via the Fuzzy Simplified Best-Worst Method (F-SBWM), contributing to the overall credibility of the multi-criteria decision-making process.

Fuzzy Combined Compromise Solution (F-CoCoSo) Method

The classical CoCoSo method, proposed by Yazdani et al. (2019), is based on an integrated model combining Simple Additive Weighting (SAW) and Exponential Weighting (EW). After determining the alternatives and the relevant criteria, the solution to a decision-making problem is obtained using the Fuzzy CoCoSo method by following the steps outlined below (Ulutaş et al., 2021).

Step 1: A fuzzy decision matrix is constructed in which each alternative is evaluated with respect to each criterion.

$$\tilde{\boldsymbol{Z}} = \left[\tilde{\boldsymbol{z}}_{\boldsymbol{ij}}\right]_{\boldsymbol{kxn}} = \begin{bmatrix} \tilde{\boldsymbol{z}}_{\boldsymbol{11}} & \cdots & \tilde{\boldsymbol{z}}_{\boldsymbol{1n}} \\ \vdots & \ddots & \vdots \\ \tilde{\boldsymbol{z}}_{\boldsymbol{k1}} & \cdots & \tilde{\boldsymbol{z}}_{\boldsymbol{kn}} \end{bmatrix}_{\boldsymbol{kxn}} \tag{7}$$

Here $\tilde{\boldsymbol{z}}_{\boldsymbol{ij}}$;

$$\tilde{\boldsymbol{z}}_{\boldsymbol{ij}} = \left(\boldsymbol{z}_{\boldsymbol{ij}}^{\boldsymbol{l}}, \boldsymbol{z}_{\boldsymbol{ij}}^{\boldsymbol{m}}, \boldsymbol{z}_{\boldsymbol{ij}}^{\boldsymbol{u}}\right)$$

are triangular fuzzy numbers.

Step 2. A normalization process is performed for the criteria. For cost-based criteria, the normalization is calculated as follows:

$$\tilde{r}_{ij} = \left(r_{ij}^{l}, r_{ij}^{m}, r_{ij}^{u}\right) = \frac{\max(\tilde{z}_{ij}) - \tilde{z}_{ij}}{\max(\tilde{z}_{ij}) - \min(\tilde{z}_{ij})} = \left(\frac{max\left(z_{ij}^{u}\right) - z_{ij}^{u}}{maxz_{ij}^{u} - minz_{ij}^{l}}, \frac{max\left(z_{ij}^{u}\right) - z_{ij}^{m}}{maxz_{ij}^{u} - minz_{ij}^{l}}, \frac{max\left(z_{ij}^{u}\right) - z_{ij}^{l}}{maxz_{ij}^{u} - minz_{ij}^{l}}\right); \tag{8}$$

For benefit-based criteria:

$$\tilde{r}_{ij} = \left(r_{ij}^{l}, r_{ij}^{m}, r_{ij}^{u}\right) = \frac{\tilde{z}_{ij} - \min(\tilde{z}_{ij})}{\max(\tilde{z}_{ij}) - \min(\tilde{z}_{ij})} = \left(\frac{z_{ij}^{l} - min\left(z_{ij}^{l}\right)}{maxz_{ij}^{u} - minz_{ij}^{l}}, \frac{z_{ij}^{m} - min\left(z_{ij}^{l}\right)}{maxz_{ij}^{u} - minz_{ij}^{l}}, \frac{z_{ij}^{u} - min\left(z_{ij}^{l}\right)}{maxz_{ij}^{u} - minz_{ij}^{l}}\right) \tag{9}$$

carried out using formulas.

Step 3. For each alternative, the weighted comparability fuzzy sum $(\tilde{S}_i)$ and the power-weighted comparability sequences $(\tilde{P}_i)$ are calculated using equations (10) and (11).

$$\tilde{S}_i = \left(S_i^l, S_i^m, S_i^u\right) = \sum_{j=1}^{n} \widetilde{w}_{jc}.\tilde{r}_{ij} = \left(\sum_{j=1}^{n} w_{jc}^l.r_{ij}^l, \sum_{j=1}^{n} w_{jc}^m.r_{ij}^m, \sum_{j=1}^{n} w_{jc}^u.r_{ij}^u\right) \tag{10}$$

$$\tilde{P}_i = \left(P_i^l, P_i^m, P_i^u\right) = \sum_{j=1}^{n}\left(\tilde{r}_{ij}\right)^{\widetilde{w}_{jc}}. = \left(\sum_{j=1}^{n}\left(r_{ij}^l\right)^{w_{jc}^u}, \sum_{j=1}^{n}\left(r_{ij}^m\right)^{w_{jc}^m}, \sum_{j=1}^{n}\left(r_{ij}^u\right)^{w_{jc}^l}\right) \tag{11}$$

Step 4. The fuzzy appraisal scores $(\tilde{f}_{ia}, \tilde{f}_{ib}, \tilde{f}_{ic})$ are obtained using equations (12), (13), and (14).

$$\tilde{f}_{ia} = \left(f_{ia}^l, f_{ia}^m, f_{ia}^u\right) = \frac{\tilde{P}_i + \tilde{S}_i}{\sum_{i=1}^{k}(\tilde{P}_i + \tilde{S}_i)} = \left(\frac{P_i^l + S_i^l}{\sum_{i=1}^{k}(P_i^u + S_i^u)}, \frac{P_i^m + S_i^m}{\sum_{i=1}^{k}(P_i^m + S_i^m)}, \frac{P_i^u + S_i^u}{\sum_{i=1}^{k}(P_i^l + S_i^l)}\right) \tag{12}$$

$$\tilde{f}_{ib} = \left(f_{ib}^l, f_{ib}^m, f_{ib}^u\right) = \frac{\tilde{S}_i}{\min(\tilde{S}_i)} + \frac{\tilde{P}_i}{\min(\tilde{P}_i)} = \left(\frac{S_i^l}{\min(S_i^l)} + \frac{P_i^l}{\min(P_i^l)}, \frac{S_i^m}{\min(S_i^l)} + \frac{P_i^m}{\min(P_i^l)}, \frac{S_i^u}{\min(S_i^l)} + \frac{P_i^u}{\min(P_i^l)}\right) \tag{13}$$

$$\tilde{f}_{ic} = \left(f_{ic}^l, f_{ic}^m, f_{ic}^u\right) = \frac{\lambda\left(\tilde{S}_i\right) + (1-\lambda)\left(\tilde{P}_i\right)}{\lambda max\left(\tilde{S}_i\right) + (1-\lambda)\max(\tilde{P}_i)}$$

$$= \left(\frac{\lambda\left(S_i^l\right) + (1-\lambda)(P_i^l)}{\lambda max(S_i^u) + (1-\lambda)max(P_i^u)}, \frac{\lambda(S_i^m) + (1-\lambda)(P_i^m)}{\lambda max(S_i^u) + (1-\lambda)max(P_i^u)}, \frac{\lambda(S_i^u) + (1-\lambda)(P_i^u)}{\lambda max(S_i^u) + (1-\lambda)max(P_i^u)}\right) \tag{14}$$

The λ value used in the equation is determined by the decision-makers and is typically taken as 0.5.

Step 5. The fuzzy evaluation scores $\left(\tilde{f}_{ia}, \tilde{f}_{ib}, \tilde{f}_{ic}\right)$ are defuzzified using Equations (15), (16), and (17), and converted into crisp evaluation scores (f_{ia}, f_{ib}, f_{ic}).

$$f_{ia} = \frac{f_{ia}^l + f_{ia}^m + f_{ia}^u}{3} \tag{15}$$

$$f_{ib} = \frac{f_{ib}^l + f_{ib}^m + f_{ib}^u}{3} \tag{16}$$

$$f_{ic} = \frac{f_{ic}^{l} + f_{ic}^{m} + f_{ic}^{u}}{3} \quad (17)$$

Step 6. The crisp evaluation scores are aggregated using Equation (17) to obtain the final score (f_i) for each alternative.

$$f_i = (f_{ia} . f_{ib} . f_{ic})^{1/3} + \frac{f_{ia} + f_{ib} + f_{ic}}{3} \quad (18)$$

The alternative with the highest score is considered the best alternative.

Tractor Selection Using an Integrated Fuzzy SBWM and Fuzzy CoCoSo Approach

The practical application of this study focuses on selecting the most suitable tractor for a farmer engaged in agricultural activities in the Aegean region. For this purpose, five decision-makers who play a significant role in tractor procurement were identified. The study included a total of six participants, all of whom are farmers producing various agricultural products such as cereals, vegetables, fruits, and industrial crops. The participants were selected based on their professional experience and expertise in agricultural mechanization and tractor use. On average, they have 15 years of practical field experience in the sector, and their selection was made considering their hands-on knowledge and familiarity with machinery use in farming operations. The farming experience of the participants ranges from 10 to 30 years. Specifically, one farmer has been engaged in cereal (wheat and barley) production for 25 years, another has cultivated maize for 15 years, a third has 20 years of experience in vegetable production, a fourth has managed a fruit orchard for 30 years, and a fifth has produced cotton for 18 years with extensive experience in intensive field operations. The interviews were conducted face-to-face, which enabled the farmers to directly convey their practical insights. The number of participants was limited to five decision-makers because the accessible farmers who are direct decision-makers in tractor selection and possess long-standing field experience were constrained to this level. Therefore, the participants were considered qualified, representative, and appropriate for the aim of the study. Based on both a comprehensive literature review and the evaluations of these five decision-makers, a total of 18 criteria were established to guide the tractor selection process. These criteria were grouped under four main categories, as presented in Table 1.

Çizelge 1. Traktör Seçim Kriterleri
Table 1. Tractor Selection Criteria

Main Criteria			
C1: Economic Factors	C2: Technical Features	C3: Usability Features	C4: Brand and Image
Sub-Criteria			
C11: Purchase Cost	C21: Engine Power	C31: Ergonomics	C41: Brand Reliability
C12: Operating Cost	C22: Fuel Efficiency	C32: Field of Vision	C42: User Satisfaction
C13: Second-Hand Value	C23: Durability	C33: Maneuverability	C43: Prestige
C14: Financing Options	C24: Ease of Maintenance	C34: Noise and Vibration	
	C25: Technological Equipment		
	C26: Land Compatibility		
	C27: Capacity		

Tractor selection is shaped by a multidimensional framework supported extensively in the literature. In terms of Economic Factors, purchase cost and operating cost emerge as the most decisive variables, directly influencing financial feasibility and long-term planning (Sağlam & Çetin, 2017; Sağlam & Çevik, 2012; Baybaş & Aksoy, 2021; Aksoy et al., 2019; Aybek, 2002; Unakıtan & Abdikoğlu, 2022). Similarly, second-hand value and financing options are highlighted as complementary dimensions that enhance investment returns and provide flexibility for farmers (Baybaş & Aksoy, 2021; Unakıtan & Abdikoğlu, 2022). Regarding Technical Features, criteria such as engine power, fuel efficiency, durability, ease of maintenance, and technological equipment are emphasized as determinants of operational efficiency and sustainability (Sağlam & Çetin, 2017; Sağlam & Çevik, 2012; Baybaş & Aksoy, 2021; Unakıtan & Abdikoğlu, 2022). Land compatibility and capacity are also noted as key aspects ensuring adaptability to different soil structures and farm sizes (Unakıtan & Abdikoğlu, 2022). With respect to Usability Features, ergonomics, operator comfort, maneuverability, and reduced noise and vibration are repeatedly associated with productivity and operator satisfaction (Sağlam & Çevik, 2012; Baybaş & Aksoy, 2021). Finally, Brand and Image considerations, including brand reliability, user satisfaction, and prestige, are reported as influential in shaping farmers' purchasing behaviors, with brand loyalty and market perception playing a crucial role (Baybaş & Aksoy, 2021; Aksoy et al., 2019; Unakıtan & Abdikoğlu, 2022). Collectively, these findings indicate that the criteria defined in this study are consistent with previous empirical evidence and provide a comprehensive framework for tractor selection.

A total of 14 tractor brands subjected to evaluation were identified by the decision-makers, who also conducted the necessary research regarding these brands. The selected tractor brands are presented in Table 2.

Çizelge 2. Alternatif Traktör Markaları
Table 2. Alternative Tractor Brands

Tractor Brands			
A1: New Holland	A5: Case	A9: Başak	A13: Landını
A2: Same	A6: Massey Ferguson	A10: Solıs	A14: John Deere
A3: Deutz	A7: Tümosan	A11: Hattat	
A4: Fahr	A8: Erkunt	A12: Kubota	

In the first stage of the evaluation, the weights of the criteria were determined. To identify these weights, each decision-maker selected the best and worst among the main criteria as well as among the sub-criteria of each main criterion. The importance levels of the best criterion in comparison to the other criteria, and of the other criteria in comparison to the worst criterion, were identified by each decision-maker (Table 3). Using the F-SBWM method, the criterion weights were calculated, and the average values were taken to determine the final weights of the criteria (Table 5).

Çizelge 3. Dilsel İfadeler ve Üçgen Bulanık Sayı Karşılıkları
Table 3. Linguistic Expressions and Triangular Fuzzy Number Equivalents

Linguistic Terms	**Fuzzy Scales**
Equally importance (EI)	(1,1,1)
Weakly important (WI)	(1,2,3)
Moderate importance (MI)	(2,3,4)
Moderate plus importance (MP)	(3,4,5)
Strong importance (SI)	(4,5,6)
Strong plus importance (SP)	(5,6,7)
Very strong importance (VS)	(6,7,8)
Extreme importance (EX)	(7,8,9)

The calculation of the main criteria weights according to Decision-Maker 3 is as follows:

Decision-Maker 3 identified C3 (Operational Features) as the best (most important) main criterion and C4 (Brand and Image) as the worst (least important) criterion (Table 4). Based on the selected criteria, the corresponding evaluation table is as follows:

Çizelge 4. DM3 için Kriter Değerlendirme Tablosu
Table 4. Criteria Evaluation Table for DM3

		C1	**C2**	**C3**	**C4**
BO	Best C3	EI	WP	EI	VS
OW	Worst C4	VS	SP	VS	EI

It is as follows. Using Equation (1):

$$\widetilde{W'_{C3}} = \frac{1}{\frac{1}{(1,1,1)} + \frac{1}{(1,2,3)} + \frac{1}{(1,1,1)} + \frac{1}{(6,7,8)}}$$

$\widetilde{W'_{C3}} = (0.316, 0.378, 0.407)$

The values of $\widetilde{W'_{C1}}, \widetilde{W'_{C2}}$ ve $\widetilde{W'_{C4}}$ are then calculated using Equation (2) as follows:

$$\widetilde{W'_{C1}} = \frac{(0.316, 0.378, 0.407)}{(1,1,1)} = (0.316, 0.378, 0.407)$$

$$\widetilde{W'_{C2}} = \frac{(0.316,0.378,0.407)}{(1,2,3)} = (0.105,0.189,0.407)$$
$$\widetilde{W'_{C4}} = \frac{(0.316,0.378,0.407)}{(6,7,8)} = (0.039,0.054,0.068)$$

These values represent the fuzzy weights of the criteria relative to the best criterion as computed by the Fuzzy Simplified Best-Worst Method (F-SBWM).

The values of $\widetilde{w}''_W$ *and* $\widetilde{w}''_j$ are calculated using Equation (3) and Equation (4), respectively.

$$\widetilde{w}''_{C4} = \frac{1}{(6,7,8)+(4,5,6)+(6,7,8)+(1,1,1)} = (0.043,0.050,0.059)$$
$$\widetilde{w}''_{C1} = (0.043,0.050,0.059)x(6,7,8) = (0.261,0.350,0.471)$$
$$\widetilde{w}''_{C2} = (0.043,0.050,0.059)x(4,5,6) = (0.174,0.250,0.353)$$
$$\widetilde{w}''_{C3} = (0.043,0.050,0.059)x(6,7,8) = (0.261,0.350,0.471)$$

It has been determined as follows. The final criterion weights obtained from the evaluation made by Decision Maker 3 for the main criteria were calculated using Equation (5):

$$\widetilde{w}'^*_{C1} = \frac{(0.316,0.378,0.407)+(0.261,0.350,0.471)}{(2,2,2)} = (0.288,0.364,0.439)$$
$$\widetilde{w}'^*_{C2} = \frac{(0.105,0.189,0.407)+(0.174,0.250,0.353)}{(2,2,2)} = (0.288,0.364,0.439)$$
$$\widetilde{w}'^*_{C3} = \frac{(0.316,0.378,0.407)+(0.261,0.350,0.471)}{(2,2,2)} = (0.288,0.364,0.439)$$
$$\widetilde{w}'^*_{C4} = \frac{(0.039,0.054,0.068)+(0.043,0.050,0.059)}{(2,2,2)} = (0.041,0.052,0.063)$$

The local weights of the sub-criteria were obtained by calculating the arithmetic mean of the criterion weights computed using the F-SBWM method for all decision makers. The global weights of the sub-criteria were then determined by multiplying these local weights with the corresponding main criterion weights (Table 6).

Çizelge 5. Ana Kriter Ağırlıkları
Table 5. Main Criteria Weights

Main Criteria	Fuzzy Weights	Crips
W*C1	(0.268, 0.360, 0.488)	0,366
W*C2	(0.163, 0.239, 0.368)	0,248
W*C3	(0.205, 0.280, 0.382)	0,284
W*C4	(0.093, 0.121, 0.157)	0,122

Çizelge 6. Alt Kriter Ağırlıkları.
Table 6. Sub-Criteria Weights.

Sub-Criteria	Local Fuzzy Weights	Sub-Criteria	Global Fuzzy Weights	Crips
W*C11	(0.264, 0.351, 0.481)	W*C11	(0.071, 0.126, 0.235)	0,1352
W*C12	(0.254, 0.339, 0.453)	W*C12	(0.068, 0.122, 0.221)	0,1296
W*C13	(0.136, 0.185, 0.269)	W*C13	(0.036, 0.067, 0.131)	0,0725
W*C14	(0.089, 0.125, 0.176)	W*C14	(0.024, 0.045, 0.086)	0,0482
W*C21	(0.050, 0.087, 0.146)	W*C21	(0.008, 0.021, 0.054)	0,0242
W*C22	(0.195, 0.260, 0.327)	W*C22	(0.032, 0.062, 0.121)	0,0669
W*C23	(0.144, 0.206, 0.315)	W*C23	(0.024, 0.049, 0.116)	0,0561
W*C24	(0.084, 0.135, 0.229)	W*C24	(0.014, 0.032, 0.084)	0,0379
W*C25	(0.066, 0.096, 0.131)	W*C25	(0.011, 0.023, 0.048)	0,0251
W*C26	(0.098, 0.150, 0.236)	W*C26	(0.016, 0.036, 0.087)	0,0411
W*C27	(0.042, 0.066, 0.105)	W*C27	(0.007, 0.016, 0.039)	0,0181
W*C31	(0.095, 0.148, 0.227)	W*C31	(0.019, 0.041, 0.086)	0,0453
W*C32	(0.192, 0.302, 0.523)	W*C32	(0.039, 0.084, 0.200)	0,0961
W*C33	(0.322, 0.439, 0.572)	W*C33	(0.066, 0.123, 0.218)	0,1293
W*C34	(0.073, 0.111, 0.169)	W*C34	(0.015, 0.031, 0.064)	0,0338
W*C41	(0.260, 0.360, 0.517)	W*C41	(0.024, 0.044, 0.081)	0,0467
W*C42	(0.437, 0.545, 0.674)	W*C42	(0.041, 0.066, 0.106)	0,0685
W*C43	(0.076, 0.095, 0.118)	W*C43	(0.007, 0.011, 0.019)	0,0119

The consistency ratios for expert evaluations of both the main and sub-criteria were calculated according to Equation (6) (Table 7). The computed consistency ratios are below 10%, indicating that the evaluations made by the experts are consistent.

Çizelge 7. Kriter Tutarlılık Tablosu
Table 7. Criterion Consistency Table

CR Values					
	Main Criteria	C1 Criterion	C2 Criterion	C3 Criterion	C4 Criterion
KV1	0,0833	0,0306	0,0627	0,0339	0,0724
KV2	0,0044	0,0047	0,0155	0,0187	0,0590
KV3	0,0025	0,0502	0,0164	0,0088	0,0313
KV4	0,0418	0,0414	0,0056	0,0142	0,0830
KV5	0,0193	0,0250	0,0096	0,0296	0,0108

Based on expert evaluations, the most important main criterion was identified as Economic Factors (0.366), while the least important was Brand and Image (0.122). The weight score of the Technical Specifications main criterion was found to be 0.248, and that of the Usage Characteristics criterion was 0.284. Among the sub-criteria, Purchase Cost was evaluated as the most significant with a weight of 0.1352, followed by Operating Cost (0.1296) and Maneuverability (0.1293) as the second and third most important criteria, respectively. On the other hand, Engine Power (0.0242), Capacity (0.0181), and Prestige (0.0119) were identified by the experts as the least important sub-criteria.

A total of 14 tractor brands were evaluated based on 18 criteria. The selection of these brands was based on the statistical data provided by TARMAKBİR (Turkish Association of Agricultural Machinery and Equipment Manufacturers), ensuring that the evaluated brands represent the actual conditions of the Turkish agricultural machinery market. The evaluation was conducted using the linguistic expressions specified in Table 8, and the arithmetic mean of the triangular fuzzy number equivalents corresponding to these linguistic terms, as rated by the five experts, was calculated. This resulted in the evaluation matrix presented in Table 9.

Çizelge 8. Alternatiflerin Değerlendirilmesine Yönelik Dilsel İfadeler ve Üçgen Bulanık Sayı Karşılıkları
Table 8. Linguistic Expressions and Triangular Fuzzy Number Equivalents for Alternatives Evaluation

Linguistic Terms	**Fuzzy Scales**
Very Poor (VP)	(0,0,1)
Poor (P)	(0,1,3)
Moderate Poor (MP)	(1,3,5)
Average (A)	(3,5,7)
Moderate Good (MG)	(5,7,9)
Good (G)	(7,9,10)
Very Good (VG)	(9,10,10)

Çizelge 9. Birleştirilmiş Alternatif Değerlendirme Matrisi
Table 9. Combined Alternative Evaluation Matrix

	C11	**C12**	**C13**	**C14**	**C21**
A1	(9.0, 10.0, 10.0)	(9.0, 10.0, 10.0)	(7.4, 9.2, 10.0)	(6.6, 8.6, 9.8)	(7.0, 9.0, 10.0)
A2	(2.2, 4.2, 6.2)	(2.6, 4.6, 6.6)	(2.0, 3.8, 5.8)	(3.0, 5.0, 7.0)	(5.4, 7.4, 9.2)
A3	(3.4, 5.4, 7.4)	(2.6, 4.6, 6.6)	(2.0, 3.8, 5.8)	(3.4, 5.4, 7.4)	(5.8, 7.8, 9.4)
A4	(3.4, 5.4, 7.4)	(2.2, 4.2, 6.2)	(2.0, 3.8, 5.8)	(3.4, 5.4, 7.4)	(5.4, 7.4, 9.2)
A5	(7.0, 9.0, 10.0)	(6.6, 8.6, 9.8)	(3.4, 5.4, 7.2)	(5.8, 7.8, 9.4)	(6.6, 8.6, 9.8)
A6	(4.6, 6.6, 8.4)	(7.0, 9.0, 10.0)	(5.0, 7.0, 8.8)	(6.6, 8.6, 9.8)	(7.0, 9.0, 10.0)
A7	(5.8, 7.6, 9.0)	(6.6, 8.6, 9.8)	(4.4, 6.2, 8.0)	(6.6, 8.6, 9.8)	(6.2, 8.2, 9.6)
A8	(5.4, 7.4, 9.2)	(7.0, 9.0, 10.0)	(3.6, 5.4, 7.4)	(6.6, 8.6, 9.8)	(4.6, 6.6, 8.6)
A9	(5.4, 7.4, 9.2)	(7.0, 9.0, 10.0)	(2.8, 4.6, 6.6)	(6.6, 8.6, 9.8)	(4.6, 6.6, 8.6)
A10	(2.6, 4.6, 6.6)	(3.4, 5.4, 7.4)	(1.6, 3.4, 5.4)	(2.0, 3.8, 5.8)	(3.4, 5.4, 7.4)
A11	(2.6, 4.6, 6.6)	(5.0, 7.0, 8.8)	(2.8, 4.6, 6.6)	(6.6, 8.6, 9.8)	(4.6, 6.6, 8.6)
A12	(2.2, 4.2, 6.2)	(1.8, 3.8, 5.8)	(2.2, 4.2, 6.2)	(3.0, 5.0, 6.8)	(5.0, 7.0, 8.8)
A13	(0.6, 2.2, 4.2)	(1.6, 3.4, 5.4)	(2.0, 3.8, 5.8)	(1.6, 3.4, 5.4)	(3.4, 5.4, 7.4)
A14	(5.2, 7.0, 8.4)	(6.2, 8.2, 9.6)	(5.8, 7.8, 9.4)	(6.6 8.6, 9.8)	(7.4, 9.2, 10.0)

	C22	C23	C24	C25	C26
A1	(5.4, 7.4, 9.0)	(7.0, 9.0, 10.0)	(9.0, 10.0, 10.0)	(8.6, 9.8, 10.0)	(7.0, 9.0, 10.0)
A2	(3.8, 5.8, 7.8)	(7.0, 9.0, 10.0)	(6.2, 8.2, 9.6)	(6.6, 8.6, 9.8)	(4.2, 6.2, 8.2)
A3	(3.4, 5.4, 7.4)	(5.0, 7.0, 8.8)	(4.6, 6.6, 8.6)	(6.2, 8.2, 9.6)	(4.6, 6.6, 8.6)
A4	(3.0, 5.0, 7.0)	(4.6, 6.6, 8.4)	(3.0, 5.0, 7.0)	(6.6, 8.6, 9.8)	(4.6, 6.6, 8.6)
A5	(5.0, 7.0, 8.8)	(7.0, 9.0, 10.0)	(7.0, 8.8, 9.8)	(7.0, 8.8, 9.8)	(6.6, 8.6, 9.8)
A6	(5.8, 7.8, 9.4)	(7.0, 9.0, 10.0)	(7.0, 9.0, 10.0)	(7.0, 9.0, 10.0)	(7.0, 9.0, 10.0)
A7	(5.0, 7.0, 8.8)	(6.2, 8.2, 9.4)	(7.0, 9.0, 10.0)	(7.0, 9.0, 10.0)	(6.6, 8.6, 9.8)
A8	(3.8, 5.8, 7.8)	(5.0, 7.0, 8.8)	(7.0, 9.0, 10.0)	(6.6, 8.6, 9.8)	(5.8, 7.8, 9.2)
A9	(4.2, 6.2, 8.2)	(4.6, 6.6, 8.6)	(7.0, 9.0, 10.09	(6.6, 8.6, 9.8)	(6.2, 8.2, 9.4)
A10	(3.4, 5.4, 7.4)	(4.6, 6.6, 8.6)	(3.8, 5.8, 7.8)	(6.6, 8.6, 9.8)	(4.2, 6.2, 8.2)
A11	(4.2, 6.2, 8.2)	(4.6, 6.6, 8.6)	(7.0, 9.0, 10.0)	(6.2, 8.2, 9.6)	(6.2 8.2, 9.4)
A12	(4.2, 6.2, 8.0)	(6.2, 8.2, 9.6)	(4.2, 6.2, 8.2)	(7.0, 9.0, 10.0)	(7.0, 9.0, 10.0)
A13	(3.4, 5.4, 7.4)	(3.8, 5.8, 7.8)	(4.2, 6.2, 8.2)	(6.6, 8.6, 9.8)	(4.2, 6.2, 8.2)
	(5.8, 7.6, 9.2)	(7.0, 8.8, 9.8)	(6.2, 8.2, 9.4)	(8.2, 9.6, 10.0)	(7.0, 9.0, 10.0)

	C27	C31	C32	C33	C34
A1	(7.8, 9.4, 10.0)	(7.0, 9.0, 10.0)	(7.0, 9.0, 10.0)	(7.0, 9.0, 10.0)	(7.0, 9.0, 10.0)
A2	(4.6, 6.6, 8.6)	(4.6, 6.6, 8.6)	(5.0, 7.0, 8.6)	(5.8, 7.8, 9.4)	(6.6, 8.6, 9.8)
A3	(5.8, 7.8, 9.2)	(4.6, 6.6, 8.6)	(5.8, 7.8, 9.2)	(5.0, 7.0, 9.0)	(6.2, 8.2, 9.6)
A4	(6.2, 8.2, 9.4)	(4.6, 6.6, 8.6)	(5.4, 7.4, 8.8)	(5.0, 7.0, 9.0)	(6.6, 8.6, 9.8)
A5	(6.2, 8.2, 9.6)	(7.0, 9.0, 10.0)	(6.2, 8.2, 9.6)	(6.6, 8.6, 9.8)	(7.0, 8.2, 9.4)
A6	(6.6, 8.6, 9.8)	(6.6, 8.4, 9.6)	(5.8, 7.8, 9.2)	(6.6, 8.6, 9.8)	(6.6, 8.6, 9.8)
A7	(6.6, 8.6, 9.8)	(5.8, 7.8, 9.2)	(7.0, 9.0, 10.0)	(6.2, 8.2, 9.6)	(7.0, 9.0, 10.0)
A8	(5.8, 7.8, 9.2)	(6.6, 8.6, 9.8)	(7.0, 9.0, 10.0)	(6.2, 8.2, 9.4)	(7.0, 9.0, 10.0)
A9	(6.2, 8.2, 9.4)	(5.4, 7.4, 9.2)	(7.0, 9.0, 10.0)	(6.2, 8.2, 9.4)	(7.0, 9.0, 10.0)
A10	(4.2, 6.2, 8.2)	(6.2, 8.2, 9.6)	(7.0, 9.0, 10.0)	(5.8, 7.8, 9.2)	(6.6, 8.6, 9.8)
A11	(5.4, 7.4, 9.0)	(5.8, 7.8, 9.4)	(6.6, 8.6, 9.8)	(5.8, 7.8, 9.2)	(6.6, 8.6, 9.8)
A12	(6.2, 8.2, 9.6)	(6.2, 8.2, 9.6)	(6.6, 8.6, 9.8)	(5.0, 7.0, 9.0)	(7.0, 9.0, 10.0)
A13	(5.8, 7.8, 9.2)	(5.4, 7.4, 9.2)	(5.4, 7.4, 8.8)	(4.6, 6.6, 8.6)	(4.6, 6.6, 8.4)
	(8.2, 9.6, 10.0)	(6.2, 8.0, 9.2)	(7.0, 9.0, 10.0)	(7.0, 9.0, 10.0)	(7.0, 9.0, 10.0)

	C41	C42	C43
A1	(7.0, 9.0,10.0)	(7.0, 9.0,10.0)	(8.6, 9.8,10.0)
A2	(5.0, 7.0, 8.6)	(4.2, 6.2, 8.2)	(4.6, 6.6, 8.6)
A3	(5.0, 7.0, 8.8)	(4.2, 6.2, 8.2)	(3.4, 5.4, 7.4)
A4	(5.0, 7.0, 8.8)	(3.8, 5.8, 7.8)	(3.4, 5.4, 7.4)
A5	(7.0, 8.6, 9.8)	(5.4, 7.4, 9.2)	(6.6, 8.6, 9.8)
A6	(7.0, 9.0,10.0)	(6.2, 8.2, 9.6)	(7.0, 8.8, 9.8)
A7	(5.4, 7.4, 9.0)	(6.2, 8.2, 9.6)	(6.2, 8.2, 9.4)
A8	(5.8, 7.8, 9.2)	(6.2, 8.2, 9.4)	(5.0, 7.0, 8.8)
A9	(6.2, 8.2, 9.4)	(5.4, 7.4, 9.0)	(4.6, 6.6, 8.6)
A10	(5.4, 7.4, 9.0)	(4.2, 6.2, 8.0)	(4.6, 6.6, 8.6)
A11	(6.2, 8.2, 9.4)	(5.8, 7.8, 9.2)	(5.0, 7.0, 8.8)
A12	(5.8, 7.8, 9.4)	(5.4, 7.4, 9.2)	(5.4, 7.4, 9.2)
A13	(4.2, 6.2, 8.2)	(3.0, 5.0, 7.0)	(2.6, 4.6, 6.6)
A14	(7.4, 9.2,10.0)	(7.0, 8.8, 9.8)	(7.0, 8.8, 9.8)

The steps of the F-CoCoSo method were applied to the obtained evaluation matrix, and the $\tilde{S}_i and\ \tilde{P}_i$ values were calculated (Appendix A).

Using the calculated $\tilde{S}_i and\ \tilde{P}_i$ values, the fuzzy evaluation scores $\tilde{f}_{ia,}\tilde{f}_{ib}, \tilde{f}_{ic}$ were obtained based on Equations (12), (13), and (14) (Appendix B).

Using Equations (15), (16), and (17), the fuzzy evaluation scores $\tilde{f}_{ia}, \tilde{f}_{ib}, \tilde{f}_{ic}$ were defuzzified to obtain the crisp scores f_{ia}, f_{ib}, f_{ic}. Subsequently, Equation (18) was applied to calculate the final score values of the alternatives (Table 10).

Çizelge 10. $\tilde{f}_{ia}, \tilde{f}_{ib}, \tilde{f}_{ic}$ ve Skor Değerleri.
Table 100. $\tilde{\boldsymbol{f}}_{ia}, \tilde{\boldsymbol{f}}_{ib}, \tilde{\boldsymbol{f}}_{ic}$ and Score Values.

	$\boldsymbol{f}_{ia}$	$\boldsymbol{f}_{ib}$	$\boldsymbol{f}_{ic}$	**Score**
A1	0,08	73,24	0,93	26,51
A2	0,07	47,33	0,83	17,48
A3	0,07	47,15	0,83	17,43
A4	0,07	44,88	0,81	16,62
A5	0,08	65,50	0,91	23,83
A6	0,08	65,86	0,92	23,96
A7	0,08	64,55	0,91	23,50
A8	0,08	62,26	0,91	22,71
A9	0,08	61,33	0,90	22,39
A10	0,07	47,93	0,81	17,66
A11	0,07	55,92	0,88	20,49
A12	0,07	50,62	0,87	18,67
A13	0,06	37,17	0,70	13,81
A14	0,08	67,89	0,92	24,66

The score values of the alternatives were ranked as A1> A14> A6> A5> A7> A8> A9> A11> A12> A10> A2> A3> A4> A13. Among these, the alternative with the highest score, A1, was identified as the most suitable tractor brand. Based on the evaluation criteria considered in the study, the New Holland tractor was determined to be the optimal choice. According to the alternative score rankings, John Deere ranked second, while Massey Ferguson was placed third. The results also indicate that experts evaluated Massey Ferguson (A6), Case (A5), and Tümosan (A7) similarly in terms of meeting the specified criteria. On the other hand, the Landini (A13) tractor was identified as the least preferred brand in terms of fulfilling the desired criteria.

Sensitivity Analysis

Sensitivity analysis is designed to validate the results obtained. It allows decision-makers to verify the outcomes of the applied method by making certain modifications to the solution model. In this study, a weight variation strategy was implemented to conduct the sensitivity analysis. For this purpose, the weights of the criteria were modified to generate 18 different scenarios (Table 11). According to the 18 scenarios created, alternative scores were recalculated and alternative rankings were obtained. The score points and rankings of the alternatives are as in Appendix C and Table 12, respectively.

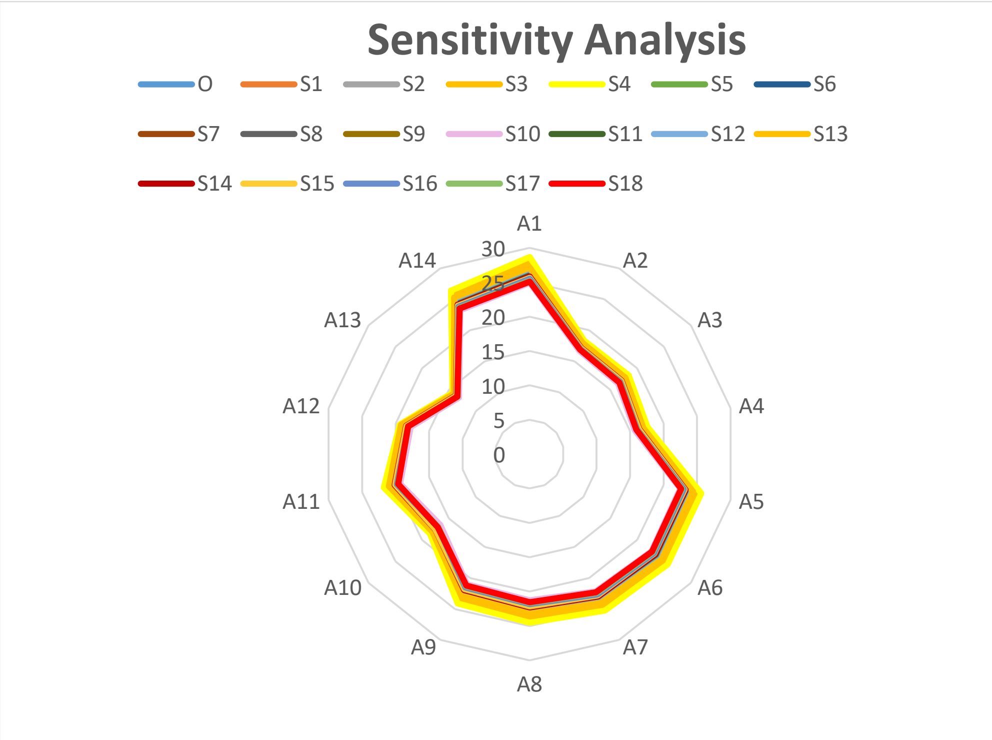
Çizelge 11. Duyarlılık Analizi Senaryoları
Table 11. Sensitivity Analysis Scenarios

Scenario	Description
S1	W*C1 increased by 5%. Other weights proportionally decreased.
S2	W*C1 increased by 10%. Other weights proportionally decreased.
S3	W*C1 increased by 15%. Other weights proportionally decreased.
S4	W*C1 increased by 20%. Other weights proportionally decreased.
S5	W*C3 increased by 5%. Other weights proportionally decreased.
S6	W*C3 increased by 10%. Other weights proportionally decreased.
S7	W*C2 increased by 5%. Other weights proportionally decreased.
S8	W*C2 increased by 10%. Other weights proportionally decreased.
S9	W*C2 increased by 15%. Other weights proportionally decreased.
S10	W*C2 increased by 20%. Other weights proportionally decreased.
S11	W*C4 increased by 10%. Other weights proportionally decreased.
S12	W*C4 increased by 15%. Other weights proportionally decreased.
S13	W*C4 increased by 20%. Other weights proportionally decreased.
S14	W*C3 increased by 15%. Other weights proportionally decreased.
S15	W*C3 increased by 20%. Other weights proportionally decreased.
S16	W*C1 decreased by 5%, W*C2 increased by 10%. Other weights recalculated.
S17	W*C1 decreased by 10%, W*C2 increased by 10%. Other weights recalculated.
S18	W*C1 decreased by 15%, W*C2 increased by 10%. Other weights recalculated.

Çizelge 12. Duyarlılık Analizi Alternatif Sıralamaları
Table 12. Sensitivity Analysis Ranking of Alternatives

Scenario	Alternative Rankings
Original	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13
S1	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13
S2	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A3>A2>A4>A13
S3	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A3>A2>A4>A13
S4	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A3>A2>A4>A13
S5	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13
S6	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13
S7	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13
S8	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13
S9	A1>A14>A6>A5>A7>A8>A9>A11>A12>A2>A10>A3>A4>A13
S10	A1>A14>A6>A5>A7>A8>A9>A11>A12>A2>A10>A3>A4>A13
S11	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13
S12	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13
S13	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13
S14	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13
S15	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13
S16	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13
S17	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13
S18	A1>A14>A6>A5>A7>A8>A9>A11>A12>A10>A2>A3>A4>A13

In all scenarios developed for the sensitivity analysis, the best alternative was found to be A1, as in the original solution. Although the overall ranking remained nearly consistent across all scenarios, increasing the weight of the main criterion WC1 caused a swap in the rankings of alternatives A2 and A3. Similarly, increasing the weight of the main criterion WC2 by more than 5% led to a change in the ranking of alternatives A2 and A10. Nevertheless, it was concluded that the variations in criterion weights did not significantly affect the final determination of the best alternative. The alternative rankings for each scenario are presented in Figure 2.



Şekil 1. Duyarlılık Analizi Grafiği.
Figure 2. Sensitivity Analysis Graph.

RESEARCH RESULTS and DISCUSSION

Agriculture has always maintained its importance as the sector that meets the most fundamental human need:

food. Due to factors such as the growing global population, increasing environmental issues, and climate change, agriculture has become a strategic sector in today's world, and it is evident that its strategic significance will continue to grow in the future.

Mechanization enhances productivity in the agricultural sector by accelerating activities such as planting, sowing, harvesting, and crop collection. Among mechanized tools, the tractor stands out as a highly functional machine used in nearly all types of farming. However, with the influence of modern marketing strategies, the essential role of the tractor as a work machine is often overshadowed, leading to suboptimal choices that do not align with farmers' actual needs. Choosing an unsuitable tractor not only results in financial losses for farmers but also hinders the achievement of desired productivity levels.

This study aims to determine the most suitable tractor for a farmer operating in the Aegean region of Turkey. To this end, relevant criteria for tractor selection were initially identified, and among 14 tractor brands, the one that best met these criteria was selected. In decision-making environments where conflicting criteria exist, Multi-Criteria Decision-Making (MCDM) techniques are widely used. In this study, fuzzy logic-based MCDM methods were adopted to address the uncertainties in preferences. Specifically, the Fuzzy Simplified Best-Worst Method (F-SBWM) was employed to determine the weights of criteria, and the Fuzzy Combined Compromise Solution (F-CoCoSo) method was used for alternative selection. The identification of evaluation criteria and the assessment of tractor brands were carried out by a team of five experienced experts.

A total of 18 sub-criteria were identified under four main criteria: Economic Factors, Technical Features, Usability, and Brand & Image. The weights of both main and sub-criteria were determined using the F-SBWM method. According to expert evaluations, the most important main criterion was Economic Factors (0.366), while the least important was Brand and Image (0.122). The weight scores for Technical Features and Usability were found to be 0.248 and 0.284, respectively. Among the sub-criteria, Purchase Cost was evaluated as the most significant (0.1352), followed by Operating Cost (0.1296) and Maneuverability (0.1293). On the other hand, Engine Power (0.0242), Capacity (0.0181), and Prestige (0.0119) were considered the least important sub-criteria by the experts.

The fact that economic factors emerged as the most decisive criterion in tractor selection can be considered an indication that both the purchasing and operating costs significantly strain the financial capacity of farmers. On the other hand, the second-hand value (0.0725) is also recognized by farmers as one of the important factors in the decision-making process. The obtained weight values demonstrate that usability features of tractors are more decisive than technical specifications during the selection phase. In particular, the prominence of the field of vision as a key criterion reflects that farmers attach great importance to safety. Furthermore, the results indicate that user satisfaction is also a determining factor in the selection process. Despite having the lowest weight score, it is evident that the brand's prestige, although the tractor is essentially a work machine, is still taken into account in the decision-making process.

In the next phase of the study, the 14 selected tractor brands were evaluated against each criterion using linguistic variables by a team of five decision-makers, resulting in the formation of a fuzzy evaluation matrix suitable for the application of the F-CoCoSo method. The evaluation was conducted under the assumption that all criteria are benefit-oriented. For instance, although purchase cost is inherently a cost-type criterion, the alternative with the lowest cost was considered the best, whereas for a benefit-type criterion, such as field of vision, the alternative with the best visibility was ranked highest. This approach was adopted to eliminate potential evaluation errors by the decision-makers.

The individual evaluation matrices generated by each decision-maker were aggregated into a single collective decision matrix. Subsequently, the F-CoCoSo method was applied to this matrix to obtain score values for each alternative. The alternative with the highest score was selected as the most preferable. According to the scores, the alternatives were ranked in descending order as follows: A1 > A14 > A6 > A5 > A7 > A8 > A9 > A11 > A12 > A10 > A2 > A3 > A4 > A13. Based on this ranking, A1 (New Holland, score: 26.51) was determined to be the best alternative. A14 (John Deere, score: 24.66) ranked second, while A6 (Massey Ferguson, score: 23.96), A5 (Case, score: 23.83), and A7 (Tümosan, score: 23.50) followed in third, fourth, and fifth place, respectively. The least preferred tractor brand was A13 (Landini, score: 13.81).

A sensitivity analysis was conducted to test how changes in criterion weights would affect the alternative rankings and to verify the robustness of the obtained results. In this analysis, scenarios were created by systematically varying the weights of the main criteria within a ±10–20% range. This range was selected based on practices commonly adopted in the MCDM literature, where moderate adjustments are applied to test the robustness of results under plausible changes in decision-maker priorities. The variation ratios were determined to reflect realistic shifts in importance that farmers or experts might assign to economic, technical, usability, and brand-related factors in practice. For this purpose, 18 scenarios involving different modifications of the main criteria weights were generated, and the alternative rankings were recalculated for each scenario. According to all the generated scenarios, the alternative with the highest score remained unchanged. While increasing the weight of the Economic Factors criterion led to a change in the rankings of A2 and A3, increasing the weight of the Technical Features criterion resulted in a shift in the rankings of A10 and A2.

According to the Monthly Tractor Statistics Reports of the Turkish Agricultural Machinery Manufacturers Association (TARMAKBİR) (Appendix D), New Holland was the most preferred tractor brand in Turkey during the years 2022, 2023, and 2024. The findings of this study are consistent with these sales figures. A notable point is that although the John Deere brand achieved the second-highest score in this study, it did not rank among the top 10 in actual sales figures. The domestic brand Tümosan, however, ranked fifth in both the study results and real-world sales figures. The findings of this study are largely consistent with previous research conducted both in Turkey and internationally. For instance, Gürsoy et al. (2021) emphasized that tractor power selection in Turkish farms is strongly influenced by farm size, soil structure, and operating conditions, which aligns with the importance of technical and operational criteria identified in this study. Similarly, Sağlam and Çevik (2012) and Sağlam and Çetin (2017) found that government incentives and credit availability significantly shape farmers' preferences, often leading to the selection of lower-horsepower tractors due to financial constraints. These results support the present study's emphasis on economic factors such as cost and financing opportunities. On the international level, García-Alcaraz et al. (2016) applied a hybrid multi-attribute approach to tractor selection and highlighted the combined role of economic, technical, and operational factors, which parallels the integrated framework used in this research. Likewise, Amini and Asoodar (2016) reported that maintenance costs and price are decisive factors in tractor selection in Iran, while Fargnoli and Lombardi (2019) underlined the safety aspects of tractor use. These similarities confirm that the criteria identified in this study—such as cost, reliability, and service network—are not only relevant in the Turkish context but also reflect global priorities in tractor selection. At the same time, the originality of this study lies in the integration of the Fuzzy SBWM and Fuzzy CoCoSo methods, providing a novel and systematic decision-making framework compared to previous studies.

Agriculture is one of the most strategically important sectors globally. Rapid loss of agricultural land, climate change, the negative impact of industrialization on agriculture, and the declining population engaged in farming all signal the potential for serious crises in the agricultural sector in the coming years.

In addition to the wide variety of policies that can be implemented to increase agricultural production, improving productivity is also a primary priority. Although the use of machinery in agriculture is a factor that enhances productivity, machines acquired without proper awareness may lead to inefficient use of resources. Especially in small-scale farming operations, selecting the most appropriate machinery is crucial both from a financial perspective and for carrying out agricultural activities more effectively. Therefore, it is important to inform and guide farmers on this subject.

This study is not only aimed at contributing to the selection of the most suitable tractor for a farmer through scientific methods, but is also intended to highlight the importance of the issue. It is evident that applying scientific methods in all agricultural activities—from machinery and equipment selection to appropriate agricultural practices and harvesting—can have a positive impact on both efficiency and profitability.

This study offers a novel perspective on the application of multi-criteria decision-making (MCDM) methods in the context of tractor selection in agricultural mechanization. Unlike the work of Puška et al. (2024), which employs conventional AHP and TOPSIS techniques for the selection of agricultural machinery, the present study introduces an extended set of evaluation criteria developed through expert consultations and contextual relevance. Furthermore, the incorporation of fuzzy logic-based analytical processes allows for a more realistic modeling of decision variables under uncertainty. In this regard, the study provides a significant methodological and practical contribution to the literature, both in terms of analytical depth and contextual applicability.

A limitation of this study is that it was conducted within a specific region and for a specific type of producer. However, the fact that the most prominent alternative identified in the study aligns with the most preferred brand in recent years (as shown in Appendix A) should not be considered a coincidence. Broader-scale studies that identify region-specific criteria can contribute to the development and leadership of the domestic tractor industry by guiding the production of tractors accordingly. It is clear that such progress will positively affect both productivity and the retention of economic resources within the country.

Future research could expand the scope by including a larger and more diverse group of farmers from different regions. In addition, integrating hybrid MCDM approaches with simulation or optimization techniques may provide deeper insights into the decision-making process. Comparative studies across different countries could also strengthen the generalizability and practical applicability of the findings.

Author's Contributions

The authors declare that they have contributed equally to the article.

Funding Statement
The author(s) received no specific funding for this study.

Ethics Approval
Voluntary consent for participation was obtained from the participating experts within the scope of this study. The study was approved by the Dokuz Eylül University Social and Human Sciences Scientific Research and Publication Ethics Board with decision number 30 dated 18/06/2025.

KAYNAKLAR
Adame-García, J., Luna-Rodríguez, M., & Iglesias-Andreu, L. G. (2016). Vanilla rhizobacteria as antagonists against *Fusarium oxysporum* f. sp. *vanillae*. *International Journal of Agriculture and Biology, 18*(1), 23–30.

Aktan, Z. C., & Soylu, S. (2020). Diyarbakır ilinde yetişen badem ağaçlarından endofit ve epifit bakteri türlerinin izolasyonu ve bitki gelişimini teşvik eden mekanizmalarının karakterizasyonu. *Kahramanmaraş Sütçü İmam Üniversitesi Tarım ve Doğa Dergisi, 23*(3), 641–654. https://doi.org/10.18016/ksutarimdoga.vi.659802

Aksoy, H. M., Kaya, Y., Ozturk, M., Secgin, Z., Onder, H., & Okumus, A. (2017). *Pseudomonas putida*–induced response in phenolic profile of tomato seedlings (*Solanum lycopersicum* L.) infected by *Clavibacter michiganensis* subsp. *michiganensis*. *Biological Control, 105*, 6–12. https://doi.org/10.1016/j.biocontrol.2016.11.001

Alaylar, B., Güllüce, M., Karadayi, M., & Isaoglu, M. (2019). Rapid detection of phosphate-solubilizing bacteria from agricultural areas in Erzurum. *Current Microbiology, 76*(7), 804–809. https://doi.org/10.1007/s00284-019-01688-7

Alexandrova, M., Zaccardelli, M., Stefani, E., & Bazzi, C. (1995). Testing for Pseudomonas syringae pv. atrofaciens and Xanthomonas campestris pathovars on cereals in Italy. *EPPO Bulletin*, 25(3), 437-448. https://doi.org/10.1111/j.1365-2338.1995.tb00577.x

Almoneafy, A. A., Kakar, K. U., Nawaz, Z., Li, B., Saand, M. A., Chun-lan, Y., & Xie, G. L. (2014). Tomato plant growth promotion and antibacterial-related mechanisms of four rhizobacterial *Bacillus* strains against *Ralstonia solanacearum*. *Symbiosis, 63*(2), 59–70. https://doi.org/10.1007/s13199-014-0288-9

Anonymous (2023). FAOSTAT, World Production Data. Food and Agriculture Organization of the United Nations. http://www.fao.org/faostat/en/#data/QC/visualize

Aydın, E. (2025). Yozgat İlinde Toplanan Buğday Tohumlarında Bakteriyel Kavuz Dibi Çürüklüğüne Neden Olan Pseudomonas Syringae Pv. Atrofaciensin İzolasyonu Ve Karakterizasyonu (Tez no 920631). [Yüksek Lisans Tezi, Yozgat Bozok Üniversitesi Fen Bilimleri Enstitüsü Tarım Bilimleri Ana Bilim Dalı]. Yükseköğretim Kurulu Ulusal Tez Merkezi.

Bale, J. S., Van Lenteren, J. C., & Bigler, F. (2008). Biological control and sustainable food production. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1492), 761-776. https://doi.org/10.1098/rstb.2007.2182

Beitsayahi, F., Enayatizamir, N., Nejadsadeghi, L., & Nasernakhaei, F. (2025). Plant growth-promoting bacteria are associated with some salt-tolerant plants. *Journal of Basic Microbiology, 65*(2), e2400446. https://doi.org/10.1002/jobm.202400446

Bragard, C., Singer, E., Alizadeh, A., Vauterin, L., Maraite, H., & Swings, J. (1997). *Xanthomonas translucens* from small grains: diversity and phytopathological relevance. *Phytopathology*, *87*(11), 1111-1117. https://doi.org/10.1094/PHYTO.1997.87.11.1111

Butsenko, L.M. & Pasichnyk, L.A. (2018). Genetic heterogeneity of *Pseudomonas syringae* pv. *atrofaciens* strains based on RAPD-PCR analysis *Microbiolohichnyi Zhurnal*, *80*(5), 48–62. https://doi.org/10.15407/microbiolj80.05.048

Butsenko, L., Pasichnyk, L., Kolomiiets, Y., Kalinichenko, A., Suszanowicz, D., Sporek, M., & Patyka, V. (2020). Characteristic of *Pseudomonas syringae* pv. *atrofaciens* isolated from weeds of wheat field. *Applied Sciences*, *11*(1), 286. https://doi.org/10.3390/app11010286

Cappuccino, J. G., & Sherman, N. (1992). *Microbiology: A laboratory manual* (3rd ed., pp. 125–179). New York: Benjamin/Cummings Publishing Company.

Glickman, E., & Dessaux, Y. (1995). A critical examination of the specificity of the Salkowski reagent for indolic compounds produced by phytopathogenic bacteria. *Applied and Environmental Microbiology*, *61*(2), 793–796. https://doi.org/10.1128/AEM.61.2.793-796.1995

Cherchali, A., Boukhelata, N., Kaci, Y., Abrous-Belbachir, O., & Djebbar, R. (2019). Isolation and identification of a phosphate-solubilizing *Paenibacillus polymyxa* strain GOL 0202 from durum wheat (*Triticum durum* Desf.) rhizosphere and its effect on some seedlings' morphophysiological parameters. *Biocatalysis and Agricultural Biotechnology, 19*, 101087. https://doi.org/10.1016/j.bcab.2019.101087

Duman, K., & Soylu, S. (2019). Characterization of plant growth-promoting traits and antagonistic potentials of endophytic bacteria from bean plants against *Pseudomonas syringae* pv. *phaseolicola*. *Plant Protection*

Bulletin, 59(3), 59–69. https://doi.org/10.16955/bitkorb.597214

Eshaghi, E., Nosrati, R., Owlia, P., Malboobi, M. A., Ghaseminejad, P., & Ganjali, M. R. (2019). Zinc solubilization characteristics of efficient siderophore-producing soil bacteria. *Iranian Journal of Microbiology, 11*(5), 419–426.

Ganeshan, G., & Kumar, A. M. (2005). *Pseudomonas fluorescens*, a potential bacterial antagonist to control plant diseases. *Journal of Plant Interactions, 1*(3), 123–134. https://doi.org/10.1080/17429140600907043

Harvianti, Y., & Kasiamdari, R. S. (2021). Biological control activities of plant growth-promoting rhizobacteria from organic and nonorganic rice fields against rice sheath blight pathogen (*Rhizoctonia solani* Kühn). *Microbiology and Biotechnology Letters, 49*(4), 374–383. https://doi.org/10.48022/mbl.2103.03005

Hazarika, S. N., Saikia, K., Borah, A., & Thakur, D. (2021). Prospecting endophytic bacteria endowed with plant growth-promoting potential isolated from *Camellia sinensis*. *Frontiers in Microbiology*, 12, 738058. https://doi.org/10.3389/fmicb.2021.738058

Hossain, A., Ali, M. A., Lin, L., Luo, J., You, Y., Masum, M. M. I., Jiang, Y., Wang, Y., Li, B., & An, Q. (2023). Biocontrol of soft rot *Dickeya* and *Pectobacterium* pathogens by broad-spectrum antagonistic bacteria within *Paenibacillus polymyxa* complex. *Microorganisms, 11*(4), 817. https://doi.org/10.3390/microorganisms 11040817

Iacobellis, N. S., Figliuolo, G., Janse, J., Scortichini, M., & Ciuffreda, G. (1997). Characterization of *Pseudomonas syringae* pv. *atrofaciens*. In *Pseudomonas Syringae* Pathovars and Related Pathogens (pp. 500-504). Dordrecht: *Springer* Netherlands.

Iswanto, T., Shovitri, M., Altway, A. L. I., Widjaja, T. R. I., Kusumawati, D. I., & Lisdiyanti, P. (2019). Isolation and identification of caffeine-degrading bacteria from soil, coffee pulp waste, and excreted coffee bean in Luwak feces. *Biodiversitas Journal of Biological Diversity, 20*(6), 1660–1666.

Kazempour, M. N., Kheyrgoo, M., Pedramfar, H., & Rahimian, H. (2010). Isolation and identification of bacterial glum blotch and leaf blight on wheat (*Triticum aestivum* L.) in Iran. *African Journal of Biotechnology*, 9(20), 2866-2871

Kumar, P., Dubey, R. C., & Maheshwari, D. K. (2012). *Bacillus* strains isolated from the rhizosphere showed plant growth-promoting and antagonistic activity against phytopathogens. *Microbiological Research*, *167*(8), 493–499. https://doi.org/10.1016/j.micres.2012.05.002

López, J. L., Alvarez, F., Príncipe, A., Salas, M. E., Lozano, M. J., Draghi, W. O., ... & Lagares, A. (2018). Isolation, taxonomic analysis, and phenotypic characterization of bacterial endophytes present in alfalfa (*Medicago sativa*) seeds. *Journal of Biotechnology, 267*, 55–62. https://doi.org/10.1016/j.jbiotec.2017.12.020

León, H. D., Sáenz-Mata, J., Véliz-Deras, F. G., Flores-Salas, J. M., Carrillo-Moreno, D. I., Arellano-Rodríguez, F., & Núñez-Colima, J. A. (2024). Rhizobacteria inoculation and its effect on the productive parameters of sorghum. *Agro Productividad, 16*(12), 35–40.

Li, X., Ma, S., Meng, Y., Wei, W., Peng, C., Ling, C., Fan, S., & Liu, Z. (2023). Characterization of antagonistic bacteria *Paenibacillus polymyxa* ZYPP18 and the effects on plant growth. *Plants, 12*(13), 2504. https://doi.org/10.3390/plants12132504

Maraite, H., & Weyns, J. (1997). *Pseudomonas syringae* pv. *aptata* and pv. *atrofaciens*, specific pathovars or members of pv. syringae? In *Pseudomonas syringae* pathovars and related pathogens (pp. 515-520). Dordrecht: Springer Netherlands.

Maraite, H., Bragard, C., & Duveiller, E. (2007). The status of resistance to bacterial diseases of wheat. Pages 37-49 in: Wheat Production in Stressed Environments. H. T. Buck, J. E. Nisi, and N. Salomon, eds. *Springer*, New York. https://doi.org/10.1007/1-4020-5497-1_4

Matveeva, I. E. V., Pekhtereva, E. S., Polityko, V. A., Ignatov, A. N., Nikolaeva, E. V., & Schaad, N. W. (2003). Distribution and virulence of *Pseudomonas syringae* pv. *atrofaciens*, causal agent of basal glume rot, in Russia. In *Pseudomonas syringae* and related pathogens: *Biology and Genetics* (pp. 97-105). Dordrecht: Springer, Netherlands.

McCulloch, L. (1920) Basal glume rot of wheat. *Journal of Agricultural Research* 18, 543–551.

Messiha, N. A. S., Elhalag, K. M. A., Balabel, N. M., Farag, S. M. A., Matar, H. A., Hagag, M. H., ... & Farag, N. S. (2019). Microbial biodiversity as related to crop succession and potato intercropping for management of brown rot disease. *Egyptian Journal of Biological Pest Control, 29*, 84. https://doi.org/10.1186/s41938-019-0173-2

Padda, K. P., Puri, A., & Chanway, C. P. (2017). *Paenibacillus polymyxa: A prominent biofertilizer and biocontrol agent for sustainable agriculture*. In V. Meena, P. Mishra, J. Bisht, & A. Pattanayak (Eds.), *Agriculturally important microbes for sustainable agriculture* (pp. 165–186). Springer. https://doi.org/10.1007/978-981-10-5343-6_6

Panpatte, D. G., Jhala, Y. K., Shelat, H. N., & Vyas, R. V. (2016). *Pseudomonas fluorescens: A promising biocontrol agent and PGPR for sustainable agriculture*. In *Microbial inoculants in sustainable agricultural productivity: Vol. 1: Research perspectives* (pp. 257–270). Springer India.

Pasichnyk, L. A. (2000). Properties of bacteria of pathovars of *Pseudomonas syringae* affecting cereals. *Mikrobiolohichnyi Zhurnal (Kiev, Ukraine: 1993), 62*(5), 18-22.

Patten, C. L., & Glick, B. R. (2002). Role of *Pseudomonas putida* indoleacetic acid in the development of the host plant root system. *Applied and Environmental Microbiology*, *68*(8), 3795–3801. https://doi.org/10.1128/AEM.68.8.3795-3801.2002

Pekcan, G. (2006). Food and nutrition policies: what's being done in Turkey. *Public Health Nutrition, 9*(1a), 158-162. https://doi.org/10.1079/PHN2005939

Perneel, M., Heyrman, J., Adiobo, A., De Maeyer, K., Raaijmakers, L. M., De Vos, P., & Höfte, M. (2007). Characterization of CMR5c and CMR12a, novel fluorescent *Pseudomonas* strains from the cocoyam rhizosphere with biocontrol activity. *Journal of Applied Microbiology*, *103*(4), 1007–1020. https://doi.org/10.1111/j.1365-2672.2007.03333.x

Pungrasmi, W., Lee, H. S., Yokota, A., & Ohta, A. (2008). *Pseudomonas japonica* sp. nov., a novel species that assimilates straight-chain alkylphenols. *The Journal of General and Applied Microbiology, 54*(1), 61–69.

Rajaram, S. (2010). Challenges in wheat research and development. The International Dimension of the American Society of Agronomy: *Past and Future*, 39-47. https://doi.org/10.2134/2010.internationaldimension.c6

Raza, W., Yang, W., & Shen, Q. R. (2008). *Paenibacillus polymyxa*: Antibiotics, hydrolytic enzymes, and hazard assessment. *Journal of Plant Pathology, 90*(3), 419–430.

Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., & Nelson, A. (2019). The global burden of pathogens and pests on major food crops. *Nature Ecology & Evolution*, *3*(3), 430-439. https://doi.org/10.1038/s41559-018-0793-y

Schulz, B., & Boyle, C. (2006). What are Endophytes? In: Schulz, B.J.E., Boyle, C.J.C., Sieber, T.N. (eds) Microbial Root Endophytes. Soil Biology, vol 9. Springer, Berlin, Heidelberg. https://doi.org/10.1007/3-540-33526-9_1

Schwyn, B., & Neilands, J. B. (1987). Universal chemical assay for the detection and determination of siderophores. *Analytical Biochemistry*, *160*(1), 47–56. https://doi.org/10.1016/0003-2697(87)90612-9

Shreshtha, K., Prakash, A., Pandey, P. K., Pal, A. K., Singh, J., Tripathi, P., & Tripathi, V. (2025). Isolation and characterization of plant growth-promoting rhizobacteria from cacti roots under drought conditions. Current Research in Microbial Sciences, 8, 100319. https://doi.org/10.1155/2012/692350

Singh, R. R., & Wesemael, W. M. (2022). Endophytic *Paenibacillus polymyxa* LMG27872 inhibits *Meloidogyne incognita* parasitism, promoting tomato growth through a dose-dependent effect. *Frontiers in Plant Science, 13*, 961085. https://doi.org/10.3389/fpls.2022.961085

Slovareva, O. Y. (2020). Detection and identification of wheat and barley phytopathogens in Russia. *Microbiology Independent Research Journal*, *7*(1), 13-23.

Soylu, S., Kara, M., Uysal, A., Kurt, Ş., Soylu, E. M., Üremiş, İ., Sertkaya, E., Bozkurt, İ. A., & Öztürk, M. (2022). Amik Ovası havuç ekim alanlarında sorun olan fungal ve bakteriyel hastalık etmenlerin belirlenmesi. *Kahramanmaraş Sütçü İmam Üniversitesi Tarım ve Doğa Dergisi, 25*(6), 1326–1340. https://doi.org/10.18016/ksutarimdoga.vi.1015936

Taghavi, S. M., & Keshavarz, K. (2003). Identification of the causal agent of bacterial wheat leaf blight in fars and Kohgiluyeh & Boyrahmad Provinces and the Reaction of certain wheat cultivars to them. *Isfahan University of Technology-Journal of Crop Production and Processing*, *6*(4), 171-180.

Tambong, J. (2022). *Bacterial pathogens of wheat: Symptoms, distribution, identification, and taxonomy*. IntechOpen. https://doi.org/10.5772/intechopen.102855

Tariq, M., Khan, A., Asif, M., Khan, F., Ansari, T., Shariq, M., & Siddiqui, M. A. (2020). Biological control: a sustainable and practical approach for plant disease management. *Acta Agriculturae Scandinavica, Section B—Soil & Plant Science*, 70(6), 507-524.

Toben, H., Mavridis, A., & Rudolph, K. W. E. (1989). Basal glume rot (*Pseudomonas syringae* pv. *atrofaciens*) on wheat and barley in FRG and resistance screening of wheat. *EPPO Bulletin*, 19(1), 119-125. https://doi.org/10.1111/j.1365-2338.1989.tb00137.x

Toben, H, Mavridis A, & Rudolph K (1991) Zum Vorkommen der basalen Spelzenfäule an Weizen und Gerste, hervorgerufen durch *Pseudomonas syringae* pv. *atrofaciens*, in Westdeutschland. *Zeitschrift für Pflanzenkrankheiten und Pflanzenschutz,* 98(3), 225–235

Ullah, S., Ejaz, M., & Ali Shad, S. (2017). Study of synergism, antagonism, and resistance mechanisms in insecticide-resistant *Oxycarenus hyalinipennis* (Hemiptera: Lygaeidae). *Journal of Economic Entomology*, 110(2), 615–623. https://doi.org/10.1093/jee/tow310

Varhan, R., & Bozkurt, İ. A. (2021). Maydanoz bakteriyel yaprak leke hastalığı (*Pseudomonas syringae* pv. *apii*) ile biyolojik mücadelede antagonist bakterilerin kullanım olanaklarının araştırılması. *Mustafa Kemal Üniversitesi Tarım Bilimleri Dergisi, 26*(3), 649–660. https://doi.org/10.37908/mkutbd.917150

Vassilev, V., Lavermicocca, P., Di Giorgio, D., & Iacobellis, N. S. (1996). Production of syringomycins and syringopeptins by *Pseudomonas syringae* pv. *atrofaciens*. *Plant Pathology*, 45(2), 316-322.

Vidhyasekaran, P., Kamala, N., Ramanathan, A., Rajappan, K., Paranidharan, V., & Velazhahan, R. (2001). Induction of systemic resistance by *Pseudomonas fluorescens* Pf1 against *Xanthomonas oryzae* pv. *oryzae* in rice leaves. *Phytoparasitica, 29*, 155–166. https://doi.org/10.1007/BF02983959

Young, J. M. (2010). Taxonomy of *Pseudomonas syringae*. *Journal of Plant Pathology*, S5-S14.

Yörük, B., & Mirik, M. (2021). Determination of in vitro biocontrol potentials of antagonist bacterial isolates against the walnut blight disease agent *Xanthomonas arboricola* pv. *juglandis*. *Journal of Tekirdağ Agricultural Faculty, 18*(3), 569–577. https://doi.org/10.33462/jotaf.880817

Zaharieva, M., & Vassilev, V. (1995). Study of the adult wheat and Aegilops resistance to *Pseudomonas syringae* pathovar *atrofaciens*. *Agronomie*, 15(1), 21-24. hal-00885667

Zhang, F., Li, X. L., Zhu, S. J., Ojaghian, M. R., & Zhang, J. Z. (2018). Biocontrol potential of *Paenibacillus polymyxa* against *Verticillium dahliae* infecting cotton plants. *Biological Control, 127*, 70–77. https://doi.org/10.1016/j.biocontrol.2018.09.004

Zhao, X., Zhai, Y., Wei, L., Xia, F., Yang, Y., Yi, Y., Wang, H., Qiu, C., Wang, F., & Zeng, L. (2024). Isolation and identification of a novel *Bacillus velezensis* strain JIN4 and its potential for biocontrol of kiwifruit bacterial canker caused by *Pseudomonas syringae* pv. *actinidiae*. *Frontiers in Plant Science, 15*, 1513438. https://doi.org/10.3389/fpls.2024.1513438

Appendix A
Çizelge 10. $\tilde{S}_i ve\ \tilde{P}_i$Değerleri.
Table 11. $\tilde{S}_i and\ \tilde{P}_i$Values.

	$\tilde{S}_i$			$\tilde{P}_i$		
A1	(0.32,	0.88,	1.98)	(16.96,	17.86,	18.00)
A2	(0.08,	0.47,	1.47)	(12.51,	17.23,	17.82)
A3	(0.08,	0.46,	1.48)	(12.87,	17.22,	17.83)
A4	(0.07,	0.43,	1.42)	(11.95,	17.15,	17.81)
A5	(0.23,	0.74,	1.86)	(16.35,	17.69,	17.96)
A6	(0.23,	0.75,	1.87)	(16.37,	17.70,	17.97)
A7	(0.22,	0.72,	1.85)	(16.29,	17.67,	17.96)
A8	(0.21,	0.69,	1.79)	(16.03,	17.62,	17.94)
A9	(0.20,	0.68,	1.78)	(15.92,	17.59,	17.93)
A10	(0.09,	0.48,	1.47)	(11.49,	17.24,	17.83)
A11	(0.15,	0.59,	1.66)	(14.71,	17.47,	17.89)
A12	(0.11,	0.51,	1.55)	(14.98,	17.30,	17.84)
A13	(0.02,	0.33,	1.24)	(5.55,	16.89,	17.72)
A14	(0.26,	0.78,	1.90)	(16.63,	17.75,	17.97)

Appendix B

Çizelge 11. $\tilde{f}_{ia}, \tilde{f}_{ib}, \tilde{f}_{ic}$Değerleri.
Table 12. $\tilde{f}_{ia}, \tilde{f}_{ib}, \tilde{f}_{ic}$ Values.

	$\tilde{f}_{ia}$			$\tilde{f}_{ib}$			$\tilde{f}_{ic}$		
A1	(0.06,	0.07,	0.10)	(24.39,	61.11,	134.22)	(0.86,	0.94,	1.00)
A2	(0.05,	0.07,	0.10)	(7.86,	34.05,	100.08)	(0.63,	0.89,	0.97)
A3	(0.05,	0.07,	0.10)	(7.50,	33.18,	100.76)	(0.65,	0.88,	0.97)
A4	(0.04,	0.07,	0.10)	(6.47,	31.44,	96.74)	(0.60,	0.88,	0.96)
A5	(0.06,	0.07,	0.10)	(18.30,	51.97,	126.21)	(0.83,	0.92,	0.99)
A6	(0.06,	0.07,	0.10)	(18.30,	52.45,	126.83)	(0.83,	0.92,	0.99)
A7	(0.06,	0.07,	0.10)	(17.58,	51.00,	125.06)	(0.83,	0.92,	0.99)
A8	(0.06,	0.07,	0.10)	(16.44,	48.89,	121.47)	(0.81,	0.92,	0.99)
A9	(0.06,	0.07,	0.10)	(15.82,	47.80,	120.38)	(0.81,	0.91,	0.99)
A10	(0.04,	0.07,	0.10)	(8.29,	35.03,	100.46)	(0.58,	0.89,	0.97)
A11	(0.05,	0.07,	0.10)	(12.67,	42.37,	112.71)	(0.74,	0.90,	0.98)
A12	(0.06,	0.07,	0.10)	(9.65,	37.01,	105.19)	(0.75,	0.89,	0.97)
A13	(0.02,	0.07,	0.09)	(2.00,	24.68,	84.83)	(0.28,	0.86,	0.95)
A14	(0.06,	0.07,	0.10)	(20.07,	54.81,	128.79)	(0.85,	0.93,	0.99)

Appendix C
Çizelge 14. Duyarlılık Analizi Skorları
Table 14. Sensitivity Analysis Scores

Alternative Original	Score Value	Alternative S1	Score	Alternative S2	Score	Alternative S3	Score
A1	26,449	A1	26,968	A1	27,509	A1	28,073
A14	24,602	A14	25,018	A14	25,453	A14	25,905
A6	23,906	A6	24,328	A6	24,768	A6	25,227
A5	23,785	A5	24,221	A5	24,674	A5	25,147
A7	23,453	A7	23,881	A7	24,326	A7	24,790
A8	22,670	A8	23,101	A8	23,549	A8	24,016
A9	22,342	A9	22,762	A9	23,200	A9	23,655
A11	20,456	A11	20,770	A11	21,097	A11	21,438
A12		A12		A12		A12	
		A10		A10			

A10	18,626	A2	18,808	**A3**	18,998	A10	19,196
A2	17,637	A3	17,859	**A2**	18,091	**A3**	18,333
A3	17,451	A4	17,660	A4	17,894	**A2**	18,164
A4	17,386	A13	17,635	A13	17,878	A4	18,105
A13	16,578		16,821		17,074	A13	17,337
	13,767		13,899		14,037		14,180

Alternative	Score	Alternative	Score	Alternative	Score	Alternative	Score
S4		S5		S6		S7	
A1	28,661	A1	26,247	A1	26,048	A1	26,044
A14	26,377	A14	24,437	A14	24,275	A14	24,247
A6	25,706	A6	23,719	A6	23,534	A6	23,576
A5	25,641	A5	23,618	A5	23,454	A5	23,437
A7	25,274	A7	23,295	A7	23,139	A7	23,110
A8	24,504	A8	22,538	A8	22,408	A8	22,298
A9	24,131	A9	22,207	A9	22,074	A9	21,989
A11	21,794	A11	20,350	A11	20,246	A11	20,156
A12	19,403	A12	18,558	A12	18,491	A12	18,403
A10	18,585	A10	17,616	A10	17,596	A10	17,359
A3	18,445	**A2**	17,369	A2	17,288	A2	17,247
A2	18,342	**A3**	17,303	A3	17,220	A3	17,153
A4	17,612	A4	16,504	A4	16,432	A4	16,346
A13	14,329	A13	13,737	A13	13,708	A13	13,607
S8		S9		S10		S11	
A1	25,652	A1	25,273	A1	24,906	A1	26,784
A14	23,904	A14	23,572	A14	23,251	A14	24,931
A6	23,257	A6	22,949	A6	22,650	A6	24,220
A5	23,101	A5	22,776	A5	22,461	A5	24,077
A7	22,777	A7	22,456	A7	22,145	A7	23,736
A8	21,939	A8	21,591	A8	21,254	A8	22,952
A9	21,647	A9	21,316	A9	20,996	A9	22,614
A11	19,866	A11	19,585	A11	19,313	A11	20,735
A12	18,187	A12	17,978	A12	17,775	A12	18,896
A10	17,091	**A2**	16,860	**A2**	16,675	**A10**	17,861
A2	17,050	**A10**	16,831	**A10**	16,580	**A2**	17,668
A3	16,927	**A3**	16,709	**A3**	16,497	**A3**	17,601
A4	16,122	A4	15,904	A4	15,694	A4	16,781
A13	13,452	A13	13,301	A13	13,156	A13	13,928
S12		S13		S14		S15	
A1	26,955	A1	27,129	A1	25,852	A1	25,660
A14	25,099	A14	25,270	A14	24,116	A14	23,959
A6	24,381	A6	24,544	A6	23,353	A6	23,175
A5	24,227	A5	24,379	A5	23,292	A5	23,133
A7	23,880	A7	24,027	A7	22,985	A7	22,834
A8	23,096	A8	23,243	A8	22,280	A8	22,154
A9	22,752	A9	22,893	A9	21,942	A9	21,813
A11	20,877	A11	21,022	A11	20,143	A11	20,042

A12	19,034	A12	19,174	A12	18,425	A12	18,360
A10	17,975	A10	18,092	A10	17,576	A10	17,556
A2	17,779	A2	17,892	A2	17,208	A2	17,130
A3	17,711	A3	17,823	A3	17,139	A3	17,059
A4	16,885	A4	16,991	A4	16,360	A4	16,289
A13	14,011	A13	14,094	A13	13,679	A13	13,650

Alternative	Score	Alternative	Score	Alternative	Score
S16		S17		S18	
A1	25,524	A1	25,226	A1	26,048
A14	23,807	A14	23,590	A14	24,275
A6	23,152	A6	22,911	A6	23,534
A5	22,995	A5	22,751	A5	23,454
A7	22,673	A7	22,436	A7	23,139
A8	21,841	A8	21,618	A8	22,408
A9	21,549	A9	21,326	A9	22,074
A11	19,798	A11	19,658	A11	20,246
A12	18,153	A12	18,111	A12	18,491
A10	17,055	A10	17,002	A10	17,596
A2	17,003	A2	16,915	A2	17,288
A3	16,871	A3	16,759	A3	17,220
A4	16,068	A4	15,961	A4	16,432
A13	13,426	A13	13,395	A13	13,708

Appendix D

Pazar Paylarına Göre İlk 10 Marka, Adet

Marka	Yıllar, Adet ve Pazar Payı (%)						Dönemsel Değişim (%)		
	03 / 2022		03 / 2023		03 / 2024		'22-23	'22-24	'23-24
New Holland	2.006	40,2	2.731	34,3	2894	40,7	36,8	21,8	-10,9
Case	551	11,0	710	8,9	857	12,0	38,8	64,4	18,5
Massey Ferguson	352	7,1	785	9,9	641	9,0	89,3	54,4	-18,4
Deutz	363	7,3	762	9,6	525	7,4	167,1	109,6	-21,5
Tümosan	485	9,7	729	9,2	454	6,4	66,5	-3,5	-42,0
Başak	275	5,5	422	5,3	319	4,5	44,7	10,7	-23,5
Erkunt	300	6,0	542	6,8	309	4,3	60,4	21,2	-24,5
Same	95	1,9	497	6,2	298	4,2	288,6	286,0	-0,7
Solıs	86	1,7	94	1,2	190	2,7	54,2	175,9	78,9
Hattat	337	6,8	258	3,2	157	2,2	15,9	-15,1	-26,8
Diğer	138	2,8	429	5,4	471	6,6	187,5	222,5	12,2
Toplam	**4.988**		**7.959**		**7.115**				

Source: Turkish Agricultural Machinery Industry (TARMAKBİR) Monthly Tractor Statistics Report