Advanced Technologies in Water Efficiency

homepage:https://atwe.razi.ac.ir Online ISSN:2783-4964

Assessment and provincial ranking of crop suitability via the OPLO–POCOD MCDM framework: case study of Wheat, Barley, and Sugar Beet

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Article Info

Article type:
Research Article

Article history:
Received 04 September 2025
Received in revised form 03 November 2025
Accepted 04 December 2025
Available online 22 December 2025

Keywords:

Water culture pattern

Provincial rankings

OPLO-POCOD

Multi-criteria decision making (MCDM)

Strategic agricultural products

ABSTRACT

Objective: This study ranks Iranian provinces on their irrigated potential for wheat, barley, and sugar beet using a weighted multi-criteria framework that evaluates agronomic performance, water resources, and mechanization. It identifies provinces with comparative advantages, highlights mismatches with current cultivation, and offers guidance for reallocating cropping patterns to boost productivity and water-use efficiency.

Method: We built a weighted, normalized province-level decision matrix using six agronomic and water-related criteria and applied the OPLO–POCOD method to calculate each province's Degree of Opportunity Loss and Percent of Opportunity Achieved for wheat, barley, and sugar beet. Using expert-derived weights, we produced crop-specific suitability rankings and compared them with current cultivation patterns to identify misallocations and opportunities for more water-efficient cropping.

Results: The OPLO–POCOD rankings show that humid and water-rich provinces (e.g., Mazandaran, Golestan, Khuzestan) have the strongest suitability for irrigated wheat, barley, and sugar beet, while arid southern provinces consistently underperform. Comparing these rankings with current cropping patterns reveals major misallocations, indicating substantial opportunities to shift cultivation toward high-scoring provinces to boost national returns and water productivity without increasing water use.

Conclusions: The study uses the OPLO–POCOD framework to rank Iran's provinces for irrigated wheat, barley, and sugar beet based on agronomic performance, water use, and mechanization capacity, revealing clear spatial patterns of suitability. Comparing these rankings with current cropping areas highlights misallocations and actionable opportunities to improve national crop productivity, water efficiency, and net returns without increasing overall water use.

Cite this article: Asli Charandabi, M.R., Taghizade Firozjaee, T., Emamgholizadeh, S., Khoshnevisan, S., & Khakzad, S. (2025). Assessment and provincial ranking of crop suitability via the OPLO–POCOD MCDM framework: case study of Wheat, Barley, and Sugar Beet. *Advanced Technologies in Water Efficiency, 5* (4), 68-91. https://doi.org/ 10.22126/atwe.2025.12724.1189

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Introduction

Accelerating inequalities in water access under climate change threaten the sustainability of agricultural systems across many dryland and semi-arid regions (Richey et al., 2015). Satellite gravimetry reveals that recent shifts in global freshwater availability are tightly coupled with groundwater depletion in high-consumption agricultural hotspots, notably South Asia and parts of the Middle East (Rodell et al., 2018). Independent estimates further indicate that cumulative groundwater loss since the early twentieth century has measurably contributed to sea-level rise and undermined the long-term viability of irrigation (Konikow & Bredehoeft, 2020; Scanlon et al., 2012). Within this context, cereals such as wheat and barley, along with sugar beet, hold strategic importance for food security and agro-industrial linkages; recent trends in guaranteed procurement policies, production volatility, and import needs in Iran amplify this relevance (U.S. Department of Agriculture, 2025). Concurrently, soil salinity, driven by suboptimal water use and inadequate drainage, erodes yields while imposing substantial economic and environmental costs (Daliakopoulos et al., 2016). Together, these global signals and country-specific warnings underscore the need to shift from traditional crop-allocation practices toward evidence-based, water-productivity-oriented approaches (Madani, 2014).

In modern agricultural research, water productivity (yield per unit of water consumed or evapotranspired) has become a pivotal metric at both field and regional scales for spatial crop-pattern design (Zwart & Bastiaanssen, 2004; Bouman, 2007). Because crop-allocation decisions are inherently multi-criteria, balancing yield potential, water requirements, surface/groundwater access, rainfall and climate, mechanization, and salinity/quality risks, multi-criteria decision analysis (MCDA) has gained systematic traction, moving from qualitative judgments to defensible quantitative rankings (Chen et al., 2010; Malczewski, 2006; Mendoza & Martins, 2006). Methodologically, newer MCDM[1] formulations can enhance the robustness of provincial rankings; the Opportunity-Loss–Polar-Distance framework (OPLO–POCOD) has shown competitive performance relative to established methods (Sheikh & Senfi, 2024). Given Iran's pronounced climatic heterogeneity, ranging from arid to semi-arid zones to humid temperate regions, substantial spatial variability in irrigation-based crop suitability is expected, motivating the development of province-level rankings supported by integrative decision frameworks.

Illustratively, One study developed a spatial MCDA for rainfed wheat in Kurdistan Province, delineating homogeneous zones with comparable yield potential. Phenological timing (germination, flowering, and grain filling) was determined using growing-degree-days. Four primary criteria (rainfall, temperature, soil, and topography) and 20 sub-criteria were selected based on literature and expert judgment. Factor weights were assigned using fuzzy AHP, and aggregation was performed through a weighted linear combination. Suitability classes followed the FAO scheme (S1, S2, S3, N1, N2), with spatial shares of ~1.2% (S1), 37.8% (S2), 24.7% (S3), 19.2% (N1), and 4.4% (N2). Validation against 2018–2019 to 2020–2021 farm data showed a ratio of observed-to-potential yield of ~75% in S1 and 20% in N2, with a correlation of 0.94 between the computed potential and observed yields. These results highlight the value of spatial MCDA for precision agriculture, crop planning, risk transfer (e.g., insurance), and sustainable water management under scarcity (Pooya et al., 2025).

In another study, researchers prioritized the sustainability of rice cultivation in three provinces, Mazandaran, Fars, and Khuzestan, using an integrated approach. Eco-efficiency was defined as the ratio of "net income" to "environmental burden" per hectare, combined with the Best–Worst

[1] Multi-criteria decision making

Method to weight criteria across energy, labor, economic, and environmental dimensions. The methodological framework applied a life cycle assessment (LCA) that covered the entire process, from land preparation to harvest. Emissions were separated into foreground and background categories and quantified using the Ecoinvent 3.5 and Agri-footprint 5.0 databases, with the IMPACT World+ method implemented in SimaPro software (Alijani et al., 2025). Regarding energy flows, total energy consumption was approximately 9,018,689,923 and 97,549 MJ per hectare in Mazandaran, Fars, and Khuzestan, respectively. Diesel fuel accounted for more than half of the total energy use across all regions, followed by irrigation water. Economically, Mazandaran achieved the highest gross production value, net income, and benefit–cost ratio. Eco-efficiency results similarly placed Mazandaran first (~8,988 USD per environmental burden unit), followed by Fars and Khuzestan. Final Best–Worst rankings indicated that economic (≈0.33) and environmental (≈0.31) criteria carried the most significant weight, yielding composite scores of 0.98, 0.93, and 0.85 for Mazandaran, Fars, and Khuzestan, respectively. The study concludes that all three regions suffer from energy inefficiencies; however, Mazandaran demonstrates superior energy efficiency, reduced losses, and higher profitability, though at the cost of a greater environmental burden. This misalignment underscores the need for targeted management interventions.

In a study aimed at providing a comprehensive overview of potato-producing provinces in Iran, They used efficiency as the first step toward sustainability, applying Data Envelopment Analysis (DEA) for ranking and TOPSIS for integrating results for the 2018 cropping year. In this framework, “yield” and “gross profit” were selected as indicators of production and profitability. Findings showed that when “gross profit” was used as the output, mean technical, pure, and scale efficiencies were lower compared to when “yield” served as the output. Results also indicated that different DEA models produced varying rankings, underscoring the need for multi-model integration to achieve more accurate assessments. In the final integrated ranking, Mazandaran, Kerman, and West Azerbaijan consistently ranked among the top provinces under both output measures, serving as benchmarks for improving efficiency. Correlation analysis revealed negative relationships between efficiency scores (under both outputs) and the use of seed, potash fertilizer, and pesticides, suggesting that biofertilizers and integrated pest management are preferable alternatives. Notably, several major producers, Hamedan, Ardabil, Isfahan, South Kerman, Fars, and Kurdistan, did not rank highly in efficiency. This indicates that producers in these provinces have prioritized higher yields over profitability, highlighting the necessity of cost management and input-use optimization to enhance sustainability (Esfahani & Barikani, 2022).

In another study analyzing environmental management strategies in Iran’s agricultural sector, applied the Analytic Hierarchy Process (AHP) with input from 117 managers, experts, and researchers to compare three management paradigms: Frontier Economics, Eco-development, and Deep Ecology. The findings revealed that formal managers preferred the Frontier Economics paradigm and independent reactive strategies. At the same time, researchers and the private sector leaned toward Eco-development, and environmental specialists favored Deep Ecology. The study emphasized the need to align paradigms with practical strategies to ensure more sustainable management of natural resources and the environment. Recent research also highlights climate variables as key drivers of variability in irrigated crop yields across Iran. Wheat yields peak in provinces with cold winters, where the seasonal mean temperatures range between –3.5 and 0.98 °C, reaching up to 3.88 t/ha under irrigation (Ebrahimi Sirizi et al., 2023). By contrast, spring rainfall exceeding 153 mm is identified as the main factor driving higher barley yields (Kheyruri et al., 2024). Areas with high evaporation (>227 mm), especially in southeastern Iran, are largely unsuitable for barley and lentil cultivation. Sugar beet demonstrates strong adaptation to moderate temperatures and adequate relative humidity; in land suitability assessments in Fars Province, some physiographic units were classified as highly suitable (S1) under qualitative evaluation methods (Azadi & Baghernejad, 2018).

Agro-climatic zoning studies further underscore the substantial spatial variability of crop potential. In Kermanshah Province, a GIS-based multi-criteria analysis using the Analytic Hierarchy Process (AHP) identified elevation, precipitation, slope, and crop water requirement as the principal determinants of sugar beet suitability, and classified the province into four classes: high potential, moderate potential, low potential, and non-potential (Parmah & Negaresh, 2014). Similar climate-driven patterns have been reported at the national scale for wheat; the impacts of climate change on irrigated wheat differ significantly between arid and semi-arid provinces, with limited temporal adaptation and higher vulnerability of irrigated wheat in arid regions to warming and reduced rainfall (Pakrooh & Kamal, 2023). Efficiency studies provide additional insight into provincial disparities. Using Stochastic Frontier Analysis, estimated technical, allocative (price), and economic efficiencies for irrigated wheat across 27 provinces at 69%, 63%, and 45%, respectively, indicating substantial scope for policy and technological interventions. A separate econometric analysis in the three Khorasan provinces found constant returns to scale for wheat and barley, while sugar beet in South Khorasan exhibited decreasing returns, highlighting the need for localized production planning (Koopahi et al., 2008).

Within agriculture, MCDM techniques have been applied to both production optimization and resource prioritization. In Mazandaran, linear programming under land and profitability constraints identified wheat, barley, and sugar beet as components of an export-oriented optimal cropping pattern (Moazzez & Habibi, 2014). Integrated GIS–MCDM frameworks have been utilized for siting renewable energy sources, demonstrating methodological versatility. Despite their utility, conventional MCDMs face two common limitations that the recently proposed OPLO–POCOD approach addresses (Zandi & Lotfata, 2025). High water use and low productivity remain significant challenges in Iran; MCDM models that jointly consider climatic, edaphic, and topographic indicators can identify optimal cultivation zones, selecting provinces with lower water requirements and higher yields, thereby reducing misallocation and pressure on water resources (Rashidi & Sharifian, 2022; Radmehr et al., 2022). Avoiding cultivation on unsuitable lands also mitigates risks such as soil salinization, groundwater decline, and biodiversity loss, as corroborated internationally (Abuzaid et al., 2025; Gurara, 2020) while enabling the use of underutilized lands and more balanced spatial opportunities (Nabiollahi et al., 2024).

This study integrates various criteria, including yield, crop water requirement, agricultural water use, mean precipitation, mechanization capacity, and productivity, to assess provincial suitability for three strategically important irrigated crops wheat, barley, and sugar beet and to derive a province-level ranking relative to current sown-area rankings. We employ the OPLO–POCOD MCDM framework. The contribution lies in applying this recent MCDM to rank Iranian provinces by crop suitability and directly comparing the outputs with the existing pattern to reveal gaps and recommend cropping pattern adjustments, ultimately identifying provincial comparative advantages for the target crops.

Method

Study Area

Iran lies at the junction of the Iranian Plateau and the broader Middle East in Southwest Asia. Its climate is predominantly arid to semi-arid, with hot, dry summers and cold winters across the interior, except along the Caspian littoral and parts of the west. Seasonally, most precipitation occurs from November to May, with a dry period from June to October. Long-term mean annual rainfall is reported at roughly 240–250 mm nationwide, with a steep spatial gradient from <100 mm in central/eastern deserts (Lut) to >1,000 mm on the Caspian plain and windward Alborz slopes (exceeding 1,500–1,800 mm at some stations). Century-scale time series indicate means near 228–246 mm.

In this study, Iran is analyzed at the provincial scale for three strategic irrigated crops: wheat, barley, and sugar beet. Wheat yield is evaluated across 31 provinces, while sugar beet and barley yields are evaluated across 23 and 31 provinces, respectively. Yield (t ha^{-1}) and related data were sourced from the Ministry of Agriculture Jihad. Given water and land-use constraints, a multi-criteria decision-making (MCDM) framework is employed to rank provinces for irrigated cultivation based on key indicators: yield per hectare, crop water use, mean precipitation, agricultural water availability, mechanization, and water productivity (yield per unit water). Fig. 1 shows the provincial map of Iran.

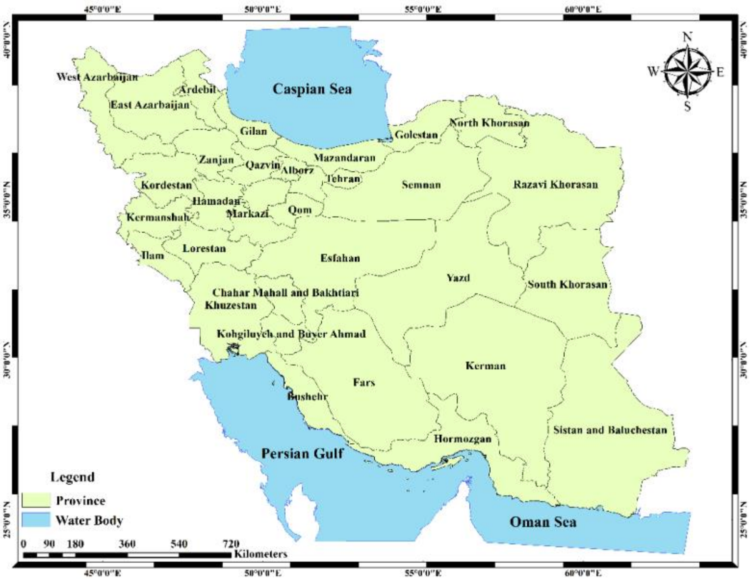

Figure 1. Location pf Provinces in Iran

Multi-Criteria Decision-Making (MCDM) methods are recognized as effective tools for addressing complex problems that require the simultaneous consideration of multiple criteria. Their main advantage lies in enabling the evaluation of various alternatives based on a diverse set of indicators. By providing a structured framework for comparing operational objectives through the assessment of different criteria, these approaches facilitate the ranking process and support the selection of the most suitable option among a range of alternatives.

Opportunity Loss Technique Based on Polar Coordinate Distance

The Opportunity Loss Technique, based on polar coordinate distance, is a key concept in economics and management, serving as a foundation for assessing the value of information. First introduced by Sheikh and Senfi in 2024, this approach builds on the core idea of opportunity loss. By calculating the degree of loss associated with each alternative, it compares the condition of that alternative with the optimal state using distance measures in polar coordinate space.

Steps of the OPLO–POCOD Approach

The calculation steps of this method are explained as follows.

Step 1: Construction of the initial decision matrix

The initial decision matrix *A*, comprising m alternatives and n criteria, is formed based on the data and information collected from the decision-makers.

$$X=\begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}_{m\times n} \quad , \quad i=1 \text{ to } m \; ; \quad j=1 \text{ to } n. \tag{1}$$

Step 2: Normalization

For data normalization, the following formula is applied, utilizing logarithmic normalization with linear scaling.

$$N_{ij}=\frac{\log_{10}(x_{ij})-\log_{10}(\min_i x_{ij})}{\log_{10}(\max_i x_{ij})-\log_{10}(\min_i x_{ij})}\times 0.9+0.1 \tag{2}$$

In the above formula, *i* and *j* represent the alternative number and the criterion number, respectively. Moreover, the *max* and *min* of each criterion correspond to the highest and lowest values of that criterion across all alternatives. Finally, the output of the formula, applied independently to all criteria, falls within the range of 0.1 to 1.

$$n_{ij}=\frac{X_{ij}}{\sum_{i=1}^{m} X_{ij}} \qquad \text{Benefit-Nature}$$

$$n_{ij}=\frac{1/X_{ij}}{\sum_{i=1}^{m} 1/X_{ij}} \qquad \text{Cost-Nature}$$

Step 3: Construction of the Opportunity Loss Matrix

In this step, the opportunity loss of each alternative is calculated for all criteria. The calculation is based on the difference between each value in a column and the maximum value of that column (if the criterion has a positive or benefit nature), and the difference between each value in a column and the minimum value of that column (if the criterion has a negative or cost nature).

$$\begin{array}{c} \begin{matrix} c_1 & \quad & c_j & \quad & c_n \end{matrix} \\ X=\begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}_{m\times n} \\ \begin{matrix} x^*_{i1} & \quad & x^*_{ij} & \quad & x^*_{in} \end{matrix} \end{array} \quad , \quad i=1 \text{ to } m\,;\, j=1 \text{ to } n. \tag{3}$$

The best value is achieved by maximizing the benefit criteria and minimizing the cost criteria.

$$\begin{array}{c} \begin{matrix} c_1 & \quad & c_j & \quad & c_n \end{matrix} \\ X=\begin{bmatrix} x_{11-x_1^*} & \cdots & x_{1j-x_j^*} & \cdots & x_{1n-x_n^*} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1-x_1^*} & \cdots & x_{ij-x_j^*} & \cdots & x_{in-x_n^*} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1-x_1^*} & \cdots & x_{mj-x_j^*} & \cdots & x_{mn-x_n^*} \end{bmatrix}_{m\times n} \end{array} \quad , \quad i=1 \text{ to } m\,; \quad j=1 \text{ to } n. \tag{4}$$

$$\text{Opportunity Loss (opl)}=\left|x_{ij}-x_{best}\right| \quad \text{for } \forall\, x_{ij} \quad i=1 \text{ to } m; \quad j=1 \text{ to } n. \tag{5}$$

Based on Equations (3) to (5), the matrix is constructed using the obtained opportunity losses.

$$\begin{array}{c} \begin{matrix} c_1 & \quad & c_j & \quad & c_n \end{matrix} \\ OPL=\begin{bmatrix} opl_{11} & \cdots & opl_{1j} & \cdots & opl_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ opl_{i1} & \cdots & opl_{ij} & \cdots & opl_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ opl_{m1} & \cdots & opl_{mj} & \cdots & opl_{mn} \end{bmatrix}_{m\times n} \end{array} \quad , \quad i=1 \text{ to } m\,;\, j=1 \text{ to } n. \tag{6}$$

Step 4: Construction of the Ordered-Pair Matrix

The ordered-pair matrix is created by combining the elements of the initial decision matrix and the opportunity loss matrix.

$$X_{pair_{ij}}=\left(x_{ij}, OPL_{ij}\right), \quad i=1 \text{ to } m\,; \quad j=1 \text{ to } n$$

$$X_{pair}=\begin{bmatrix} (x_{11}, opl_{11}) & \cdots & (x_{1j}, opl_{1j}) & \cdots & (x_{1n}, opl_{1n}) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ (x_{i1}, opl_{i1}) & \cdots & (x_{ij}, opl_{ij}) & \cdots & (x_{in}, opl_{in}) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ (x_{m1}, opl_{m1}) & \cdots & (x_{mj}, opl_{mj}) & \cdots & (x_{mn}, opl_{mn}) \end{bmatrix}_{m\times n} \quad i=1 \text{ to } m\,; \quad j=1 \text{ to } n. \tag{7}$$

Step 5: Construction of the Distance Matrix in Polar Space

In this step, the distance of each alternative from the best value of the same criterion is calculated. For this purpose, each alternative is represented as (x_{ij}, opl_{ij}), while the best value of the corresponding criterion is denoted as $(x_{best}, opl_{x_{best}})$. It should be noted that the opportunity loss for the best value is always equal to zero. The distance between these two points in the coordinate space is then computed using the following formula:

$$d_{ij} = \sqrt{A_{ij}^2+B_{ij}^2-2A_{ij}B_{ij}\cos(\theta_2-\theta_1)}\,,$$

$$A = (x_{ij}, opl_{ij}) \text{ and } B = (x_{best}, opl_{x_{best}}) \text{ and } (A, \theta_1) \text{ and} (B,\ \theta_2). \tag{8}$$

$$A.B = \| A \| \| B \| \cos\theta \tag{9}$$

The cosine of the angle between the two vectors is also obtained from Equation (9).

$$\cos(\theta_2-\theta_1) = \frac{A.B}{\|A\| \|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \tag{10}$$

Finally, based on the obtained values, the distance matrix **D** is constructed.

$$D=\begin{bmatrix} d_{11} & \cdots & d_{1j} & \cdots & d_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{i1} & \cdots & d_{ij} & \cdots & d_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{m1} & \cdots & d_{mj} & \cdots & d_{mn} \end{bmatrix}_{m\times n} \quad , \quad i=1 \text{ to } m\,; \quad j=1 \text{ to } n. \tag{11}$$

Step 6: Construction of the Weighted Distance Matrix

$$\bar{d}_{ij} = w_j * d_{ij} \tag{12}$$

$$D_w=\begin{bmatrix} \bar{d}_{11} & \dots & \bar{d}_{1j} & \dots & \bar{d}_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{d}_{i1} & \dots & \bar{d}_{ij} & \dots & \bar{d}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{d}_{m1} & \dots & \bar{d}_{mj} & \dots & \bar{d}_{mn} \end{bmatrix}_{m\times n} \quad , \quad i=1 \text{ to } m\,; \quad j=1 \text{ to } n. \tag{13}$$

Step 7: Calculation of the Total Distance for Each Alternative

$$S_i=\sum_{j=1}^{n}\bar{d}_{ij}\ ,\ i=1 \text{ to } m. \tag{14}$$

$$S_T=\sum_{i=1}^{m}S_i \tag{15}$$

Step 8: Calculation of the Degree of Opportunity Loss (DOL) and the Percentage of Opportunity Achieved (POA)

$$(DOL_i)=\frac{S_i}{S_T}, \tag{16}$$

In this relation:

$$\sum_{i=1}^{m}DOL_i=1.$$

$$(POA_i)=1\text{-}DOL_i. \tag{17}$$

Step 9: Ranking of Alternatives

It should be noted that the value of DOL always lies within the range of 0 to 1. A value of zero indicates that the alternative has achieved the best performance across all criteria and has incurred no opportunity loss. The closer this value is to zero, the fewer the opportunity losses and, consequently, the higher the relative ranking of that alternative compared with others. In contrast, the POL index behaves inversely: values closer to 100 reflect greater success and higher utilization of available opportunities. To determine the weights of the criteria within the OPLO–POCOD framework, a structured expert elicitation process was conducted, fully aligned with the computational components of the method (opportunity loss matrices, polar distances, and weighted aggregation). Six criteria, including yield per hectare, water consumption, mean precipitation, available agricultural water, mechanization, and water productivity (output per unit of water), were defined operationally and categorized by effect type (benefit/cost) for expert evaluation. Each expert then assigned a score between 0 and 100 to represent the marginal effect of moving from the worst to the best state of each criterion (without pairwise comparisons). Scores were normalized at the individual level (divided by each expert's total score) and then aggregated by calculating the mean of the normalized values. To mitigate the influence of extreme judgments, a 5% trimmed mean was applied, along with content-based constraints relevant to irrigated cropping. Specifically, the weight of available water was set higher than that of other factors, while precipitation and mechanization were assigned lower weights, given their secondary role in irrigation systems.

After normalization, the final weights were: available agricultural water = 0.30, yield = 0.20, water consumption = 0.20, water productivity = 0.20, precipitation = 0.05, and mechanization = 0.05. These weights were directly incorporated into the construction of the weighted distance matrix in the OPLO–POCOD method. Subsequently, weighted polar distances, Degree of Opportunity Loss (DOL), and Percentage of Opportunity Achieved (POA/POL) were computed for each alternative. The resulting weights for each indicator, derived through the integrated OPLO–POCOD approach, are presented in Table 1.

Table 1. Weights of the criteria derived using the integrated OPLO–POCOD method

Criterion	Weight
Yield Per Hectare	0.2
Water consumption	0.2
Mean precipitation	0.05
Available agricultural water	0.3
Mechanization	0.05
Water productivity	0.2

Results

Comprehensive Ranking Analysis Based on Multi-Criteria Decision-Making for Sugar Beet Cultivation in the Provinces of Iran

In this study, the performance of 23 provinces in Iran during the 2022–2023 agricultural year was evaluated for sugar beet cultivation, using the most recent official data released by the Ministry of Jihad Agriculture in September 2024. Based on key indicators such as water consumption, precipitation, agricultural mechanization ratio, and product price, the final ranking of provinces was determined through the OPLO–POCOD multi-criteria decision-making technique. The results revealed substantial differences in agricultural capacity across provinces.

Khuzestan (Rank 1) was placed at the top with a significant margin. Its remarkably low water consumption per hectare, high availability of agricultural water resources, and favorable productivity provided optimal conditions for sugar beet cultivation, despite its relatively weak mechanization ratio. Razavi Khorasan (Rank 2) and Kermanshah (Rank 3) also ranked highly due to balanced performance across multiple indicators, reflecting minimal opportunity losses. Provinces such as Fars, West Azerbaijan, Golestan, and Mazandaran followed, indicating considerable potential, although they often faced challenges in sub-indicators, such as the availability of agricultural water. At the other end, Ardabil (Rank 23) exhibited the highest opportunity loss, performing poorly in terms of productivity and yield per hectare, despite relatively low water consumption, making it the least suitable province. East Azerbaijan, Lorestan, and North Khorasan also ranked low. Notably, provinces such as Semnan and Alborz, although among the best in yield per hectare, were classified in mid-level rankings due to limitations in available agricultural water, average precipitation, and water consumption per hectare. Fig. 2 illustrates the applied indicators and their respective weights for sugar beet in each province.

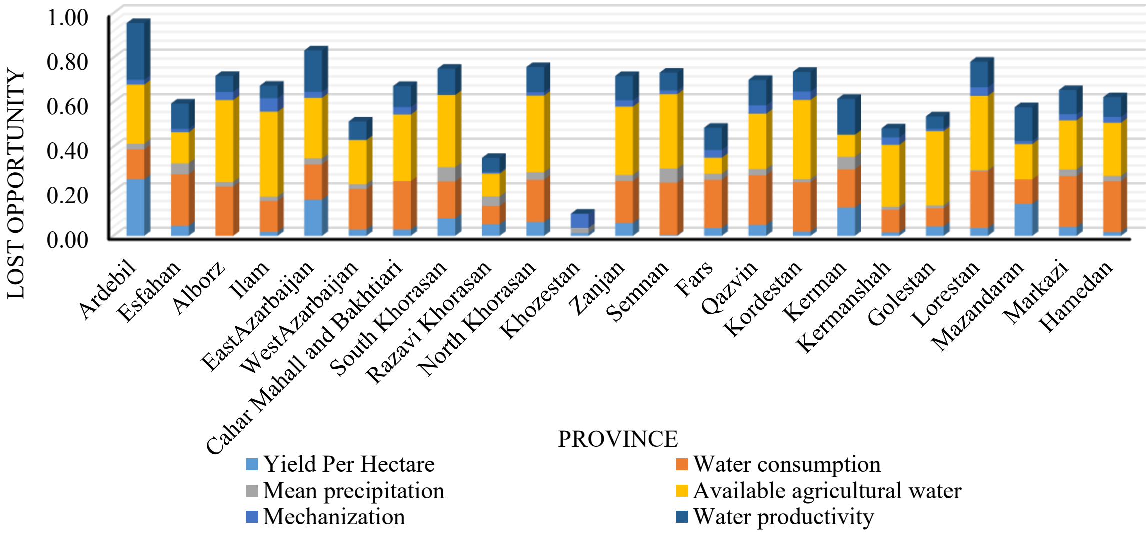

Figure 2. Applied indicators and their weights in each province for sugar beet cultivation

Ranking Based on the Current Cultivated Area of Sugar Beet in the Provinces of Iran

The ranking of Iranian provinces based on the current cultivated area of sugar beet shows that West Azerbaijan ranks first with 27,907 hectares. Razavi Khorasan (20,536 ha) and Khuzestan (17,962 ha) follow in second and third place, respectively. These three provinces account for the largest cultivated areas of sugar beet in the country. Next in rank are Fars (8,777 ha), North Khorasan (2,141 ha), Golestan (2,042 ha), and Isfahan (1,831 ha). Provinces such as Semnan (1,797 ha), Ardabil (1,611 ha), Chaharmahal and Bakhtiari (1,563 ha), Kurdistan (1,389 ha), and Markazi (1,016 ha) fall within the mid-level group (Ministry of Agriculture Jihad Statistical Yearbook, 2024).

Conversely, several provinces have very limited cultivation areas. Qazvin (554 ha), Ilam (496 ha), and South Khorasan (480 ha) belong to the low-cultivation group. Moreover, Mazandaran, East Azerbaijan, Alborz, Zanjan, and Kerman each report an area of less than 100 hectares, with Kerman recording the lowest area at only 3 hectares. Accordingly, provinces can be grouped into three categories: (1) high cultivation (>10,000 ha), represented by West Azerbaijan, Razavi Khorasan, Khuzestan, and Kermanshah; (2) medium cultivation (1,000–10,000 ha), including provinces such as Fars, Golestan, and North Khorasan; and (3) low cultivation (<1,000 ha), which comprises a considerable number of provinces. Fig. 3 presents the ranking of provinces by sugar beet cultivated area, based on the OPLO–POCOD method, using the cultivated area (hectares) as the input variable.

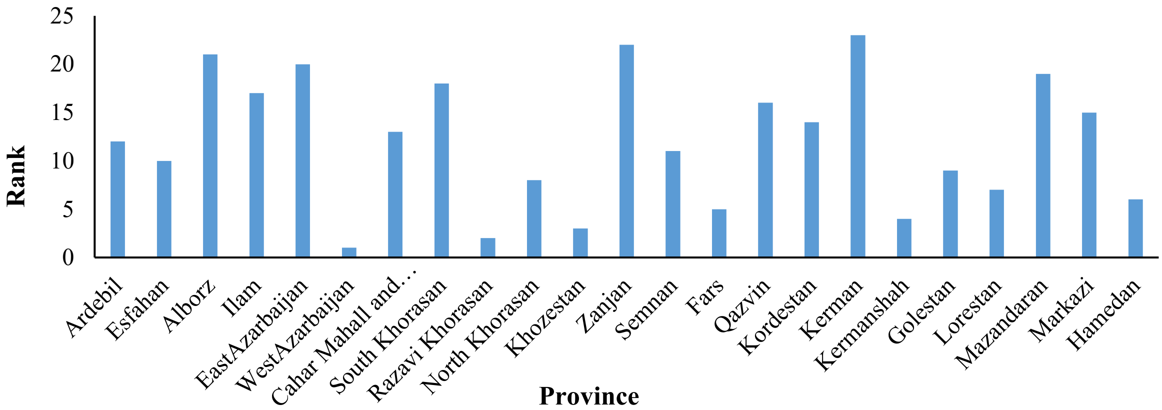

Figure 3. Ranking of Provinces by Sugar Beet Cultivated Area

The subsequent step involved comparing the ranking based on the actual cultivated area of provinces with the ranking derived from the OPLO–POCOD multi-criteria decision-making method. This comparison provides a clearer understanding of the degree of alignment between the current distribution of sugar beet cultivation and the actual desirability of provinces in terms of performance indicators.

The results showed that some provinces, such as Fars, Razavi Khorasan, Golestan, and Lorestan, occupy relatively similar positions in both rankings. For instance, Fars ranked fourth in both systems. At the same time, Razavi Khorasan held second place in both OPLO–POCOD and cultivated-area rankings, indicating a degree of alignment between current practices and optimal conditions. Conversely, Khuzestan ranked first under the OPLO–POCOD method but only third in cultivated area. This discrepancy suggests that, despite its strong potential, the province has not yet fully utilized its capacity. Similarly, Kermanshah ranked third in the OPLO–POCOD evaluation but nineteenth in terms of cultivated area, reflecting a significant mismatch between suitability and current cropping patterns. West Azerbaijan, ranked first by cultivated area, fell to fifth in the OPLO–POCOD ranking, demonstrating that extensive cultivation does not necessarily equate to optimal suitability. Other provinces, such as Ardabil, East Azerbaijan, and North Khorasan, ranked low in the OPLO–POCOD results but significantly higher in cultivated area. For example, North Khorasan placed fifth in cultivated area but only twentieth in OPLO–POCOD. Provinces like Alborz and Semnan, by contrast, ranked mid-to-low in both systems, a reflection of relatively good yield per hectare offset by severe constraints in water availability and precipitation.

Comprehensive Ranking Analysis Based on Multi-Criteria Decision-Making for Irrigated Wheat Cultivation in the Provinces of Iran

The final results indicate substantial structural and ecological differences among provinces in terms of suitability for irrigated wheat cultivation. In the overall ranking, Mazandaran secured first place with a clear margin. Despite only moderate performance on some indicators, this province achieved the lowest opportunity loss, the lowest water consumption, and favorable rainfall conditions, making it the most suitable region for wheat cultivation in Iran. Following Mazandaran, the provinces of Fars (Rank 2), Kermanshah (3), Gilan (4), and West Azerbaijan (5) were placed at the top. These provinces generally exhibited strong performance in indicators such as yield per hectare, water productivity, and efficient resource use. Within the top ten provinces, a clear geographical pattern emerged: most are located in northern, western, and southern regions, reflecting the influence of relatively wetter climates or better access to water resources compared with other areas. For example, Khuzestan, despite having a lower yield per hectare, ranked 11th due to its high agricultural water availability and favorable water consumption per hectare. Provinces such as Isfahan, Ardabil, and Tehran also ranked relatively high, driven by balanced performance across multiple indicators.

By contrast, South Khorasan (Rank 31), Bushehr (30), Hormozgan (29), and Sistan and Baluchestan (28) occupied the lowest positions. Although some of these provinces benefit from relatively acceptable water availability or water consumption per hectare, they suffer from low productivity and weak yield per unit area. This highlights the greater opportunity losses and unsuitability of provinces located in arid southern regions. Fig. 4 illustrates the applied indicators and their respective weights for wheat in each province.

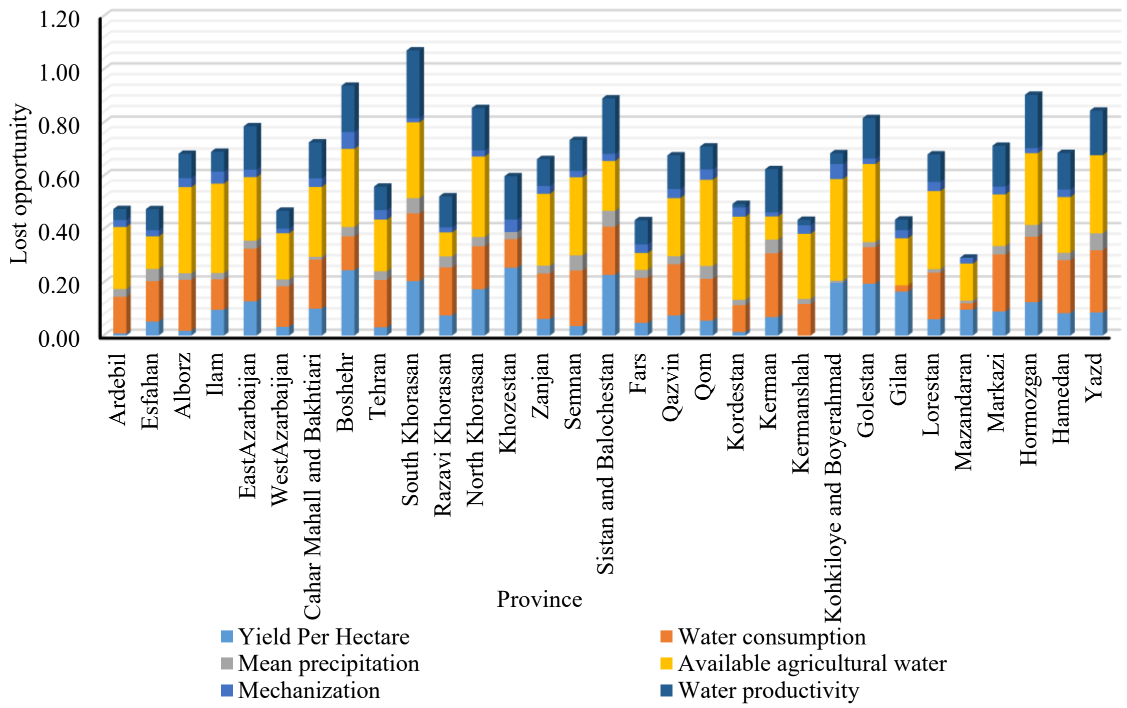

Figure 4. Applied indicators and their weights in each province for irrigated wheat cultivation

Ranking Based on the Current Cultivated Area of Irrigated Wheat in the Provinces of Iran

The analysis of provincial rankings based on the cultivated area of irrigated wheat reveals that Khuzestan, with 742,101 hectares, holds the first place and is recognized as the country's primary hub of wheat production. It is followed by Fars with 291,407 hectares and Razavi Khorasan with 171,476 hectares, ranking second and third, respectively. These three provinces, far ahead of others, account for the largest share of national wheat production.

Subsequently, Golestan (166,284 ha), West Azerbaijan (135,912 ha), Kerman (129,852 ha), Kermanshah (128,799 ha), and East Azerbaijan (85,269 ha) occupy ranks four through eight, confirming their roles as other key production areas. Ardabil (84,214 ha), Hamedan (84,058 ha), and Sistan and Baluchestan (79,966 ha) are placed ninth to eleventh. On the other hand, some provinces have extremely limited cultivation. Gilan ranks last (31st) with only 53 hectares under wheat, followed by Qom (5,731 ha), Alborz (9,587 ha), Yazd (14,210 ha), and South Khorasan (17,186 ha).

Accordingly, provinces can be categorized into three groups: (1) high-cultivation provinces (>150,000 ha), including Khuzestan, Fars, Razavi Khorasan, and Golestan, located mainly in the southwest, south, and northeast; (2) medium-cultivation provinces (50,000–150,000 ha), such as West Azerbaijan, Kerman, Kermanshah, East Azerbaijan, Ardabil, Hamedan, Sistan and Baluchestan, Isfahan, Ilam, Qazvin, Lorestan, North Khorasan, Bushehr, and Tehran; and (3) low-cultivation provinces (<50,000 ha), including Kurdistan, Kohgiluyeh and Boyer-Ahmad, Markazi, Mazandaran, Zanjan, Semnan, Hormozgan, Chaharmahal and Bakhtiari, Yazd, South Khorasan, Alborz, Qom, and Gilan. Fig. 5 presents the provincial ranking of irrigated wheat cultivated area, calculated based on hectares of sown land.

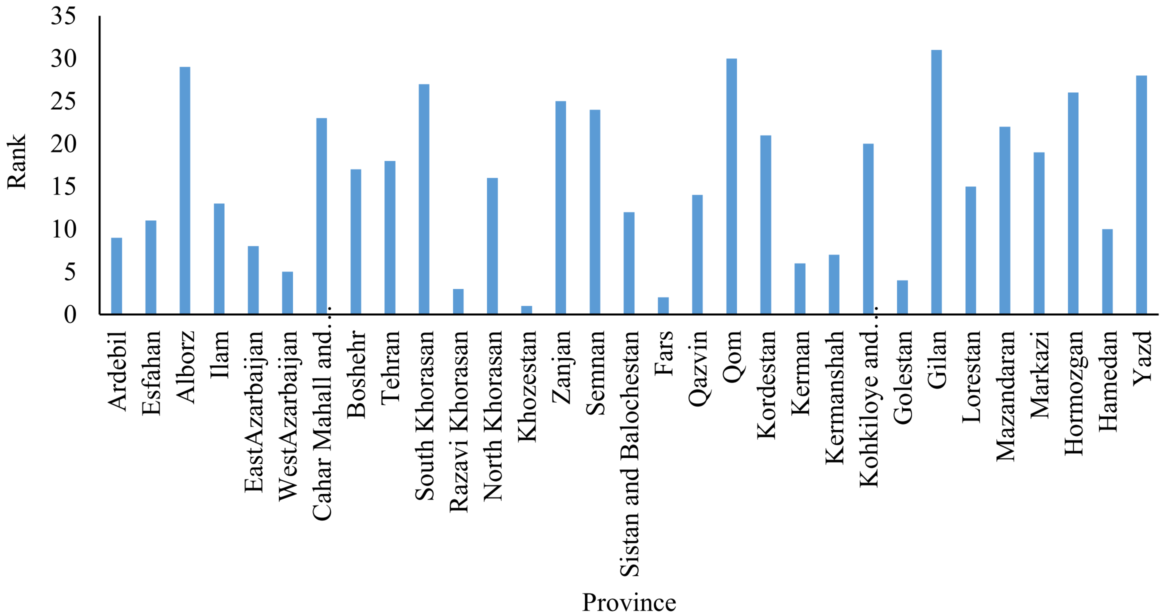

Figure 5. Ranking of Provinces by Irrigated Wheat Cultivated Area

From a geographical perspective, provinces with the largest cultivated areas of irrigated wheat are predominantly located in the western, southern, and northeastern regions of Iran. In contrast, provinces with smaller cultivated areas are mostly found in central and northern parts of the country; for example, Gilan, Alborz, Qom, and Yazd, which rank at the bottom of the list, have limited wheat cultivation due to climatic constraints, high population density, restricted arable land, or prioritization of other crops. To assess the degree of alignment between the current distribution of wheat cultivation across provinces and the optimal conditions defined by performance and resource indicators, a comparison was made between the rankings based on actual cultivated area and those derived from the OPLO–POCOD multi-criteria decision-making framework. This comparison provides a clear picture of whether current wheat distribution corresponds with the climatic, water resource, and economic capacities of each province.

The results show that some provinces occupy relatively similar positions in both rankings. For example, West Azerbaijan, ranked fifth by cultivated area, is also among the top provinces in the multi-criteria ranking, indicating that decisions there are fairly aligned with actual environmental capacities and potential. Similarly, Fars and Kermanshah appear in the upper tier in both rankings, reflecting consistency between cultivated area, climatic suitability, infrastructure, and economic conditions. However, notable discrepancies exist in some provinces. For instance, Sistan and Baluchestan ranks 28th in the multi-criteria evaluation but 12th in cultivated area. This misalignment suggests that cultivation expansion has occurred in ecologically suboptimal conditions, likely driven by regional policies, land availability, or misinformed decisions. Conversely, provinces such as Yazd, Hormozgan, Semnan, and Qom consistently appear at the bottom of both rankings, indicating that limited cultivation corresponds with weak environmental and resource conditions, making wheat production less viable in these areas.

Comprehensive Ranking Analysis Based on Multi-Criteria Decision-Making for Irrigated Barley Cultivation in the Provinces of Iran

Based on the results of the OPLO–POCOD multi-criteria decision-making method, the suitability of Iranian provinces for irrigated barley cultivation was evaluated. The final assessment was conducted using seven key indicators: yield per hectare, water consumption, agricultural rainfall, available agricultural water, mechanization, water productivity, and opportunity loss. In the overall ranking, Mazandaran achieved first place, earning the highest score across all combined indicators. This province recorded the lowest water consumption per hectare, high productivity, and the least opportunity loss, making it the most suitable region for irrigated barley cultivation. Tehran ranked second, surpassing many central producing provinces due to its balanced performance in terms of yield per hectare and productivity. Fars (Rank 3), Gilan (4), Kurdistan (5), and West Azerbaijan (6) were also among the top ten provinces. The geographical distribution of these leading provinces shows that most are located in the northern and western regions of the country, which benefit from more humid climates or better access to water resources.

At the lower end, provinces such as Kohgiluyeh and Boyer-Ahmad (Rank 31), Hormozgan (30), South Khorasan (29), Bushehr (28), and Sistan and Baluchestan (27) ranked the lowest. Despite relatively strong performances in some indicators, such as mechanization, these provinces performed poorly in terms of yield per hectare and water productivity, coupled with high opportunity loss, resulting in weak final rankings. In the middle of the ranking table, provinces such as Hamedan (Rank 8), Kermanshah (9), Markazi (10), Lorestan (11), Qom (12), and Zanjan (13) demonstrated relatively balanced performance across most indicators. Fig. 6 illustrates the applied indicators and their respective weights for barley in each province.

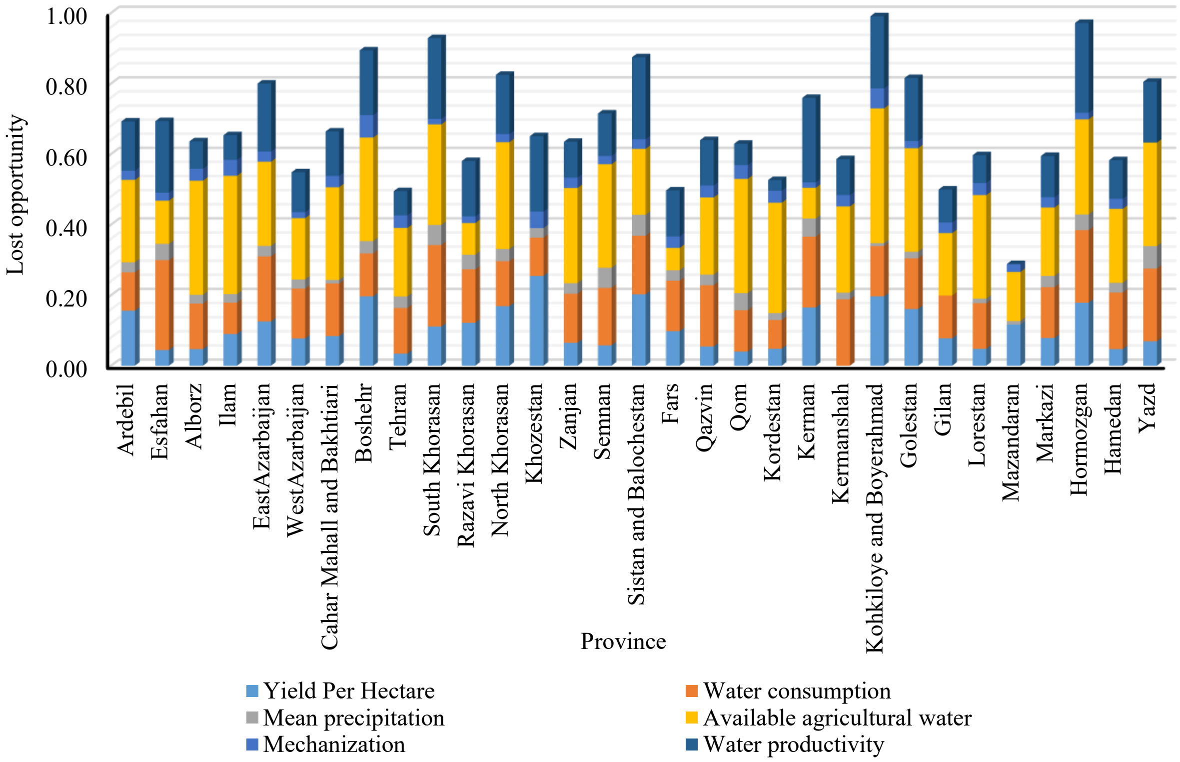

Figure 6. Applied indicators and their weights in each province for irrigated barley cultivation

Ranking Based on the Current Cultivated Area of Irrigated Barley in the Provinces of Iran

Analysis of barley cultivated areas across Iranian provinces shows that Razavi Khorasan ranks first with more than 110,000 hectares, making it the country's primary hub for this crop. Fars follows with 105,000 hectares, while Isfahan ranks third with approximately 59,000 hectares. Provinces such as Hamedan, Markazi, Qazvin, Ardabil, Sistan and Baluchestan, Tehran, and Khuzestan occupy positions 4 through 10, contributing significantly to national barley production.

On the other hand, provinces such as Gilan, Hormozgan, Ilam, Kohgiluyeh and Boyer-Ahmad, Kurdistan, and Yazd account for the lowest cultivated areas. Gilan, with only 28 hectares, ranks last. Based on these findings, provinces can be grouped into three categories: (1) high-cultivation provinces (>50,000 ha), including Razavi Khorasan, Fars, Isfahan, Hamedan, and Markazi, primarily located in the northeast, south, west, and central regions; (2) medium-cultivation provinces (20,000–50,000 ha), including Qazvin, Ardabil, Sistan and Baluchestan, Tehran, Khuzestan, Qom, East Azerbaijan, North Khorasan, Zanjan, Semnan, and Lorestan; and (3) low-cultivation provinces (<20,000 ha), such as West Azerbaijan, Kermanshah, Chaharmahal and Bakhtiari, Golestan, Mazandaran, Kurdistan, Kerman, Yazd, Alborz, Bushehr, Kohgiluyeh and Boyer-Ahmad, Hormozgan, Ilam, and Gilan. Fig. 7 presents the provincial ranking of irrigated barley cultivated area, calculated based on hectares of sown land.

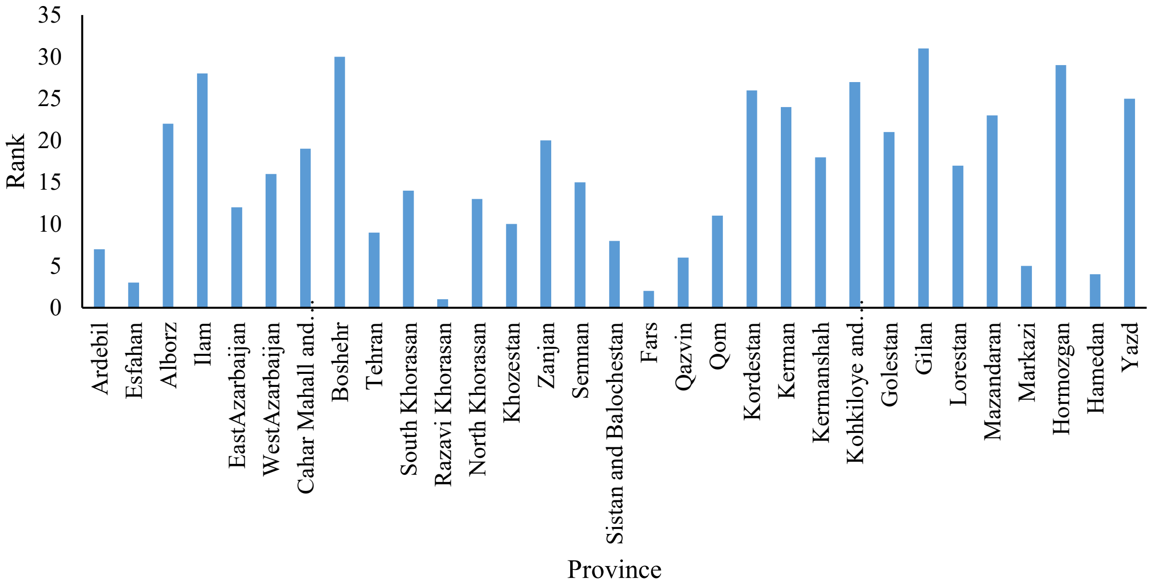

Figure 7. Ranking of Provinces by Irrigated Barley Cultivated Area

From a geographical perspective, provinces with large cultivated areas of barley are mainly concentrated in central, western, and northeastern parts of Iran. In contrast, provinces with smaller cultivated areas are located primarily in southern and northern coastal regions.

To evaluate the degree of alignment between the current distribution of barley cultivation and the optimal suitability of provinces based on performance, climatic, and resource indicators, a comparison was made between the rankings derived from actual cultivated area and those obtained using the OPLO–POCOD multi-criteria decision-making method. This comparison provides clearer insights into the consistency or inconsistency of current cropping patterns with the potential capacities of each region. The results show that certain provinces hold relatively similar positions in both rankings. Examples include Hamedan, Yazd, Hormozgan, Qom, Fars, and Chaharmahal and Bakhtiari, which indicate alignment of cultivation decisions with favorable climatic, water resource, and infrastructural conditions. Conversely, notable discrepancies exist in some provinces. For instance, Khuzestan ranks tenth in terms of cultivated area but performs significantly lower in the OPLO–POCOD ranking, suggesting that barley cultivation in this region may not fully align with resource- and indicator-based suitability. Other provinces, such as West Azerbaijan, Qazvin, Kermanshah, South and North Khorasan, Sistan and Baluchestan, Ardabil, and Lorestan, also display wide gaps between their actual cultivated-area ranking and their optimal position in the OPLO–POCOD model, reflecting a relative misalignment between cropping policies and real capacities. Fig.s 8–10 illustrate the comparison between the actual cultivated-area rankings and the OPLO–POCOD rankings for sugar beet, wheat, and barley, respectively.

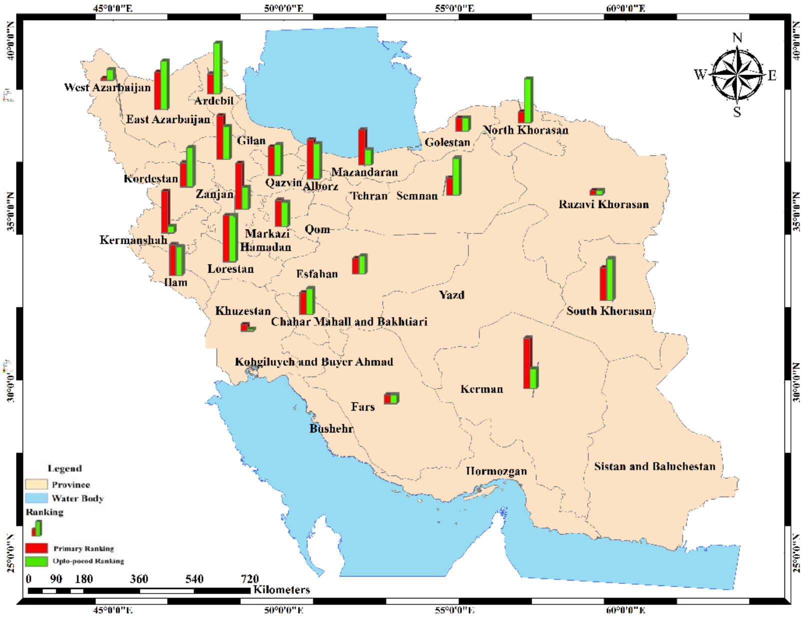

Figure 8. Comparison of Actual Cultivated-Area Ranking and OPLO–POCOD Ranking by Province (Sugar Beet)

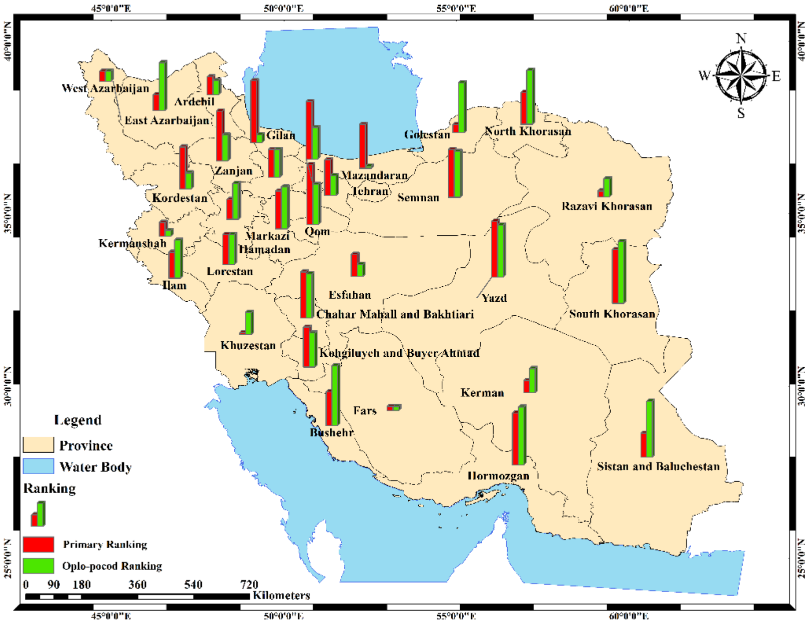

Figure 9. Comparison of Actual Cultivated-Area Ranking and OPLO–POCOD Ranking by Province (Wheat)

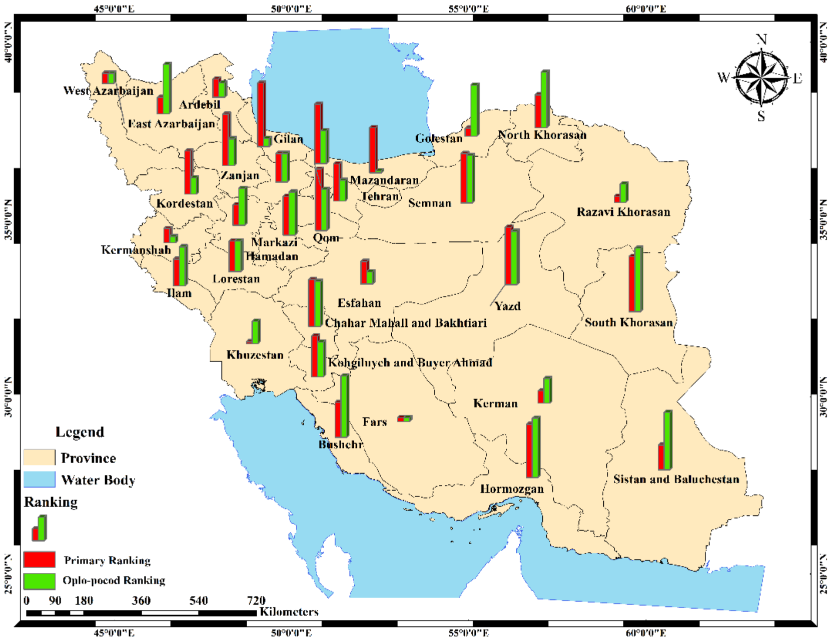

Figure 10. Comparison of Actual Cultivated-Area Ranking and OPLO–POCOD Ranking by Province (Barley)

Although the OPLO–POCOD multi-criteria decision-making method highlights provinces such as Mazandaran and Gilan as highly suitable for cultivating sugar beet, wheat, and barley in terms of resource and performance indicators, their actual cultivated area for these crops remains low. This outcome is primarily due to regional agricultural policies, prevailing cropping structures, and specific climatic characteristics. Mazandaran and Gilan are among the few provinces with sufficient climatic and water resources to support rice cultivation, which, given its higher economic value in these areas, has become the dominant crop. As a result, despite favorable potential for wheat and barley, financial priorities and policy choices have limited the exploitation of this capacity. Such cases are exceptional and restricted mainly to provinces with unique climatic advantages or policy-driven mandates, making shifts in their cropping patterns neither feasible nor reasonable in the short term.

The comparative analysis between OPLO–POCOD rankings and actual cultivated-area rankings for sugar beet, wheat, and barley reveals substantial and sometimes stark discrepancies among provinces. These differences underscore the fact that in many regions, the existing cultivated areas are not optimally aligned with climatic, water, and economic conditions. In other words, some provinces possess strong potential but remain underutilized. For example, Khuzestan excels in sugar beet cultivation, while Kermanshah excels in irrigated barley. Others, such as West Azerbaijan, which has high cultivation areas but low suitability scores, demonstrate inefficient resource use and weak agricultural policy frameworks. These mismatches highlight the urgency of revisiting regional cropping policies and resource management strategies to ensure more efficient and productive use of resources.

A major factor contributing to low productivity and excessive water consumption in Iran's agricultural sector, beyond traditional farming practices and outdated technologies, is the mismatch between cropping patterns and the actual ecological and resource capacities of provinces. Results show that in certain high-potential areas, cultivated land remains underutilized, while in unsuitable regions, cultivation is excessive. This misalignment contributes to water overuse and reduced overall efficiency. Optimizing cropping patterns through multi-criteria analysis offers a viable solution for enhancing water use efficiency and agricultural productivity. The OPLO–POCOD approach, in particular, provides an effective tool to assess the degree of consistency between actual cultivation and provincial potential. Such analyses help identify regions with the most significant mismatches, guiding policymakers to prioritize adjustments in cropping systems and resource allocation. Where discrepancies exist, reforms in agricultural policies and water management are essential to enhance productivity and secure the sustainability of agricultural production.

Conclusions

Iranian agriculture underpins food security, economic development, and the livelihoods of rural communities. Given the strategic importance of wheat, barley, and sugar beet, a scientific assessment of provincial potential for these crops is essential. In recent years, low efficiency, limited productivity, and mismatches between cultivated areas and actual capacity have led to resource losses, particularly water, and reduced economic returns. This study employed the OPLO–POCOD multi-criteria decision-making approach to evaluate and rank provinces based on their suitability for the three crops. Key indicators included yield per unit area, water consumption per hectare, mean precipitation, agricultural water availability, mechanization capacity, and water productivity per unit area. The indicator values reflect current conditions, which may change over time. Data were obtained from the National Statistics Portal and the Ministry of Agriculture Jihad. Results showed that in many provinces, current cultivation patterns do not align with relative potential; some highly capable provinces contribute little, while others with lower suitability cultivate extensively. Such mismatches contribute to production inefficiencies. By integrating technical, economic, and environmental indicators, MCDM methods provide a more comprehensive and reliable framework for managing scarce land and water resources compared with single-criterion approaches. They also highlight structural inconsistencies between potential and cultivated areas, offering a foundation for optimizing cropping patterns, reducing waste, and enhancing productivity and sustainability, thus serving as a direct tool for policymaking and resource allocation.

For future research, the inclusion of soil quality, long-term climatic trends, market-based economic indicators, and the effects of agricultural support policies is recommended. Remote sensing can improve data accuracy for climate, land use, and water resources, while longer time-series analyses would aid in forecasting future conditions. Comparing different MCDM methods and integrating them with neural networks and multi-objective optimization could further enhance accuracy. Evaluating the impacts of cropping-pattern adjustments, particularly in provinces with significant mismatches, is also essential for guiding policy reforms.

In this study, the OPLO–POCOD framework incorporated expert-derived weights for six indicators: yield, water consumption, precipitation, available water, mechanization, and water productivity to rank provincial suitability for irrigated wheat, barley, and sugar beet. Subsequently, the Degree of Opportunity Loss (DOL) and Percentage of Opportunity Achieved (POA) were calculated, and final rankings were determined by minimizing opportunity loss. The results indicated that Mazandaran leads in irrigated wheat and barley, with northern humid provinces such as Golestan and West Azerbaijan generally ranking higher. In contrast, arid southern provinces (e.g., South Khorasan, Bushehr, Hormozgan, Kohgiluyeh and Boyer-Ahmad) ranked lower. For sugar beet, Khuzestan held the top position. The comparison between potential rankings and actual cultivated areas revealed significant discrepancies. For example, Khuzestan's strong suitability for sugar beet contrasts with its relatively small current share, highlighting opportunities for spatial reallocation of cropping.

Author Contributions

Data collection: Sina Khoshnevisan, Mohammadreza Asli Charandabi, Samad Emamgholizadeh.
Research report preparation: Sina Khoshnevisan, Mohammadreza Asli Charandabi.
Data analysis: Sina Khoshnevisan, Tahereh Taghizadeh.
The contribution of authors to the article was approximately as follows:
First Author: Preparation and processing of samples, conducting experiments and data collection, performing calculations, statistical analysis of data, analysis and interpretation of information and results, drafting the manuscript.
Second Author: Research design, supervision of research stages, validation and control of results, revision, review, and finalization of the manuscript.
Third Author: Contribution to research design, supervision of the study, reviewing and revising the manuscript.
Fourth and Fifth Authors: Writing and revising the manuscript, collaboration in data collection.

Data Availability Statement

Data available on request from the authors.

Acknowledgements

The authors would like to thank all participants in the present study.

The authors thank all participants in this study.

Ethical Considerations

The authors ensured that their work was free from data fabrication, falsification, plagiarism, and misconduct.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflict of Interest

The authors declare no conflict of interest

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