Integrating Field Experiments and Multi-Criteria Decision Modelling for Sustainable Mechanisation: A Comprehensive Assessment of Olive Harvesting Technologies

A. Bozorgi[1], N. Banaeian[1*], M. Zangeneh[1], Z. Yousefi[2]

1- Department of Biosystems Engineering, Faculty of Agricultural Sciences, University of Guilan, Guilan, Iran
2- Agricultural and Natural Resources Research and Education Center of Guilan, Province, Guilan, Iran
(*- Corresponding Author Email: banaeian@guilan.ac.ir)
https://doi.org/10.22067/jam.2026.98934.1494

Abstract

Olive harvesting is one of the most labour-intensive operations in olive production, particularly in high-density orchards, where technology selection strongly affects productivity and sustainability. This study combines quantitative field experiments with a sustainability-oriented multi-criteria decision-making framework to evaluate three harvesting methods including hand rake, branch shaker, and over-the-row combine harvester, for Arbequina and Koroneiki cultivars in Iran. A factorial RCBD was implemented to measure harvesting loss, harvesting efficiency, harvesting rate, oil content, and chemical quality indices. Results showed significant differences among methods in harvesting loss, efficiency, and rate ($P < 0.01$). Hand rake achieved the highest harvesting percentage (100%) but also the highest fruit loss (3.33%). Branch shaker recorded the lowest fruit loss (1.12%) but only 53.8% efficiency. Combine harvester provided the highest harvesting rate (4429–5158 kg h^{-1}) and the greatest economic return, with benefit–cost ratios of 1.297 for Arbequina and 1.375 for Koroneiki. To integrate technical, economic, social, and environmental indicators, fuzzy AHP was used to compute criterion weights, and Grey Relational Analysis (GRA) was applied to rank alternatives. Combine harvester obtained the highest GRA score (0.812), followed by the shaker (0.774) and the hand rake (0.682). A comprehensive sensitivity analysis was conducted using ten weighting scenarios and four multi-criteria decision-making methods (GRA, TOPSIS, VIKOR, and ELECTRE), which confirmed the robustness of the rankings across different policy priorities. Also, scenario-based sensitivity analysis demonstrated that combine harvesters consistently ranked first under economic and technical priorities, while shakers became the preferred option in sustainability-oriented scenarios emphasising employment and reduced non-renewable energy use. These results confirm that no single harvesting method dominates across all performance dimensions. Proposed integrated framework provides a robust, evidence-based decision support tool for selecting olive harvesting technologies that balance operational efficiency, profitability, and long-term sustainability.

Keywords: Harvest performance indicators, Mechanisation of olive production, Multi-criteria decision-making, Scenario-based sensitivity analysis

Introduction

Sustainable agriculture is increasingly recognised as a multidimensional concept that integrates environmental stewardship, economic efficiency, technological innovation, and social responsibility. Achieving sustainability in practice therefore requires not only minimising environmental impacts but also improving productivity, profitability, and resilience of farming systems (Kizielewicz, Watrobski, & Sałabun, 2025). In this context, the adoption of appropriate agricultural technologies such as precision machinery, automation systems, and intelligent sensors play a crucial role in promoting resource efficiency, reducing labour requirements, and enhancing the long-term viability of production systems. However, technological sustainability cannot be viewed through a single lens; it demands a holistic assessment of technical, economic, environmental, and social dimensions (Reid & Wood, 2026).

Olive (*Olea europaea* L.) is one of the most important horticultural crops globally, cultivated in approximately 47 countries over extensive areas (Pavlidis *et al.*, 2024). Crop holds exceptional economic and nutritional significance due to olive oil, which is globally recognised for its high nutritional value and therapeutic properties. Numerous studies have examined the influence of olive cultivars and harvesting methods on oil yield and quality, including harvest efficiency (Ahmad, 2018), fruit detachment force and damage (Jiménez, Casanova, Casanova, Paz Suarez, & Morales-Sillero, 2017). Collectively, these investigations confirm that both cultivar characteristics and harvesting technology significantly affect oil quality (Jiménez-Jiménez *et al.*, 2013). Timely mechanical harvesting generally results in superior extra virgin olive oil, whereas delayed or improper harvesting can lead to reduced quality and higher production costs (Cicek, Sumer, & Kocabiyik, 2024).

Various types of olive harvesting machines have been developed, including trunk shakers, branch shakers, canopy harvesters, and side-mounted harvester systems (Aiello, Vallone, & Catania, 2019). Suitability of each technology depends on factors such as cultivar type, tree training systems, fruit maturity, orchard topography, and social acceptance (Ghonimy, Alharbi, & Ibrahim, 2025). Famiani *et al.* (2014) investigated olive harvesting from 2006 to 2009 using two cultivars and two harvesting methods: a tractor-mounted lateral harvester and manual pneumatic combs. Results showed that the harvesting rate was higher when using the tractor-mounted lateral combine harvester with an inverted umbrella, and the quality and harvesting cost of olive oil obtained through mechanical harvesting were also found to be high. Comparative studies demonstrate that branch shakers can serve as an effective alternative to trunk shakers, especially in multi-trunk or irregularly shaped trees, by reducing trunk damage and improving harvest control (Khan *et al.*, 2023). Similarly, Messina, Sbaglia, and Bernardi (2025) reported that manual olive harvesting requires nearly 400 labour hours per hectare, substantially increasing production costs compared to mechanised systems. Economic analyses of fruit crops such as apples and citrus indicate that optimal machinery selection must consider not only technical efficiency but also operational and maintenance costs (Hua, Zhang, Zhang, Liu, & Hu, 2025; Li *et al.*, 2025; Zhang *et al.*, 2024). These findings highlight the central role of technology choice in determining profitability, labour productivity, and sustainability in orchard management.

Given this complexity, the selection of appropriate olive harvesting technology requires a structured and scientifically grounded approach capable of handling multiple, often conflicting, criteria. Decision-making in agricultural mechanisation involves evaluating trade-offs among costs, technical performance, fuel efficiency, environmental impact, operator ergonomics, and social acceptance. Therefore, multi-criteria decision-making (MCDM) methods have emerged as essential analytical tools for technology evaluation and selection in agriculture (Cicciù, Schramm, & Schramm, 2022). Techniques such as the Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), VIKOR, and ELECTRE provide structured frameworks to rank alternatives and weigh trade-offs (Govindan, Rajendran, Sarkis, & Murugesan, 2015). In recent years, hybrid and fuzzy-based MCDM models, such as AHP–GRA, AHP–TOPSIS, and BWM–VIKOR, have enabled the integration of expert-based weighting with quantitative data, increasing robustness under uncertainty and incomplete information (Chakraborty, Raut, Rofin, & Chakraborty, 2023).

Several studies applied these methods to agricultural machinery selection. Hafezalkotob, Hami-Dindar, Rabie, and Hafezalkotob (2018) employed MULTIMOORA and WASPAS to evaluate six olive harvesting machines against nine performance criteria, identifying the most efficient and sustainable option. Similarly, Banaeian & Pourhejazy (2020) and Kenarsari, Banaeian, and Omid (2024) used AHP, Delphi, and fuzzy GRA approaches to select suppliers in food industry sectors and rice harvest machinery, highlighting the role of sustainability indicators. Comparative analyses show that fuzzy GRA methods often achieve results comparable to TOPSIS and VIKOR with lower computational complexity (Banaeian, Mobli, Fahimnia, Nielsen, & Omid, 2018). These studies demonstrate that combining analytical and hybrid models improves the reliability and transparency of technology evaluation.

However, most previous studies in technology selection relied exclusively on qualitative expert judgments or controlled laboratory data, which may not fully capture field variability and practical challenges in sustainable technology selection (Parvaneh & Hammad, 2024). To address this limitation, the current study integrates quantitative field measurements with qualitative evaluations, enabling comprehensive assessment across technical, economic, environmental, and social dimensions. Furthermore, sensitivity and scenario analyses are conducted to evaluate how variations in criterion weights or input data affect final rankings, enhancing the robustness and reliability of decision-making under uncertainty. By adopting this integrated approach, the study contributes to evidence-based decision-making in agriculture and aligns technological innovation with multidimensional sustainability objectives. Ultimately, combining field data, expert judgment, sustainability indicators, and sensitivity analysis provides a robust foundation for developing adaptive, transparent, and sustainable decision-making frameworks for selecting olive harvesting technologies. Although numerous studies have investigated olive harvesting technologies and several researchers have applied MCDM methods for machinery selection, most existing studies rely either on expert judgments or on technical performance data alone. Limited research has integrated field-based experimental measurements with sustainability-oriented MCDM frameworks under real commercial orchard conditions. Furthermore, few studies have examined the robustness of machinery ranking using multiple decision-making algorithms and scenario-based sensitivity analyses. Therefore, the main contributions of this study are: (1) Integration of statistically designed field experiments with sustainability-oriented MCDM techniques; (2) Simultaneous evaluation of technical, economic, social, and environmental indicators; (3) Development of a robust decision-support framework combining Fuzzy AHP, GRA, TOPSIS, VIKOR, and ELECTRE; and (4) Assessment of ranking stability through comprehensive scenario-based sensitivity analysis under different policy priorities.

Materials and Methods

Experimental Site

Study was conducted in Qazvin Province, located in central Iran, covering an area of about 15,821 km² between 35°37′–36°45′ N latitude and 48°45′–50°50′ E longitude. Research site, Tat Sabz Agricultural Company, is situated in the Khondan rural district of Tarom-e Sofla, one of the major olive-producing regions of Qazvin, encompassing approximately 9,750 ha of olive orchards. This company manages around 300 ha of olive groves with varieties such as Arbequina, Koroneiki, and local olives. Fig. 1 illustrates the geographical location of this study.

Studied Orchards

In this study, two important cultivars of olive were studied. First one is the Arbequina cultivar, which is one of the most important oil olive cultivars in the world, originating from the Catalonia region in Northeaster Spain (Fig.1). Due to its high oil quality, desirable economic performance, and adaptability to diverse climatic conditions, this cultivar is now widely cultivated in countries such as Spain, France, Argentina, Chile, the United States, Australia, and some regions of Iran (International Olive Council, 2020). Growth characteristics of this cultivar, including its short stature, dense canopy, and relatively thin branches, make it highly suitable for intensive and super-intensive cultivation systems. In this planting pattern, spacing of 1.5 by 4 metres is typically used, which also allows for mechanised harvesting with shaker machines (Rallo *et al.*, 2013). Arbequina olive is considered a reliable cultivar in terms of environmental resilience. It exhibits good resistance to drought, soil salinity, high humidity, and mild cold (Connor, Gómez-del-Campo, Rousseaux, & Searles, 2014). However, it is sensitive to certain pests, such as olive fruit fly, and in windy areas, it may suffer damage due to its delicate branches (Daane & Johnson, 2010).

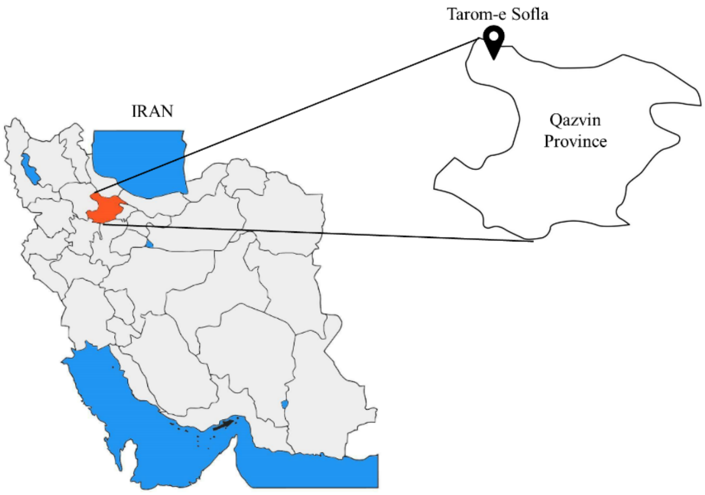

Fig.1. Geographical location of the studied region

The second cultivar studied in this research is Koroneiki which is one of the most well-known and widely used oil olive cultivars in the world, particularly in Greece, where it occupies about 60% of the country's olive cultivation area (Rallo *et al.*, 2013) (Fig.2). Due to its production of high-quality oil, stable yield, and adaptability to various climatic conditions, this cultivar has also been introduced and cultivated in many countries, such as Spain, Italy, the United States, Chile, Australia, and Iran (International Olive Council, 2020). Koroneiki tree is medium-sized with low to moderate vigour and a compact structure. Its rooting ability is moderate, making it suitable for establishing high-density and mechanised orchards (Gomez-del-Campo, Pérez, & García, 2023). In terms of flowering time, this cultivar is an early-flowering with relatively early bloom initiation, whereas fruit ripening generally occurs from the middle to the late part of the harvesting season, depending on climatic conditions (Barranco, Fernández-Escobar, & Rallo, 2022). From a productivity perspective, Koroneiki has a moderate to high yield, and its consistency in annual bearings is acceptable. This cultivar is also suitable for mechanised harvesting and can be well managed in intensive planting systems (Rallo *et al.*, 2013). Its fruit size is small (between 1 and 1.5 grams), but oil extraction percentage is very high, ranging from 20% to 27%, which varies depending on environmental conditions and farm management practices (Connor *et al.*, 2014).

Studied orchard had a planting density of 1,400 trees per hectare. In this study, the trees used were 8 years old, and targeted pruning operations had been performed to ensure compatibility with harvesting equipment. As a result, the lowest branches were positioned at a height of 60 cm, and the highest branches were at 2.5 metres above ground level. Furthermore, to facilitate machinery passage and increase the efficiency of mechanised harvesting, the canopy width of the trees was set at a maximum of 1.5 metres. This training and pruning pattern maintain a balance between vegetative and reproductive growth in trees while enabling the effective use of shaker machines and mechanised harvesting in high-density systems. In this planting pattern, trees are spaced 4 metres between rows and 1.8

metres between trees within a row, which also allows for mechanised harvesting using shaker machines; the harvesting operation was carried out in December 2024 and lasted for four days.

(b)

(c)

(a)

Fig. 2. Studied orchards and olive cultivars: (a) Tat Sabz Company Olive Orchard, (b) Arbequina olive cultivar, and (c) Koroneiki olive cultivar

Studied Olive Harvesting Technologies

Harvesting operations began on December 15, 2024, and continued for 4 consecutive days. In this phase, Arbequina and Koroneiki olive cultivars were harvested under controlled conditions using designated experimental harvesting machines.

Olive Hand Rake

An olive hand rake is a manual, non-mechanised tool used to expedite the olive harvesting process. These combs are typically made with flexible teeth that aid in collecting fruit without damaging trees. One of the important features of olive rakes is the flexibility of the teeth, which allows olives to be easily detached from branches without causing significant harm to trees (Fig. 3).

Olive branch shaker

Motorised portable shaker, Cifarelli model SC800, made in Italy, is one of the advanced and efficient machines in the olive harvesting industry, specifically designed for harvesting olive trees. This device, with a vibration frequency of over 2000 RPM and a branch vibration amplitude of 62 mm, demonstrates its high capability in harvesting oil-rich and oil-saturated olives (Fig. 3). This motorised shaker has a power of 3 horsepower, making it highly suitable for performing high-precision harvesting operations in olive orchards (Cifarelli, 2021).

Over-the-row olive harvester

Braud 10.90X olive harvester, manufactured by New Holland from the United States, is one of the most advanced mechanised olive harvesting machines, specifically designed and produced for intensive and super-intensive olive orchards (Fig. 3). This machine was developed with the aim of increasing harvesting efficiency and reducing time and labour costs in the olive harvesting process. This device is considered one of the most important mechanised tools in the olive industry and is used in various countries, including large and dense orchards (New Holland Agriculture, 2020). According to the harvester operator’s report at Tat Sabz Company olive orchard, the olive harvesting machine is capable of harvesting approximately 5 hectares per day, with a planting density of 1,400 trees per hectare, operating for 8 hours at a forward speed of 3 km h^{-1} and a vibration frequency of 800 rpm, while consuming about 80 litres of diesel fuel during this period.

(a) (b) (c)

Fig.3. Olive harvesting technologies evaluated in this study: (a) Manual olive hand rake, (b) Portable motorised branch shaker (Cifarelli SC800), and (c) Over-the-row olive harvester (New Holland Braud 10.90X)

Research Procedure

Research was conducted in two main stages: field phase (quantitative data collection) and the theoretical phase (qualitative data collection). During the field **phase**, mechanical harvesting of olive cultivars was implemented under controlled conditions in orchards (Fig. 4).

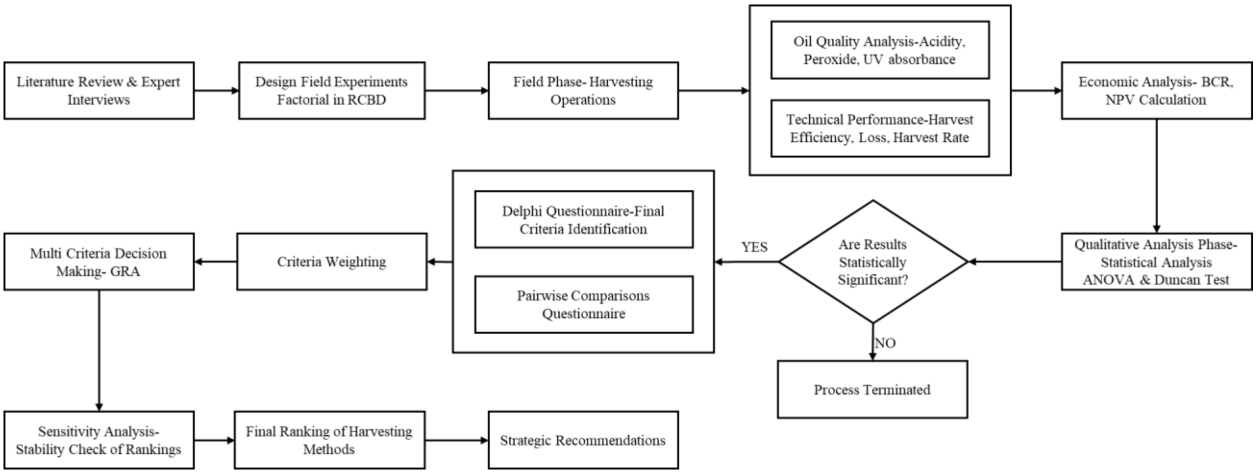

Fig.4. Decision-making multi-step framework

Experimental Design

Field experiments were conducted using a factorial experiment arranged in a Randomised Complete Block Design (RCBD) with three replications during the 2024–2025 growing season. Experimental structure followed a strip split-plot arrangement, where harvesting methods and cultivars were considered as crossed fixed factors.

Factors and Levels

Factor A: Harvesting Method (3 levels)

A_1: Hand rake

A_2: Branch shaker

A_3: Over-the-row combine harvester

Factor B: Olive Cultivar (2 levels)

B_1: Arbequina

B_2: Koroneiki

Treatments

The experiment consisted of 6 treatment combinations, which are shown in Table 1.

Table 1- Treatment combinations

Treatment	Harvesting Method	Cultivar
T_1	Hand rake	Arbequina
T_2	Hand rake	Koroneiki
T_3	Branch shaker	Arbequina
T_4	Branch shaker	Koroneiki
T_5	Combine harvester	Arbequina
T_6	Combine harvester	Koroneiki

Plot Dimensions and Sample Size

- Each RCBD block contained all six treatment combinations.
- Each treatment plot consisted of nine trees, arranged in a rectangular layout matching the orchard's planting design.
- Three central trees were used for measurements to avoid border effects, resulting in: Sample size = 3 trees × 6 treatments × 3 replications = 54 measured trees (Fig. 5).
- Spacing between rows and within rows followed the orchard's high-density planting system.
- Treatments were randomly allocated to plots within each block according to RCBD principles.

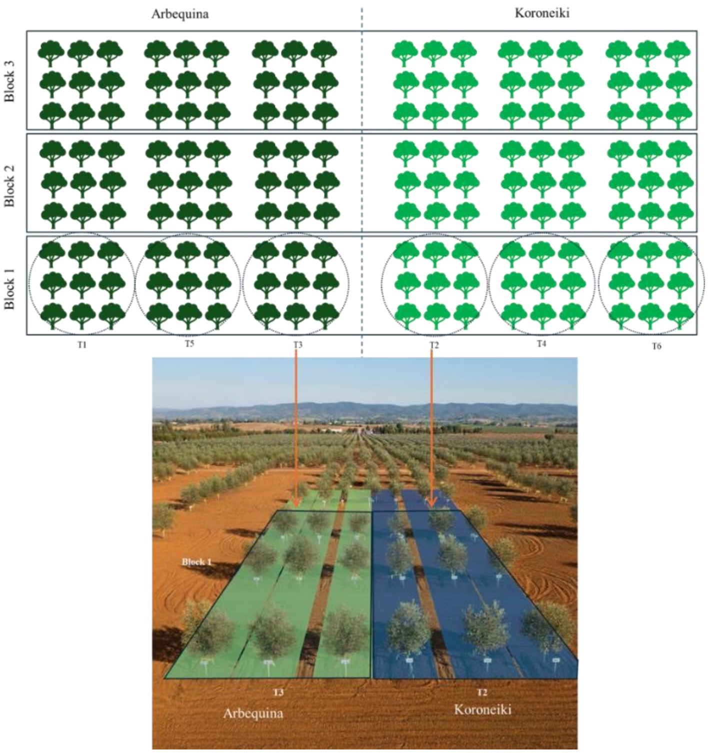

Fig. 5. Experimental design of current study

Orchard Management and Harvest Conditions

All orchard management practices, including irrigation, fertilisation, pruning, and pest control, were uniformly applied across all experimental plots according to the standard management program of Tat Sabz Agricultural Company. Harvesting operations were conducted under dry weather conditions with average daytime temperatures ranging between 12°C and 16°C and relative humidity between 50% and 60%. Fruit maturity was assessed using the Jaén Ripening Index. At the time of harvesting, the average ripening index ranged between 3.5 and 4.0, indicating commercial maturity suitable for oil extraction. Treatment allocation within each block was performed using a computer-generated randomisation procedure to ensure unbiased assignment of harvesting methods.

For oil percentage determination, a solid-liquid continuous extraction method was employed using a Soxhlet apparatus. Accordingly, after olive harvesting, ten fruits were randomly selected from the produce of three trees per treatment. In the laboratory, their pits were removed using a destoner. Fruit flesh was then placed in an oven at 105°C. After 48 hours of drying, two grams of flesh from each sample were ground using a laboratory grinder. Oil extraction was subsequently performed with a Soxhlet apparatus using diethyl ether as a solvent, and the oil percentage of the sample was determined. Subsequently, the olive oil extraction process was conducted, which included four main steps. First, samples of Arbequina and Koroneiki varieties were washed with warm water to remove impurities. Next, olives were crushed using a hammer mill, producing a uniform paste that facilitates oil release. In the third step, the resulting paste was then malaxed (kneaded) for 30–40 minutes to promote oil droplet coalescence under controlled conditions. Finally, oil was separated by centrifugation at 3000 rpm, efficiently isolating the oil from water and solid residues. Olive oil extraction was performed at the Olive Research Centre in Rudbar, followed by quality analyses.

To evaluate different olive harvesting methods, several technical and quality parameters were measured, including fruit losses, labour productivity, harvesting efficiency, and oil quality. Fruit loss was determined by a random sampling method via gathering three kilograms of harvested olives and calculating the percentage of physically damaged fruits (Eq. 1). Labour requirement was recorded as total worker-hours per treatment, serving as an indicator of manpower efficiency. Harvesting efficiency was calculated as a ratio of harvested to total available fruit (Eq. 2), while the harvesting rate represented the amount of fruit collected per worker per hour (Eq. 3).

$$Fruit\ Loss = \frac{Damaged\ Fruits}{Sample\ Weight} \times 100 \quad (1)$$

$$Harvest\ Efficiency = \frac{Harvested\ Fruits}{Total\ Fruits} \times 100 \quad (2)$$

$$\mathrm{Rw} = \frac{\mathrm{Ww}}{\mathrm{Tr}} \quad (3)$$

where, Rw: Harvesting rate in kilograms per hour; Ww: Amount of fruit harvested by one worker; Tr: Time required for fruit harvesting

To evaluate the financial viability of each olive harvesting method, an economic index was calculated using the Benefit-Cost Ratio (BCR). This included estimating initial investment, annual maintenance, labour costs, and projected revenues, with all values discounted to present value using appropriate interest rates. BCR was used as a key indicator, where a value equal to or greater than one signifies economic feasibility. This approach enabled a direct comparison of the profitability of each harvesting method.

Also, statistical analyses were conducted to evaluate technical, qualitative and economic performances. IBM SPSS 26 software was used for data processing, and Duncan's Multiple Range Test (DMRT) was applied to compare mean differences among harvesting methods at 1% and 5% significance levels. Since laboratory data alone were insufficient to determine the optimal method, they were integrated with qualitative insights from questionnaires using an MCDM process.

Decision making

To identify the most suitable olive harvesting technology, in addition to technical data obtained from field and laboratory experiments, MCDM methods were employed to evaluate sustainability indicators, including technical, economic, social, and environmental factors. Qualitative data were collected through expert questionnaires and integrated with quantitative indicators.

Criteria weighting

In this study, the Analytic Hierarchy Process (AHP) was applied to determine the relative weights of the evaluation criteria based on expert (8 persons) pairwise comparisons. Expert panel consisted of eight specialists, including prominent farmers, experts from the Mechanisation Department of the Agricultural Jihad Organisation, and university professors. AHP structures the decision problem into a hierarchy of objectives, criteria, and alternatives (Brunelli, 2015) and is well suited for complex, multi-attribute assessments. This method allows the integration of both quantitative and qualitative indicators (Taherdoost, 2017), making it appropriate for evaluating olive harvesting technologies.

Weighting process was conducted in two stages. First, experts completed structured questionnaires to compare criteria pairwise, following the framework of Banaeian & Pourhejazy (2020). Quantitative technical and economic indicators were combined with qualitative social and environmental criteria. Consistency ratio (CR) was calculated to confirm the reliability of comparisons, with CR < 0.10 deemed acceptable (Brunelli, 2015). Final AHP hierarchy included seven criteria and three harvesting alternatives, as illustrated in Fig. 6.

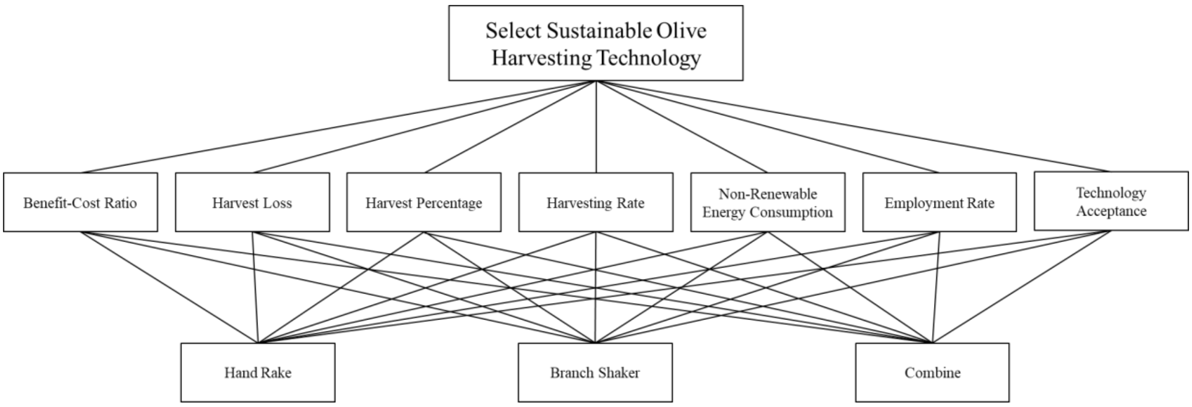

Fig. 6. Hierarchy of sustainable olive harvesting technology selection

Then, fuzzy set theory was applied to convert linguistic variables into triangular fuzzy numbers and construct the decision matrix. Criteria weights and option rankings were derived by averaging expert judgments. Questionnaire consisted of pairwise comparison matrices developed according to Saaty's nine-point scale. Experts evaluated the relative importance of all criteria and sub-criteria. Individual judgments were aggregated using the geometric mean method before fuzzy transformation.

Triangular Fuzzy Number (TFN) is the most popular form for representing fuzzy numbers with three points. For example $\tilde{A} = (l_1, m_1, u_1), \tilde{B} = (l_2, m_2, u_2)$, and the distance between $\tilde{A}$ and $\tilde{B}$ is calculated using the following formula (Banaeian *et al.*, 2018; Auguściak, Więckowski, & Sałabun, 2024):

$$d\,(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{3}[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2]} \quad (4)$$

Defuzzification can convert fuzzy numbers into clear real numbers (Oderanti & Wilde, 2011):

$$Crisp(\tilde{A}) = \frac{l + 2m + u}{4} \quad (5)$$

Linguistic variables are determined for measuring the importance of criteria and assigning their weights using Table 2 (Banaeian *et al.*, 2018).

Table 2- Linguistic Variables for Alternative Ranking

No.	Linguistic Variables (Criteria Weighting)	Triangular Fuzzy Numbers
1	Very Low	(0, 0.1, 0.2)
2	Low	(0.1, 0.2, 0.3)
3	Fairly Low	(0.2, 0.35, 0.5)
4	Moderate	(0.4, 0.5, 0.6)
5	Fairly High	(0.5, 0.65, 0.8)
6	High	(0.7, 0.8, 0.9)
7	Very High	(0.8, 0.9, 1)

With the identification of potential alternatives, experts select evaluation factors. According to Table (3-7), considering m alternatives, n criteria, and k decision-makers, appropriate linguistic variables are used for weighting the criteria ($\widetilde{w}_j = \tilde{l}_{ij}, \widetilde{m}_{ij}, \tilde{u}_{ij}$) and linguistic ranking of alternatives based on the criteria ($\tilde{x}_{ij}$) are determined as linguistic variables.

A decision matrix is constructed using aggregated criterion weights to rank alternatives. Alternatives are denoted by $i = 1, 2, \dots, m$ and criteria by $j = 1, 2, \dots, n$. Finally, fuzzy aggregated weight $\widetilde{w}_j$ for criterion C_j and the fuzzy aggregated ranking $\tilde{r}_{ij}$ for alternative A_i under sub-criterion C_j are added.

$$\tilde{x}_{ij} = \frac{1}{k}\left[\tilde{x}_{ij}^1 + \tilde{x}_{ij}^2 + \cdots + \tilde{x}_{ij}^k\right] \tag{6}$$

$$\widetilde{w}_j = \frac{1}{k}\left[\widetilde{w}_j^1 + \widetilde{w}_j^2 + \cdots + \widetilde{w}_j^k\right] \tag{7}$$

Aggregated fuzzy criterion weights and the decision matrix are constructed as follows:

$$\widetilde{W} = [\widetilde{w}_1, \widetilde{w}_2, \dots, \widetilde{w}_n] \ ; \quad \tilde{X} = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{8}$$

Ranking harvesting technologies using Grey Relational Analysis (GRA)

In this study, data integration for multi-criteria evaluation was conducted using a structured GRA framework. Input data for the decision-making process were sourced as follows:

- Quantitative technical and economic indicators including harvesting loss, harvesting percentage, harvesting rate, and benefit-to-cost ratio were obtained through statistical experimental design during the first stage of the study.
- Qualitative fuzzy indicators such as employment generation and technology acceptance were derived from expert questionnaires.
- Non-renewable energy consumption was calculated based on machine fuel usage: two litres of gasoline per hour for the shaker and eight litres of diesel per hour for the combine harvester, considering the energy content of each fuel type.

After normalising input data, grey relational coefficients were computed for each alternative across all criteria. These coefficients represent the degree of similarity (or closeness) between each alternative and the ideal reference sequence. To reflect the relative importance of each criterion, the coefficients were then multiplied by the corresponding criterion weights, which had been previously determined through pairwise comparisons and expert input.

This weighted multiplication yields the grey relational grade for each alternative, a composite score that integrates both performance and priority across all criteria.

Subsequently, the GRA model was used to rank harvesting machines based on normalised criteria and fuzzy weights. Grey relational coefficients and final relational grade (γ_i) were calculated for each alternative, and the final ranking was established accordingly.

GRA is employed to solve ambiguous problems and those with discrete data and incomplete information. Banaeian *et al.* (2018) demonstrated that this method is superior compared to decision-making methods like TOPSIS and VIKOR. In other words, a grey number refers to a number whose exact value is unknown, but the range that contains its value is known. This theory produces satisfactory and desirable outputs by using relatively little information and with high variability in criteria (Li, Yamaguchi, & Masatake, 2007). A grey number refers to a number whose exact value is unknown, but the range containing its value is known. Grey Relational Analysis process is described as follows (Feng, Dang, Wang, Du, & Chiclana, 2025):

1. Establishing the grey relation
2. Defining target reference series
3. Calculating grey relational coefficient

To use a fuzzy GRA, the decision matrix $(\widetilde{X})$ must be converted to a normalised decision matrix $\tilde{R}$. Considering $\tilde{r}_{ij} = (l_{ij}, m_{ij}, u_{ij})$, normalised performance ratings can be calculated as follows (Gumus, Yayla, Çelik, & Yildiz, 2013):

$$\tilde{r}_{ij} = \left({}^{l_{ij}}\!/_{u_j^+}, {}^{m_{ij}}\!/_{u_j^+}, {}^{u_{ij}}\!/_{u_j^+} \right), i = 1, \dots, m, j = 1, \dots, n \tag{9}$$

where,

$$u_j^+ = max_i\{u_{ij}\} \, \forall i \quad i = 1, \dots, m \tag{10}$$

Reference series can be determined as follows (Gumus *et al.*, 2013):

$$\tilde{R}_0 = [\tilde{r}_{01}, \tilde{r}_{02}, \dots, \tilde{r}_{0n} = max\,(\tilde{r}_{ij})] \tag{11}$$

where,

$$\tilde{r}_{0j} = max\,(\tilde{r}_{ij}) \quad j = 1, \dots, n \tag{12}$$

To form the distance matrix, the distance δ_{ij} between the reference value and each comparison value is calculated using Eq. (10). Grey relational coefficient (ξ_{ij}) will be computed via Equation (10) (Banaeian *et al.*, 2018):

$$\xi_{ij} = \frac{\delta_{min} + \rho\delta_{max}}{\delta_{ij} + \rho\delta_{max}}, \; \delta_{max} = max(\delta_{ij}), \; \delta_{min} = min(\delta_{ij}) \tag{13}$$

and also, for the resolution coefficient ρ, we have:

$$\rho \in [0,1] \tag{14}$$

To estimate grey relational grade γ_i, the defuzzification formula (Eq. 12) is applied to $\widetilde{w}_j$

$$\gamma_i = \sum_{j=1}^{n} w_j\, \xi_{ij}, \qquad i = 1, \dots, m \tag{15}$$

where: $\widetilde{w}_j$ is the weight of the jth criterion and $\sum_{j=1}^{n} w_j = 1$.

By comparing the γ_i values for each alternative with one another, the final ranking can be determined. A higher γ_i value indicates that the alternative is better.

Figure 1 presents the proposed decision-making framework for selecting sustainable olive harvesting technologies.

Sensitivity Analysis

To evaluate the robustness and stability of MCDM results, a comprehensive sensitivity analysis was performed. This analysis examined whether changes in criteria weights or decision-making methods would significantly influence the ranking of harvesting methods. Two complementary sensitivity procedures were applied: (1) scenario-based weight variation, and (2) cross-method comparison using multiple MCDM techniques.

Scenario-Based Weight Variation

A series of alternative weighting scenarios were constructed to test the sensitivity of the final ranking to changes in the relative importance of economic, technical, social, and environmental criteria (Table 3). In each scenario, a specific policy focus (e.g., employment priority, environmental sustainability, technology adoption, economic priority, technical performance, profitability and employment, innovation and sustainability, balanced focus, or actual observed weights from expert judgments) was assigned a higher weight, while remaining criteria were proportionally reduced, ensuring that the total weight summed to one. This approach allows for a comprehensive comparison of how different stakeholder perspectives or policy priorities would influence the optimal choice of olive harvesting method.

Table 3- Weighting scenarios

Scenario	Primary Weighting Focus	Description
A	High Employment Priority	employment and profitability emphasised; other criteria reduced
B	Environmental Sustainability	energy use and ecological impacts given the highest weight
C	Technology Adoption	technology acceptance maximised; economic and social criteria lowered
D	Equal Weighting Across All Criteria	all criteria weighted equally
E	Economic Priority	economic indicators assigned maximum weight; all other criteria minimised
F	Technical Performance Priority	harvesting performance indicators emphasised; economic return de-emphasised
G	Profitability and Employment	profitability and employment jointly prioritised; technical criteria secondary
H	Innovation and Sustainability	innovation and environmental sustainability are given the highest weights
I	Balanced Social, Technical, and Economic Focus	social, technical, and economic criteria balanced
J	Actual (Observed) Weighting	expert-derived weights: economic return highest, then technical and social

For each scenario (Table 3), a new decision matrix was generated and analysed using the GRA method. Relative stability or reversal of rankings across scenarios was used to assess model robustness.

Cross-Method Comparison (GRA, TOPSIS, VIKOR, and ELECTRE)

To ensure that ranking was not dependent on the choice of decision-making technique, three widely used MCDM methods, namely TOPSIS, VIKOR, and ELECTRE, were applied to the same normalised and weighted decision matrix in the following way: (1) TOPSIS was used to evaluate the relative closeness of each alternative to the ideal solution. (2) VIKOR provided a compromise ranking based on group utility and individual regret. (3) ELECTRE applied pairwise outranking relationships to identify dominant alternatives. Rankings from these methods were compared to the results of GRA to determine whether the preferred harvesting method consistently remained at the top across different algorithms.

Stability Evaluation

Stability was assessed based on two criteria: (1) Ranking consistency across scenarios:

If the top-ranked harvesting method remained unchanged across most weighting scenarios, the model was considered stable. (2) Cross-method consistency: Agreement between GRA, TOPSIS, VIKOR, and ELECTRE indicated strong robustness. This comprehensive sensitivity analysis ensured that the final recommendations were reliable and resilient to variations in model assumptions and weighting priorities.

Final Ranking and Decision Interpretation

Harvesting methods were ranked based on grey relational grades. To ensure decision robustness, rankings were compared against alternative MCDM techniques (TOPSIS, VIKOR, and ELECTRE) under multiple weighting scenarios. This multi-method, scenario-based integration improved confidence in the final recommendation and reduced the risk of model-dependent bias. Integrated decision framework facilitated a transparent and quantitatively defensible selection of the most sustainable and operationally efficient olive harvesting technology. Purpose of sensitivity analysis in MCDM is to assess the robustness and reliability of ranking results against potential variations in criterion weights or evaluation methods. This analysis enables policymakers to determine whether the final selection remains valid and defensible under different conditions.

Results and Discussion

Field experiment results

ANOVA test (Table 4) summarises the results of the performance parameters of two olive cultivars under different harvesting methods. Cultivar effect was not statistically significant for harvest loss. However, significant differences (P < 0.01) were detected for harvest efficiency, harvesting rate and benefit-to-cost ratio.

Harvesting method had a significant effect (P < 0.01) on harvest loss, harvest efficiency, and harvesting rate, highlighting the influence of mechanisation level on operational performance (Table 4). Interaction effect between cultivars and harvesting methods was generally not significant for most traits, except for harvest efficiency, which exhibited a highly significant interaction (P < 0.01), implying that the response of harvest efficiency to the harvesting method depends on the cultivar (Table 4).

Although olive oil quality analyses were also conducted in this study, results were not included in the decision-making process, as the effect of the harvesting method on evaluated quality parameters was not statistically significant. Therefore, since the primary focus of this paper is the selection of harvesting technology, the quality analysis results were excluded from further analysis and are not presented in this paper. Prior to ANOVA, residuals were examined for normality using the Shapiro-Wilk test and homogeneity of variances using Levene's test. Results confirmed that assumptions of ANOVA were satisfied (P > 0.05).

Table 4- ANOVA for Performance Traits of Two Olive Cultivars under Different Harvesting Methods

Source of Variation	df	Harvest Loss	Harvest Efficiency (%)	Harvesting Rate (kg h^{-1})	Benefit-Cost Ratio
Replication (Block)	2	1.64e–64 ^{ns}	0.412^{ns}	830.572 ^{ns}	0 ^{ns}
Cultivar (A)	1	4.05e–07 ^{ns}	7.322**	272764.98**	0.011**
Harvest Method (B)	2	0.001**	3894.16**	45124071.6**	0.235**
Interaction (A×B)	2	1.51e–07 ^{ns}	6.69**	262256.82 ^{ns}	0.002 ^{ns}

Note: ** = significant at 1% level; * = significant at 5% level; ns = not significant

Mean comparisons of evaluated parameters across harvesting methods were conducted using Duncan's multiple range test (Table 5). Results revealed significant differences ($p < 0.05$) in harvest loss, harvest efficiency, and harvesting rate, indicating that the choice of harvesting method plays a decisive role in operational effectiveness and yield performance. Relatively lower harvesting efficiency of branch shakers can be attributed to incomplete fruit detachment in dense canopy zones and limited transmission of vibration energy to distal fruit-bearing branches. In contrast, the over-the-row harvester applies vibration to the entire canopy, resulting in substantially higher fruit recovery.

Table 5- Comparison of Mean Values of Significant Parameters Based on Harvesting Method

Treatment (Harvesting Method)	Harvest Loss (%)	Harvest Efficiency	Harvest Rate (kg h^{-1})	Benefit to cost ratio
B1 (Hand Rake)	3.33^{a}	100^{a}	15.6^{a}	1.02^{a}
B2 (Shaker)	1.12^{b}	53.84^{b}	72^{a}	1.22^{b}
B3 (Combine Harvester)	2.24^{c}	95.61^{c}	4793.5^{b}	1.33^{c}

Note: Means within each column followed by the same letter are not significantly different at the 5% level according to Duncan's multiple range test.

Harvesting efficiency

Comparative assessments of different harvesting systems have highlighted the trade-off between efficiency and tree health. For instance, a mechanical bough shaker combined with a wooden stick demonstrated the highest work capacity, making it the most efficient approach, whereas a wood rake exhibited the lowest performance (Cicek *et al.*, 2024). These results emphasise that increased harvesting efficiency often comes at the cost of higher mechanical stress on trees.

Similarly, a study conducted in Spain showed that an in-row harvesting system integrating a trunk shaker and canopy collector achieved over 85% fruit recovery with less than 3% fruit damage under optimal conditions (Zipori, Fishman, Zelas, Subbotin, & Dag, 2021). However, excessive vibration intensity in this system significantly increased the likelihood of branch and bark injuries. Therefore, optimising vibration parameters and harvesting frequency is essential to balance short-term operational efficiency with long-term orchard sustainability and tree vitality.

Harvesting rate

Harvest rate using manual rakes was 100% for both Arbequina and Koroneiki olive cultivars. Branch shaker method yielded approximately 52–56%, while the combine harvester achieved around 95% (Fig. 7). Additionally, manual harvesting of Nabali Baladi and Nabali Mohassan cultivars showed an efficiency above 95%, whereas pneumatic rakes collected only about 86–88% of the fruits (Ahmad, 2018).

Harvesting rate was affected by cultivars, harvesting methods and their interaction and showed a significant difference at the 1% level, while the effect of repetition was not significant. Also, a comparison of harvesting methods showed that there was a significant difference at the 5% level between them. In the comb harvesting method, the harvesting rate for Arbequina variety was 15.2, and for Koroneiki, 16 kg h^{-1}; in the shaking method, this value was recorded as 67.6 and 76.4 kg h^{-1}, respectively, and in the combine method, it was recorded as 4429 and 5158 kg h^{-1}, respectively. In a similar study, the harvesting rate with shaking for local yellow and oil varieties was reported as 93.36 and 57.97 kg h^{-1}, respectively (Kermani, 2016).

Fruit loss/damage

According to the analysis of variance (Table 4), harvest losses were not significantly affected by replication, cultivar type, or their interaction. However, the effect of the harvesting method was statistically significant at the 1% level. As shown in Table 5, Duncan's test confirmed significant differences among methods in terms of harvest losses ($P< 0.05$).

Among tested methods, the highest harvest losses were observed in hand-held rake (3.3%), followed by the combine harvester (2.2%), while branch shaker recorded the lowest losses (1.1%) for both Arbequina and Koroneiki cultivars (Fig. 7). These findings align with previous reports showing that mechanical tools such as pneumatic or hand rakes can increase fruit bruising and surface damage up to fourfold compared with manual harvesting (Solki Cheshmeh Soltani & Jafari, 2019). Higher losses associated with the rake method are primarily attributed to olives falling onto ground sheets and being stepped on, leading to visible bruising and mechanical injury.

Economic Assessment

Comparison of harvesting methods showed that each method had a significant difference in BCR at the 5% level. Highest BCR value was recorded for the combine harvesting method (1.385 for Arbequina and 1.458 for Koroneiki), driven by dramatic gains in the harvesting rates and reduced labour dependency, while the lowest value was recorded for the manual harvesting method with a comb (about 1.02), due to intensive labour requirements. Considering that the BCR value was equal to or greater than one in all treatments, it can be concluded that olive harvesting operations are economically justified under the conditions studied. Overall, the Koroneiki cultivar demonstrated a higher economic return compared to Arbequina, and mechanised harvesting, particularly combine harvester methods, proved to be more cost-effective than manual approaches. These results emphasise that profitability is closely linked to the mechanisation levels in high-density orchards. In large-scale operations where labour cost is a major constraint, fully mechanised systems can substantially enhance economic return.

(a) (b)

Fig.7. Damage to: (a) Arbequina and (b) Koroneiki olives during harvest.

Olive Oil Quality Assessment

Supplementary Table 1 presents mean values of five olive oil quality parameters measured for each harvesting method (hand rake, branch shaker, and combine harvester). Although slight numerical differences are observed, such as marginally higher oil content for the combine (18.08%) and lower K232 for the shaker (1.34). Analysis of variance (ANOVA) confirmed that the harvesting method did not significantly affect any of these quality indicators (acidity, peroxide value, K232, K270, or oil content) at the $P > 0.05$ level. Consequently, despite being included in the initial experimental evaluation, these parameters were not considered as discriminating criteria in the final multi-criteria decision-making (MCDM) framework. This decision ensures that the subsequent ranking of harvesting technologies is based solely on criteria that exhibit statistically significant differences among the alternatives, thereby improving the validity and focus of sustainability assessment.

MCDM results

Although quantitative data obtained from statistically designed experiments in olive orchards provide insights into the performance of different harvesting methods, they are not sufficient on their own for comprehensive and sustainable decision-making. For instance, treatment B1 (hand rake) demonstrated the highest harvest percentage, the lowest peroxide value (4.13 for Arbequina and 4.2 for Koroneiki), and the highest oil content, indicating superior product quality, yet it had the lowest benefit–cost ratio (1.008 and 1.042). Treatment B2 (shaker) showed the lowest fruit loss, the highest harvest rate, and the lowest absorbance at 232 nm (1.601 and 1.097) and 270 nm (0.135 and 0.068), reflecting balanced performance in both efficiency and quality. Treatment B3 (combine harvester) achieved the lowest acidity and highest economic return (BCR of 1.297 for Arbequina and 1.375 for Koroneiki), although its performance in some quality indicators was slightly lower.

These findings reveal that no single method excels across all parameters, and relying solely on numerical indicators may lead to incomplete or unsustainable choices. In addition to technical and economic indicators, it is crucial in technology selection to incorporate social and environmental dimensions—such as technology acceptance among farmers, the impact on local employment, non-renewable energy consumption and ecological sustainability (Ferreira, Vieira, Gosta, Loures, & Lima, 2019). Thus, to achieve a realistic, balanced, and sustainability-oriented prioritisation, the integration of quantitative metrics with qualitative assessments and the application of the MCDM approach is both scientifically justified and practically necessary.

Criteria Weights (Fuzzy AHP)

Consistency ratio of AHP was calculated at 1.5% for primary criteria and 2.9% for sub-criteria, indicating a high level of reliability in expert judgments.

Results in Table 6 showed that BCR received the highest priority, while employment generation ranked lowest. Notably, “harvest percentage” was the second-highest criterion, indicating that farmers prioritise economic factors when selecting harvesting machinery.

Table 6- Criterion Weights Based on Expert Judgments Using a Pairwise Comparison Method (Scenario J)

Technical			Economic	Social		Environmental
Harvesting Loss	**Harvesting Percentage**	**Harvesting Rate**	**Benefit to Cost Ratio**	**Technology Acceptance**	**Employment Generation**	**Non-renewable Energy Consumption**
0.0374	0.1967	0.1044	0.459	0.1095	0.02498	0.0675

Grey Relational Grades (GRA)

Table 7 presents the normalised decision matrix for three harvesting alternatives (Rake, Shaker, Combine) across seven criteria. Each criterion is normalised such that values closer to 1 indicate a preferable direction (e.g. higher harvest loss is desirable, so 1 is best). This matrix directly feeds into subsequent GRA calculations to determine which alternative has the highest relational grade.

Table 7- Normalised Decision Matrix Used in MCDM Analysis

Criterion	Rake	Shaker	Combine
Harvest Loss	0	1	0.493
Harvest Percentage	1	0	0.905
Harvesting Rate	0	0.012	1
BCR	0	0.645	1
Employment	1	0.444	0
Technology Acceptance	1	0.5	0
Non-renewable Energy Consumption	1	0.556	0

Final ranking was established by comparing the grey relational grades of all alternatives. An alternative with the highest grey relational grade is considered the most favourable, as it demonstrates the closest overall proximity to an ideal solution when accounting for both performance metrics and expert-assigned importance. These results are systematically presented in Table 8, offering a transparent and reproducible basis for decision-making in olive harvesting machinery selection.

Table 8- Grey Relational Analysis (GRA) Scores for Alternative Machinery Options

No.	Harvesting Method	GRA Score
1	Rake	0.682
2	Shaker	0.774
3	Combine	0.812

Comparison of Experimental vs. MCDM Results

A comparison between experimental findings and MCDM results revealed several important insights. While experimental data emphasised operational efficiency and economic return, favouring the combine harvester, MCDM outcomes incorporated broader sustainability criteria such as technology acceptance, employment generation, and energy consumption. As a result, the shaker emerged as a competitive and sometimes superior option in scenarios prioritising environmental or social outcomes. This alignment and divergence between empirical and multi-criteria results highlight the value of integrating diverse indicators in agricultural technology selection, ensuring that decisions are not solely dictated by economic considerations but reflect long-term sustainability and stakeholder priorities.

Sensitivity Analysis

In the present study, a range of weighting scenarios was designed to simulate diverse policy priorities in the context of olive harvesting mechanisation (Table 9).

Table 9- Weighting Scenarios for Sensitivity Analysis

Scenario	Primary Weighting Focus	Harvesting Loss	Harvesting Percentage	Harvesting Rate	Benefit-to-Cost Ratio	Employment Generation	Technology Acceptance	Non-renewable Energy Consumption
A	High Employment Priority	0.05	0.15	0.10	0.30	0.25	0.05	0.10
B	Environmental Sustainability	0.05	0.10	0.10	0.20	0.10	0.05	0.40
C	Technology Adoption	0.05	0.15	0.10	0.25	0.05	0.30	0.10
D	Equal Weighting Across All Criteria	0.14	0.14	0.14	0.14	0.14	0.14	0.14
E	Economic Priority	0.05	0.10	0.10	0.60	0.05	0.05	0.05
F	Technical Performance Priority	0.05	0.30	0.20	0.10	0.05	0.05	0.05
G	Profitability and Employment	0.05	0.15	0.10	0.40	0.20	0.05	0.05
H	Innovation and Sustainability	0.05	0.10	0.10	0.15	0.05	0.30	0.25
I	Balanced Social, Technical, and Economic Focus	0.05	0.20	0.15	0.25	0.15	0.15	0.05
J	Actual (Observed) Weighting	0.0374	0.1967	0.1044	0.4590	0.02498	0.1095	0.0675

Scenario-Based Ranking

To evaluate sensitivity, rankings were generated using multiple decision-making methods, including Grey Relational Analysis (GRA), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), and ELimination Et Choix Traduisant la REalité (ELECTRE) (Table 10).

Table 10- Ranking in Each Scenario Using Different Decision-Making Methods

Scenario	ELECTRE	VIKOR	TOPSIS	GRA
A	C < S < R	C < S < R	C < S < R	C < S < R
B	C < S < R	C < S < R	C < S < R	C < S < R
C	R < S < C	R < S < C	R < S < C	R < S < C
D	R < C < S	R < C < S	R < C < S	R < C < S
E	R < S < C	R < S < C	R < S < C	R < S < C
F	R < S < C	R < S < C	R < S < C	R < S < C
G	S < C < R	S < C < R	S < C < R	S < C < R
H	S < R < C	S < R < C	S < R < C	S < R < C
I	R < S < C	R < S < C	R < S < C	R < S < C
J	R < S < C	R < S < C	R < S < C	R < S < C

Note: S: Shaker; R: Rake; C: Combine

Comparison Across MCDM Methods

A Quadrant Chart (Performance Matrix) is used to visualise the ranking of scenarios, which provides a comprehensive spatial analysis of the three olive harvesting technologies across all ten weighting scenarios and four MCDM techniques (Fig. 8). This analytical tool positions each alternative within a two-dimensional performance space, facilitating a holistic interpretation of both scenario-specific effectiveness and overall consistency. A quadrant chart is constructed using perpendicular axes that divide performance space into four distinct strategic regions. Horizontal axis (X-axis) represents Scenario-Specific Performance, ranging from Worst in Scenario on the left to Best in Scenario on the right. Vertical axis (Y-axis) quantifies Consistency of Preference, ranging from the Fewest Wins at the bottom to the Most Wins at the top. Intersection of these orthogonal dimensions creates four quadrants, each defining a categorical performance profile based on the composite evaluation of dominance in individual scenarios and robustness across the entire decision-making spectrum.

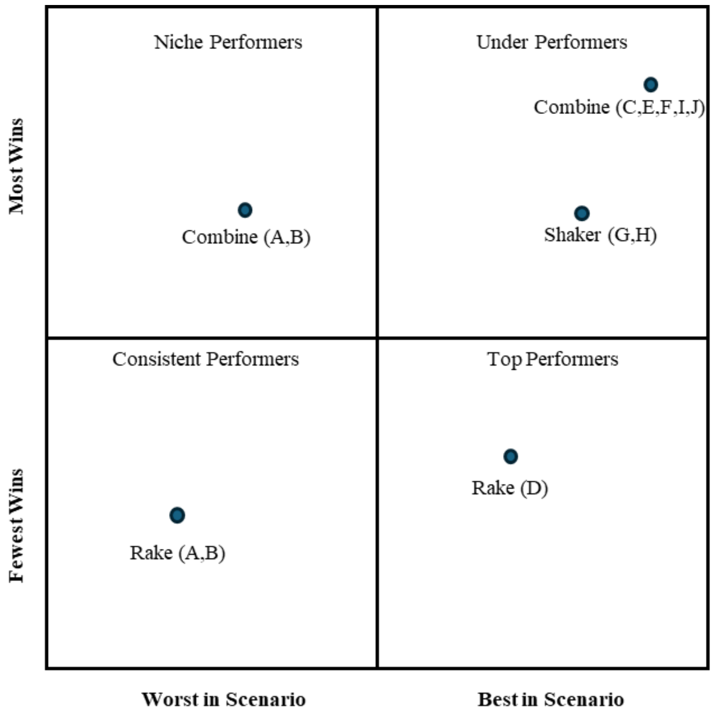

Fig. 8. Quadrant Chart (Performance Matrix) of Scenarios in all MCDM methods to select the best technology of olive harvesting

Performance quadrants and strategic positioning of scenarios can be explained as follows:

1. Quadrant 1 (Bottom-Left): Underperformers– This region is occupied by Hand Rake in Scenarios A and B, positioned at coordinates (0.2, 0.2). This placement indicates its poor performance in both employment-priority (A) and environmental-sustainability (B) scenarios, reflecting low scores in both scenario-specific success and overall win frequency.
2. Quadrant 2 (Bottom-Right): Niche Performers– Hand Rake in Scenario D is located at (0.7, 0.3). This denotes a singular instance of effective performance under the equal-weighting condition (D), but confirms its limited applicability and lack of consistent preference across diverse strategic contexts.
3. Quadrant 3 (Top-Left): Consistent Performers– This quadrant contains two clusters:
   - Combine Harvester in Scenarios A and B at (0.3, 0.7): While not the optimal choice in these specific social and environmental scenarios, it demonstrates moderate performance and notable consistency.
   - Branch Shaker in Scenarios G and H at (0.8, 0.7): This position highlights the shaker's strong and reliable performance in scenarios emphasising profitability with employment (G) and innovation with sustainability (H).
4. Quadrant 4 (Top-Right): Top Performers – Combine Harvester in Scenarios C, E, F, I, and J clusters at the optimal coordinates (0.9, 0.9). This superior placement signifies that the combine is not only the dominant performer in technology-adoption (C), economic (E), technical-performance (F), balanced (I), and actual-weighting (J) scenarios but also maintains exceptional consistency as the preferred alternative across the majority of strategic contexts.

Interpretation and Strategic Implications

Spatial distribution within the matrix yields critical insights for agricultural technology selection. Combine Harvester demonstrates the most robust and versatile performance profile, securely residing in the premier top-right quadrant. Its near-maximum coordinates affirm its status as the most effective and reliable technology under prevailing economic and technical priorities, as reflected in the actual observed weighting (Scenario J). Branch Shaker establishes itself as a strong and consistent contender, particularly when decision frameworks prioritise socio-environmental sustainability. Its position in Quadrant 3 validates its role as a viable and specialised alternative for sustainability-focused farming systems. Conversely, the Hand Rake exhibits a polarised and context-dependent profile, confirming its limitations for modern, mechanised orchard management except under very specific and equally weighted criteria.

In conclusion, quadrant analysis transcends simple ranking by visually integrating the dimensions of peak performance and decision robustness. It provides a powerful, synthesised rationale for recommending the combine harvester as the optimal choice for enhancing productivity and profitability, while simultaneously identifying the branch shaker as a strategically sound alternative for operations where sustainability and social factors are paramount. This methodological approach offers agricultural planners and policymakers a transparent, evidence-based framework for aligning mechanisation investments with specific strategic goals.

Stability Interpretation

Stability assessment showed that each harvesting machine performed best under specific policy scenarios. Shaker consistently ranked first in socially and environmentally focused scenarios (A and B), indicating strong stability under sustainability-oriented conditions. In contrast, the combine harvester excelled in scenarios emphasising technology adoption, economic profitability, and technical performance (C, E, and F), due to its high-harvesting rate and favourable economic returns.

In balanced scenarios (D and I), shaker remained the top-ranked option across all decision-making methods, including consensus-based approaches like VIKOR and ELECTRE. Under the current situation scenario (J), which reflects actual regional priorities, the combine harvester ranked first in all methods, confirming its superiority under prevailing conditions.

Sensitivity analysis revealed that GRA and TOPSIS were less affected by changes in criterion weights, offering stable results in quantitatively driven contexts. In contrast, VIKOR and ELECTRE were more responsive to weight variations and better suited for multi-objective and socially oriented evaluations.

Overall, the selection of harvesting machinery should be aligned with strategic priorities. When employment generation and environmental sustainability are emphasised, shaker is the recommended option. In contrast, if the focus is on enhancing productivity, promoting innovation, and improving technical performance, a combine harvester is preferred. For contexts with balanced objectives across social, technical, and economic dimensions, shaker remains a logical and defensible choice. Furthermore, decision-making methods should be selected based on the nature of data and the sensitivity of evaluation criteria to ensure results are both reliable and actionable.

In this study, sensitivity analysis showed that Combine harvesters consistently ranked first in all economic- and technical-priority scenarios. Branch shaker ranked first in sustainability-oriented (environmental and social) scenarios. Ranking results were highly consistent across the four MCDM methods, confirming the robustness of the decision model and reducing the likelihood of method-dependent bias.

Conclusion

This study provides a comprehensive, multi-criteria evaluation of olive harvesting methods, revealing a critical trade-off between operational efficiency, oil quality, and economic viability. A key finding is that while cultivars significantly influenced intrinsic oil quality parameters and economic return, harvesting methods primarily affected operational performance and profitability.

Although oil quality parameters were measured, no statistically significant differences among harvesting methods were observed. Therefore, harvesting technology selection was primarily influenced by operational and economic performance indicators. However, operational outcomes diverged sharply. Hand rake method, while achieving a high harvest percentage, proved to be the least economically viable due to high labour costs, resulting in the lowest benefit-cost ratio (BCR). Conversely, the combine harvester emerged as an economically superior option, delivering the highest BCR, though it involved a compromise with higher harvest losses compared to the shaker.

Application of an MCDM framework was essential to move beyond these isolated quantitative findings. By integrating technical and economic data with social and environmental criteria, analysis demonstrated that the "best" harvesting method is not absolute but is contingent upon strategic priorities. Robust sensitivity analysis confirmed that a combine harvester is the optimal choice in scenarios prioritising economic return, technical performance, and technological adoption (as reflected in actual weighting scenario J). Shaker presents a strong, balanced alternative, particularly when sustainability, social factors (like employment), and environmental impact (non-renewable energy consumption) are given higher weight.

Therefore, the final recommendation is context-dependent. For olive growers and policymakers focused on maximising profitability and productivity under current market conditions, a combine harvester is the most justified investment. However, for agricultural systems aiming for a sustainable and socially responsible model, shaker offers a compelling combination of good efficiency, lower tree damage, and better social outcomes. This research underscores the value of MCDM approaches in agricultural management, providing a transparent and flexible tool for making complex, sustainability-oriented decisions tailored to specific regional and strategic goals.

Author Contributions

A. Bozorgi: Investigation, Field experiments, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft.

N. Banaeian: Conceptualization, Supervision, Methodology, Formal analysis, Validation, Writing – review & editing, Project administration.

M. Zangeneh: Methodology, Formal analysis, Visualization, Writing – review & editing.

Z. Yousefi: Resources, Investigation, Data acquisition, Validation.

Ethics approval and consent to participate

Not applicable. This study did not involve human participants, human data, or animals.

Consent for publication

Not applicable. This manuscript does not contain any personal data in any form.

Availability of data and material

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

Funding

No funding was received for conducting this study.

References

1. Ahmad, R. L. (2018). Efficiency of mechanical tools for olive harvest and effect on fruit quality. *Acta Horticulturae*, *1199*, 315-320. https://doi.org/10.17660/ActaHortic.2018.1199.49
2. Aiello, G., Vallone, M., & Catania, P. (2019). Optimising the efficiency of olive harvesting considering operator safety. *Biosystems Engineering*, *185*, 15-24. https://doi.org/10.1016/j.biosystemseng.2019.02.016
3. Auguściak, I., Więckowski, J., & Sałabun, W. (2024). Personnel selection under Intuitionistic Fuzzy Multi-Criteria Decision Analysis evaluation. *Procedia Computer Science*, *246*, 3840-3850. https://doi.org/10.1016/j.procs.2024.09.157
4. Banaeian, N., Mobli, H., Fahimnia, B., Nielsen, I. E., & Omid, M. (2018). Green supplier selection using fuzzy group decision making methods: A case study from the agri-food industry. *Computers & Operations Research*, *89*, 337-347. https://doi.org/10.1016/j.cor.2016.02.015
5. Banaeian, N., & Pourhejazy, P. (2020). Integrating sustainability into the machinery selection decisions in the agriculture sector. *IEEE Engineering Management Review*, *48*(4), 167-173. https://doi.org/10.1109/EMR.2020.3008560
6. Barranco, D., Fernández-Escobar, R., & Rallo, L. (Eds.). (2022). *Olive Growing* (2nd English ed.). Madrid, Spain: CSIC & Mundi-Prensa.
7. Brunelli, M. (2015). *Introduction to the Analytic Hierarchy Process*. Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-319-12502-2
8. Chakraborty, S., Raut, R., Rofin, T., & Chakraborty, S. (2023). A comprehensive and systematic review of multi-criteria decision-making methods and applications in healthcare. *Healthcare Analytics*, *4*, 100232. https://doi.org/10.1016/j.health.2023.100232

9. Cicciù, B., Schramm, F., & Schramm, V. B. (2022). Multi-criteria decision making/aid methods for assessing agricultural sustainability: A literature review. *Environmental Science & Policy*, *138*, 85-96. https://doi.org/10.1016/j.envsci.2022.09.020
10. Cicek, G., Sumer, S. K., & Kocabiyik, H. (2024). Optimizing olive harvest methods for maximum yield and efficiency. *African Journal of Agricultural Marketing*, *12*(1), 1-5.
11. Cifarelli S.p.A. (2021). *SC605 shaker* [Product brochure]. Retrieved from https://www.cifarellispa.com/uploads/depliant/SC605_depliant_2021_en_web.pdf
12. Connor, D. J., Gómez-del-Campo, M., Rousseaux, M. C., & Searles, P. S. (2014). Structure, management and productivity of hedgerow olive orchards: A review. *Scientia Horticulturae*, *169*, 71-93. https://doi.org/10.1016/j.scienta.2014.02.010
13. Daane, K. M., & Johnson, M. W. (2010). Olive fruit fly: Managing an ancient pest in modern times. *Annual Review of Entomology*, *55*, 151-169. https://doi.org/10.1146/annurev-ento-112408-085542
14. Famiani, F., Farinelli, D., Rollo, S., Camposeo, S., Vaio, C., & Inglese, P. (2014). Evaluation of different mechanical fruit harvesting systems and oil quality in very large size olive trees. *Spanish Journal of Agricultural Research*, *12*(4), 960-972. https://doi.org/10.5424/sjar/2014124-5794
15. Feng, Y., Dang, Y., Wang, J., Du, J., & Chiclana, F. (2025). A GRA-based heterogeneous multi-attribute group decision-making method with attribute interactions. *Computers & Industrial Engineering*, *201*, 110920. https://doi.org/10.1016/j.cie.2025.110920
16. Ferreira, C. C., Vieira, E., Gosta, S. E. G., Loures, E. R., & Lima, E. P. (2019). Application of MCDM method for technologies selection to support energy management. *Procedia Manufacturing*, *39*, 1289-1296. https://doi.org/10.1016/j.promfg.2020.01.340
17. Ghonimy, M., Alharbi, A., & Ibrahim, M. (2025). Comprehensive performance assessment of an over-the-row olive harvester. *Heliyon*, *11*(10), e43438. https://doi.org/10.1016/j.heliyon.2025.e43438
18. Gomez-del-Campo, M., Pérez, A. G., & García, J. M. (2023). Olive Oil Quality of Cultivars Cultivated in Super-High-Density Orchard under Cold Weather Conditions. *Horticulturae*, *9*(7), 824. https://doi.org/10.3390/horticulturae9070824
19. Govindan, K., Rajendran, S., Sarkis, J., & Murugesan, P. (2015). Multi criteria decision making approaches for green supplier evaluation and selection: A literature review. *Journal of Cleaner Production*, *98*, 66-83. https://doi.org/10.1016/j.jclepro.2013.06.046
20. Gumus, A. T., Yayla, A. Y., Çelik, E., & Yildiz, A. (2013). A Combined Fuzzy-AHP and Fuzzy-GRA Methodology for Hydrogen Energy Storage Method Selection in Turkey. *Energies*, *6*(6), 3017-3032. https://doi.org/10.3390/en6063017
21. Hafezalkotob, A., Hami-Dindar, A., Rabie, N., & Hafezalkotob, A. (2018). A decision support system for agricultural machines and equipment selection: A case study on olive harvester machines. *Computers and Electronics in Agriculture*, *148*, 207-216. https://doi.org/10.1016/j.compag.2018.03.012
22. Hua, W., Zhang, Z., Zhang, W., Liu, X., & Hu, C. (2025). Key technologies in apple harvesting robot for standardized orchards: A comprehensive review of innovations, challenges, and future directions. *Computers and Electronics in Agriculture*, *235*, 110343. https://doi.org/10.1016/j.compag.2025.110343
23. International Olive Council. (2020). *Newsletter No. 159: December 2020*. Retrieved from https://www.internationaloliveoil.org/wp-content/uploads/2020/12/NEWSLETTER_159-EN.pdf
24. Jiménez-Jiménez, F., Castro-García, S., Blanco-Roldán, G. L., Ferguson, L., Ureil, R., & Jesus, G. (2013). Table olive cultivar susceptibility to impact bruising. *Postharvest Biology and Technology*, *86*, 100-106. https://doi.org/10.1016/j.postharvbio.2013.06.024

25. Jiménez, M. R., Casanova, L., Casanova, L., Paz Suarez, M., & Morales-Sillero, A. (2017). Internal fruit damage in table olive cultivars under super-high-density hedgerows. *Postharvest Biology and Technology*, *132*, 130-137. https://doi.org/10.1016/j.postharvbio.2017.06.003
26. Kenarsari, H. Q., Banaeian, N., & Omid, M. (2024). Selecting a sustainable array of machinery by integrating analytic hierarchy process with gray relational analysis. *Operations Research and Decisions*, *34*(2), 109-119. https://doi.org/10.37190/ord240207
27. Kermani, A. M. (2016). Comparison of four harvesting machines for harvesting of oil olive. *Agricultural Mechanization and Systems Research*, *16*(65), 1-18. https://doi.org/10.22092/erams.2016.105950
28. Khan, A. A., Islam, M. A., Saad, A., Raza, S. M., Ali, I., Sheraz, K., Usman, M., Ali, M. M., & Ali, M. (2023). Prospects and scope of olive mechanization: A review. *Zoo Botanica*, *1*(2), 79-93. https://doi.org/10.55627/zoobotanica.001.02.0613
29. Kizielewicz, B., Watrobski, J., & Sałabun, W. (2025). Multi-criteria decision support system for the evaluation of UAV intelligent agricultural sensors. *Artificial Intelligence Review*, *58*(7), 194. https://doi.org/10.1007/s10462-025-11201-1
30. Li, G. D., Yamaguchi, D., & Masatake, N. (2007). A grey-based decision-making approach to the supplier selection problem. *Mathematical and Computer Modelling*, *46*(3-4), 573-581. https://doi.org/10.1016/j.mcm.2006.11.021
31. Li, W., Wan, A., Li, J., Chen, K., Ma, Z., Li, Q., Jiang, R., Yang, J., & Li, T. (2025). A review of data-driven key technologies for intelligent citrus systems. *Computers and Electronics in Agriculture*, *239*, 111121. https://doi.org/10.1016/j.compag.2025.111121
32. Messina, G., Sbaglia, M., & Bernardi, B. (2025). Mechanical harvesting of olive orchards: An overview on trunk shakers. *AgriEngineering*, *7*(3), 52. https://doi.org/10.3390/agriengineering7030052
33. New Holland Agriculture. (2020). *Braud 9090X Olive Harvester* [Product brochure]. Retrieved from New Holland Agriculture brochure
34. Oderanti, F., & Wilde, P. (2011). Automatic fuzzy decision making system with learning for competing and connected businesses. *Expert Systems with Applications*, *38*(12), 14574-14584. https://doi.org/10.1016/j.eswa.2011.05.025
35. Parvaneh, F., & Hammad, A. (2024). Application of multi-criteria decision-making (MCDM) to select the most sustainable power-generating technology. *Sustainability*, *16*, 83287. https://doi.org/10.3390/su16083287
36. Pavlidis, D. E., Kafentzi, M., Rekoumi, K., Koliadima, A., Papadelli, M., Papadimitriou, K., & Kapolos, J. (2024). Turn to the wild: A comprehensive review on the chemical composition of wild olive oil. *Food Research International*, *196*, 115038. https://doi.org/10.1016/j.foodres.2024.115038
37. Rallo, L., Barranco, D., Castro-García, S., Connor, D. J., Gómez del Campo, M., & Rallo, P. (2013). High-Density Olive Plantations. PP 303-384 in J. Janick (Ed.). *Horticultural Reviews*, *41*. https://doi.org/10.1002/9781118707418.ch07
38. Reid, J., & Wood, D. (2026). Supporting sustainable mangrove management in Rio de Janeiro, Brazil: An application of the Environment–Vulnerability–Decision–Technology systems engineering framework. *Acta Astronautica*, *238*, 112-134. https://doi.org/10.1016/j.actaastro.2025.08.050
39. Solki Cheshmeh Soltani, F., & Jafari, A. (2019). Evaluation of olive waste in different harvesting methods. Proceedings of the 8th National Symposium on Losses of Agricultural Products. Tehran, Iran. https://conference.modares.ac.ir/files/site1/rds_journals/2661/article-2661-3804.pdf
40. Taherdoost, H. (2017). Decision making using the analytic hierarchy process (AHP); a step by

step approach. *International Journal of Economics and Management Systems*, *2*, 244-246. https://www.iaras.org/iaras/filedownloads/ijems/2017/007-0034%282017%29.pdf

41. Zhang, H., Fan, S., Chen, Z., Han, X., Sun, L., Sun, J., Wang, G., Fu, S., Zhang, C., Wang, J., & Liu, S. (2024). Targeting optimal power consumption: Optimizing operational parameters for orchard furrowing and fertilizing machine. *Heliyon, 10*(6), e28068. https://doi.org/10.1016/j.heliyon.2024.e28068
42. Zipori, I., Fishman, A., Zelas, Z., Subbotin, Y., & Dag, A. (2021). Effect of postharvest treatments of mechanically harvested 'Manzanilla' table olives on product quality. *Postharvest Biology and Technology*, *174*, 111462. https://doi.org/10.1016/j.postharvbio.2020.111462

Supplementary Table

Table 1- Olive Oil Quality Parameters

Harvesting Method	**Acidity (%)**	**Peroxide Value**	**K232**	**K270**	**Oil Content (%)**
Hand Rake	0.20	4.16	1.53	0.12	18.05
Shaker	0.21	4.53	1.34	0.10	17.93
Combine	0.19	4.36	1.59	0.14	18.08

ترکیب آزمایش‌های میدانی و مدل‌سازی تصمیم‌گیری چندمعیاره برای مکانیزاسیون پایدار: ارزیابی جامع فناوری‌های برداشت زیتون

ابوالفضل بزرگی[۱]، نرگس بنائیان[۱]، مرتضی زنگنه[۱]، زهرا یوسفی[۲]

تاریخ دریافت: ۱۴۰۵/۰۳/۰۹
تاریخ پذیرش: ۱۴۰۵/۰۳/۲۷

چکیده

برداشت زیتون پرزحمت‌ترین عملیات در تولید زیتون است، به‌ویژه در باغ‌های متراکم که انتخاب فناوری به شدت بر بهره‌وری و پایداری تأثیر می‌گذارد. این مطالعه آزمایش‌های کمی میدانی را با یک چارچوب تصمیم‌گیری چندمعیاره (MCDM) با محوریت پایداری ترکیب می‌کند تا سه روش برداشت شامل چنگک دستی، تکاننده شاخه (شیکر) و کمباین روی ردیف را برای ارقام آربیکن و کرونایکی در ایران ارزیابی کند. طرح بلوک‌های کامل تصادفی فاکتوریل برای اندازه‌گیری تلفات برداشت، راندمان برداشت، سرعت برداشت، میزان روغن و شاخص‌های کیفیت شیمیایی اجرا شد. چنگک دستی بالاترین درصد برداشت (۱۰۰٪) و همچنین بالاترین میزان ریزش میوه (۳/۳۳٪) را به‌دست آورد. تکاننده شاخه کمترین میزان ریزش میوه (۱/۱۲٪) را ثبت کرد، اما تنها ۵۳/۸٪ راندمان داشت. کمباین برداشت‌کننده بالاترین نرخ برداشت (۴۴۲۹–۵۱۵۸ کیلوگرم در ساعت) و بیشترین بازده اقتصادی را با نسبت سود به هزینه ۱/۲۹۷ برای آربیکن و ۱/۳۷۵ برای کرونایکی ارائه داد. برای ادغام شاخص‌های فنی، اقتصادی، اجتماعی و زیست‌محیطی، از AHP فازی برای محاسبه وزن معیارها استفاده شد و از تحلیل رابطه خاکستری (GRA) برای رتبه‌بندی گزینه‌ها استفاده شد. کمباین برداشت‌کننده بالاترین امتیاز GRA ۰/۸۱۲ را کسب کرد و پس از آن تکاننده شاخه (۰/۷۷۴) و چنگک دستی (۰/۶۸۲) قرار گرفتند. تحلیل حساسیت مبتنی بر سناریو با استفاده از GRA، TOPSIS، VIKOR و ELECTRE نشان داد که کمباین برداشت‌کننده به‌طور مداوم در اولویت‌های اقتصادی و فنی رتبه اول را کسب می‌کند، در حالی‌که شیکر در سناریوهای پایداری‌محور با تأکید بر اشتغال و کاهش مصرف انرژی‌های تجدیدناپذیر، به گزینه ترجیحی تبدیل شد.

واژه‌های کلیدی: تحلیل حساسیت مبتنی بر سناریو، تصمیم‌گیری چندمعیاره، شاخص‌های عملکرد برداشت، مکانیزاسیون تولید زیتون

۱- گروه مهندسی بیوسیستم، دانشکده علوم کشاورزی، دانشگاه گیلان، گیلان، ایران
۲- مرکز تحقیقات و آموزش کشاورزی و منابع طبیعی استان گیلان، گیلان، ایران
(*- نویسنده مسئول: Email: banaeian@guilan.ac.ir)

https://doi.org/10.22067/jam.2026.98934.1494