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Integrated Assessment of Technical and Environmental Efficiency in Irrigated Wheat Production in Iran

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Abstract

In Iran's arid and semi-arid regions, ensuring wheat production while reducing pressure on natural resources is a major challenge. This study evaluates the technical and environmental efficiency of irrigated wheat production across 377 Iranian counties during the 2023 cropping season. Technical efficiency was estimated using an input-oriented Data Envelopment Analysis (DEA) model under variable returns to scale, while environmental efficiency was assessed by incorporating undesirable agrochemical inputs through an inverse transformation approach. To capture agrochemical-related environmental pressure, an Environmental Performance Index (EPI) was constructed using Principal Component Analysis (PCA) of fertilizer and pesticide use, where higher values indicate lower environmental pressure. Counties were grouped by hierarchical clustering based on environmental efficiency and EPI, and provincial benchmarking was conducted using an equal-weighted TOPSIS framework. The novelty of this study lies in integrating DEA, PCA, hierarchical clustering, spatial analysis, and TOPSIS within a unified framework applied to 377 counties, providing one of the first nationwide county-level assessments of technical and environmental efficiency in Iran's irrigated wheat sector. The average technical and environmental efficiency scores were 0.744 and 0.929, respectively, indicating considerable potential for input savings while maintaining current production levels. Nitrogen fertilizer was identified as the main driver of environmental pressure, and substantial spatial disparities were observed across counties. Overall, the findings highlight the importance of region-specific strategies that improve environmental sustainability while maintaining agricultural productivity.

Keywords: Agricultural benchmarking, Data envelopment analysis, Environmental performance index, Spatial analysis, Sustainability assessment.

Introduction

Wheat plays a central role in global food security and is a strategic crop in Iran, where irrigated systems dominate production due to predominantly arid and semi-arid climatic conditions. Irrigated wheat contributes a substantial share of national cereal output and supports both rural

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livelihoods and food self-sufficiency policies. However, this reliance on irrigation has intensified pressure on scarce natural resources, particularly water and agrochemical inputs, raising concerns about the long-term sustainability of current production practices.

In recent decades, yield improvements in irrigated wheat systems have largely been driven by increased use of synthetic fertilizers and pesticides. While such input intensification has enhanced productivity, it has also contributed to soil degradation, water pollution, and broader environmental externalities. As a result, production systems that appear successful in terms of yield may perform poorly when environmental impacts are taken into account. This highlights the limitations of conventional productivity indicators that ignore resource use efficiency and environmental costs.

Efficiency analysis provides an alternative framework by identifying opportunities to reduce input use without sacrificing output. Among available approaches, Data Envelopment Analysis (DEA) has been widely applied in agricultural studies because it accommodates multiple inputs and outputs without imposing restrictive functional assumptions. Nevertheless, standard DEA models typically treat all inputs as desirable and therefore fail to capture the environmental consequences of excessive agrochemical use. Environmental extensions of DEA address this shortcoming by incorporating undesirable inputs or outputs, allowing technical and environmental performance to be assessed simultaneously.

Despite growing interest in environmental efficiency, many empirical studies continue to examine technical and environmental dimensions separately or rely on aggregated spatial units, which can obscure substantial local heterogeneity. Moreover, few analyses combine efficiency measures with complementary tools capable of summarizing environmental pressure and identifying groups of regions with similar performance characteristics.

To address these gaps, this study develops an integrated and spatially explicit assessment of irrigated wheat production efficiency in Iran at the county level. Technical efficiency is estimated using an input-oriented DEA model under variable returns to scale, while environmental efficiency explicitly accounts for undesirable agrochemical inputs. In addition, a composite Environmental Performance Index (EPI) is constructed using Principal Component Analysis (PCA) to summarize fertilizer and pesticide intensity. Counties are then classified using hierarchical clustering, and provincial performance is benchmarked through the TOPSIS multi-criteria decision-making method. By integrating these approaches, the study provides policy-relevant insights into how productivity gains can be reconciled with environmental sustainability in Iran’s wheat sector.

Materials and Methods

Overview of Analytical Framework

This study applies an integrated analytical framework to evaluate both technical and environmental performance of irrigated wheat production (Figure 1). Technical efficiency is first estimated using an input-oriented Data Envelopment Analysis (DEA) model under variable returns to scale. Environmental efficiency is then derived by incorporating undesirable agrochemical inputs into the DEA framework. To capture agrochemical-related environmental pressure, a composite Environmental Performance Index (EPI) is constructed using Principal Component Analysis (PCA). The EPI is intended to represent agrochemical-related environmental pressure rather than the entire spectrum of environmental sustainability. Although other environmental dimensions such as irrigation water use, greenhouse gas emissions, groundwater depletion, and soil degradation are also important, spatially consistent county-level data for these indicators were unavailable. Therefore, the present index should be interpreted within the scope of agrochemical use. Based on environmental efficiency and EPI scores, counties are classified into homogeneous groups through hierarchical clustering. Finally, provincial performance is benchmarked using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS).

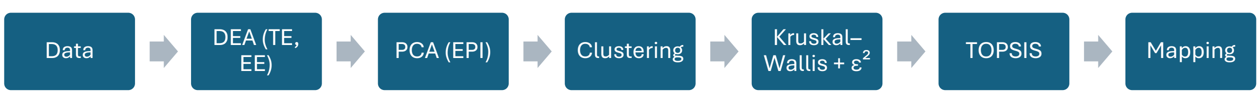

Figure 1. Analytical framework of the study.

Study Area and Data Description

The empirical analysis covers irrigated wheat production across 377 counties in Iran during the 2023 agricultural year. Iran's wheat sector operates under diverse agro-climatic conditions, ranging from humid regions in the north to arid and semi-arid zones in central and eastern areas. Such heterogeneity results in substantial variation in production practices, input use intensity, and environmental pressure, making county-level analysis particularly informative.

Counties are treated as decision-making units (DMUs). The dataset includes wheat yield as the output variable, conventional production inputs (seed, labor, machinery, and capital), and environmentally sensitive inputs such as nitrogen, phosphorus, and potassium fertilizers, as well as herbicides, pesticides, and fungicides (Table 1). Data were obtained from official statistics published by the Ministry of Agriculture-Jihad and provincial agricultural organizations. The dataset comprises county-level observations for all 377 counties included in the study and covers the 2023 agricultural year. All variables were obtained from official agricultural statistics compiled by the Agricultural Statistics Office of the Ministry of Agriculture-Jihad in cooperation with provincial agricultural organizations. Prior to analysis, the dataset was screened for completeness, consistency, and plausibility. No statistical imputation was applied, and only complete observations were included in the analysis.

The database was compiled by the Agricultural Statistics Office of the Ministry of Agriculture-Jihad in cooperation with provincial agricultural organizations. All observations correspond to county-level records for the 2023 agricultural year. Fertilizer, pesticide, and production variables were obtained directly from official agricultural records rather than being interpolated from provincial averages. Prior to analysis, the dataset was screened for completeness and consistency. No statistical imputation was required because counties with incomplete records were excluded during database preparation. All variables were checked for completeness and plausibility, and standardization was applied where required for multivariate analysis.

Table 1. Description, measurement units, and data sources of variables used in the analysis.

Variable	Category	Unit	Data Source	Description
Wheat yield	Output	kg ha^{-1}	Agricultural Statistics Office, Ministry of Agriculture-Jihad	Desirable output
Seed	Conventional input	kg ha^{-1}	Same source	Production input
Labor	Conventional input	person-days ha^{-1}	Same source	Human labor
Machinery	Conventional input	%	Same source	Share of mechanized operations
Capital	Conventional input	million Tomans ha^{-1}	Same source	Production cost
Nitrogen	Environmental input	kg ha^{-1}	Same source	Undesirable input
Phosphorus	Environmental input	kg ha^{-1}	Same source	Undesirable input
Potassium	Environmental input	kg ha^{-1}	Same source	Undesirable input
Herbicide	Environmental input	kg ha^{-1}	Same source	Undesirable input
Pesticide	Environmental input	kg ha^{-1}	Same source	Undesirable input
Fungicide	Environmental input	kg ha^{-1}	Same source	Undesirable input

Input and Output Specification

Selecting appropriate inputs and outputs is a critical step in efficiency analysis. Following the literature, wheat yield (kg ha^{-1}) was defined as the desirable output (Coelli et al., 2005). Production inputs included seed, phosphorus fertilizer, nitrogen fertilizer, potassium fertilizer, capital, labor, and machinery (Latruffe, 2010). Environmentally sensitive inputs consisted of herbicides, pesticides, and fungicides, which were treated as undesirable inputs due to their negative environmental externalities (Reinhard et al., 2000; Sueyoshi & Goto, 2012). **In this study, herbicides, pesticides, and fungicides are treated as undesirable inputs rather than undesirable outputs. Environmental efficiency is estimated using an input-adjusted DEA framework in which undesirable inputs are transformed through the inverse transformation approach, allowing them to be incorporated into the conventional input-oriented DEA model while preserving the interpretation of efficiency scores.** Machinery (%) represents the share of mechanized operations. All variables were expressed in physical or monetary units commonly used in agricultural statistics, harmonized for analytical consistency.

Technical Efficiency Measurement Using DEA

Technical efficiency was estimated using Data Envelopment Analysis (DEA) — a non-parametric frontier technique widely used in agricultural efficiency studies (Charnes et al., 1978; Coelli, 1996). An input-oriented DEA model under variable returns to scale (VRS) was employed, reflecting resource minimization under constant output levels (Banker et al., 1984). The VRS specification was selected because the counties included in this study operate under heterogeneous production conditions and differ substantially in resource endowments, management practices, and production scale. Under such circumstances, assuming constant returns to scale would be overly restrictive, whereas the VRS model provides a more realistic representation of county-level production technology.

Efficiency scores ranged from zero to one, with unity representing the efficient frontier. Technical efficiency (TE) was estimated via input-oriented Data Envelopment Analysis (DEA) under variable returns to scale (VRS), minimizing inputs for fixed output (Banker et al., 1984):

$$\min_{\theta,\lambda} \ \theta_o$$

$$\text{s.t.} \sum_{j=1}^{n} \lambda_j \, x_{ij} \leq \theta_o x_{io}, i = 1, \ldots, m$$

$$\sum_{j=1}^{n} \lambda_j \, y_{rj} \geq y_{ro}, r = 1, \ldots, s$$

$$\sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0$$

where θ_o is TE for DMUo (1= efficient), x_{ij} is input i of DMU j, y_{rj} is output r of DMU j, and λ_j is intensity weights (Charnes et al., 1978).

Environmental Efficiency Assessment

To incorporate environmental criteria, undesirable agrochemical inputs were transformed using an inverse monotonic transformation (1/(1+x)) following Seiford and Zhu (2002). The DEA model was re-estimated using these transformed inputs to obtain environmental efficiency (EE) scores, consistent with the approach of Zhou et al. (2008) and Halkos & Tzeremes (2013). Higher EE scores indicated more environmentally sustainable production.

The inverse transformation approach was selected because it enables undesirable agrochemical inputs to be incorporated within a conventional input-oriented DEA framework while preserving methodological consistency between technical and environmental efficiency estimation. Although alternative approaches such as Slack-Based Measure (SBM) or Directional Distance Functions (DDF) provide additional flexibility for modeling undesirable variables, the present study emphasizes an integrated regional assessment rather than methodological comparison. Future studies may compare different environmental DEA specifications to evaluate the robustness of efficiency estimates.

Environmental Performance Index (EPI) Construction

EPI summarized agrochemical intensity via Principal Component Analysis (PCA) on standardized N, P, K, herbicide, pesticide, and fungicide inputs (Jolliffe & Cadima, 2016):

$$\text{EPI}_j = \text{PC1}_j = \sum_{k=1}^{6} l_k \, Z_{jk}$$

where l_k are PC1 loadings and Z_{jk} are standardized inputs (k). PC1 sign was reversed for interpretability (higher EPI indicates lower environmental pressure) (Vyas & Kumaranayake, 2006).

The EPI incorporated six inputs: herbicide, pesticide, fungicide, phosphorus, nitrogen, and potassium fertilizer. Standardization to zero mean and unit variance preceded PCA to eliminate scale effects. The first principal component, explaining the highest variance, was retained as the EPI (Vyas & Kumaranayake, 2006).

Cluster Analysis

Four clusters were retained based on dendrogram inspection and interpretability. Hierarchical clustering used Ward's method with Euclidean distance on standardized EE and EPI (Everitt et al., 2011; Ward, 1963). Optimal clusters (k=4) were selected via dendrogram and silhouette analysis. Clustering was performed at the county level, while provincial patterns were obtained through aggregation.

Statistical Testing and Effect Size Estimation

Differences in EE and EPI across clusters were tested using the Kruskal–Wallis non-parametric test (Kruskal & Wallis, 1952). Where significant differences emerged, Dunn’s post hoc test with Bonferroni correction identified pairwise contrasts (Dinno, 2015). Epsilon squared (ε^2) was computed to evaluate effect sizes (Tomczak & Tomczak, 2014).

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1)$$

with Dunn's post-hoc (Bonferroni-adjusted) and effect size $\varepsilon^2 = H/(N-1)$ (Dinno, 2015; Tomczak & Tomczak, 2014).

TOPSIS-Based Provincial Ranking

To develop an integrated provincial ranking, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was implemented (Hwang & Yoon, 1981). Provincial mean values of EE and EPI served as equally weighted criteria. **Equal weights were assigned to environmental efficiency and the Environmental Performance Index because no theoretical or empirical evidence suggested that one indicator should receive greater importance than the other. This**

assumption also improves transparency and facilitates interpretation of provincial rankings. Future studies may investigate alternative weighting methods such as entropy-based or expert-driven weighting schemes.

The TOPSIS procedure normalized data, identified the ideal best and worst solutions, and computed the relative closeness of each province to the ideal. Higher scores denoted superior environmental performance. Provinces were ranked via Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) using mean EE and EPI (equal weights, Hwang & Yoon, 1981):

1. Normalization:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

2. Weighted normalized matrix:

$$v_{ij} = w_j \cdot r_{ij}$$

3. Ideal and anti-ideal solutions:

$$A^+ = \{v_1^+, v_2^+, \dots, v_n^+\}, A^- = \{v_1^-, v_2^-, \dots, v_n^-\}$$

4. Distance to ideal and anti-ideal solutions:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}$$

5. Closeness coefficient:

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-}$$

Higher C_i^* indicates superior performance. (Wang & Lee, 2009).

Spatial Analysis and Mapping

Spatial analysis was performed using provincial boundary shapefiles from the geoBoundaries database (Runfola et al., 2020). Environmental efficiency, EPI, and clusters were spatially joined and visualized as thematic maps in ArcGIS 10.8. These maps highlighted spatial disparities and helped identify policy-priority regions, consistent with spatial agricultural-environmental analyses (Maleki et al., 2022).

All efficiency analyses, statistical tests, clustering procedures, and graphical outputs were conducted using the R statistical computing environment (R version 4.x; R Core Team). Data envelopment analysis was performed using the Benchmarking package, multivariate analyses and clustering were implemented using factoextra and cluster, nonparametric tests were conducted using the FSA package, and spatial analyses and mapping were carried out using the sf and tmap packages. The use of open-source statistical software ensured transparency and reproducibility of the analytical procedures.

Results

Before interpreting numerical results, it is helpful to briefly outline what these indicators represent in practical terms. Technical efficiency (TE) reflects how effectively counties convert inputs such as seed, labor, and machinery into wheat output relative to the best-performing units. Environmental efficiency (EE) indicates the ability to maintain yield while minimizing harmful agrochemical inputs. The Environmental Performance Index (EPI), derived from PCA, provides a complementary view by summarizing the intensity of chemical use into a single measure of environmental pressure. Together, these indicators make it possible to distinguish between regions that are productive but environmentally intensive and those achieving a better balance between efficiency and sustainability.

Technical and Environmental Efficiency at the County Level

Table 2 reports descriptive statistics of technical efficiency (TE), environmental efficiency (EE), and the Environmental Performance Index (EPI) for the 377 irrigated wheat-producing counties. Mean technical efficiency is 0.744, indicating that counties could, on average, reduce conventional input use by approximately 25.6% without lowering output. Environmental efficiency shows a higher mean value of 0.929, suggesting relatively lower inefficiency in agrochemical use when environmental considerations are explicitly incorporated into the analysis.

The dispersion of efficiency scores reveals substantial heterogeneity across counties. While several counties operate close to the efficient frontier, others exhibit pronounced inefficiencies in both technical and environmental dimensions. The Environmental Performance Index ranges widely, reflecting large differences in fertilizer and pesticide intensity among regions. This variability highlights the importance of moving beyond average efficiency measures toward a more nuanced, region-specific assessment.

Table 2. Descriptive statistics of TE, EE, and EPI across counties.

Variable	mean	SD	min	max
TE	0.744	0.168	0.352	1.000
EE	0.929	0.084	0.670	1.000
EPI	0.000	1.504	-8.576	2.874

The Environmental Performance Index (EPI) is a standardized PCA-based index; thus, the reported mean of zero reflects standardization rather than absolute performance.

Figure 2 displays histograms of technical and environmental efficiency scores using fixed-width bins of 0.1 to facilitate comparison across efficiency measures, revealing a right-skewed distribution for TE and a more concentrated distribution for EE. The results of the DEA analysis indicate substantial heterogeneity in both technical efficiency (TE) and environmental efficiency (EE) among the 377 irrigated wheat-producing counties in Iran. Technical efficiency scores range from low-performing counties operating far from the production frontier to fully efficient decision-making units (DMUs), reflecting marked differences in input utilization and managerial performance across regions.

When undesirable inputs related to agrochemical use were incorporated into the analysis, environmental efficiency scores exhibited a wider dispersion compared to TE. This suggests that counties with relatively high production efficiency are not necessarily environmentally efficient. In several cases, high yields were achieved at the cost of intensive use of fertilizers and chemical inputs, leading to lower environmental efficiency scores. These findings highlight the importance of explicitly accounting for environmental pressures when evaluating agricultural performance.

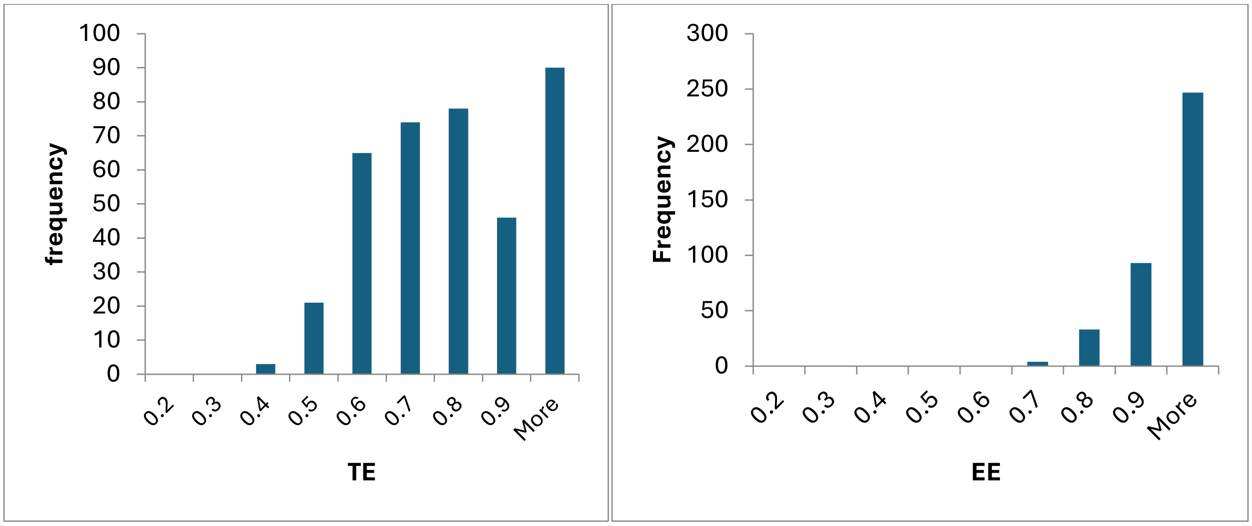

Figure 2. Histograms of technical efficiency (TE) and environmental efficiency (EE) scores (bin width = 0.1).

Overall, the gap between TE and EE highlights the presence of an environmental efficiency loss, suggesting that improvements in resource use and pollution-related inputs can be achieved without compromising output levels.

Environmental Performance Index (EPI) Based on PCA

The PCA-based Environmental Performance Index provides complementary insight into environmental pressure that is not fully captured by DEA-based efficiency scores. The first principal component, which explains the largest share of variance, is primarily driven by fertilizer and pesticide inputs, with nitrogen fertilizer exhibiting the strongest contribution. To facilitate interpretation, the index was oriented so that higher values indicate lower relative environmental pressure. Counties with negative EPI values are characterized by intensive chemical input use, whereas positive EPI values indicate more environmentally restrained production systems. The consistency observed between low EPI values and lower environmental efficiency scores reinforces the robustness of the environmental performance assessment.

Clustering of Counties Based on EE and EPI

To identify groups of counties with similar environmental performance profiles, hierarchical clustering was applied using standardized environmental efficiency and EPI scores. Four distinct clusters were identified, each representing a different combination of efficiency and environmental pressure. Cluster 1 consists of counties with high environmental efficiency and favorable EPI values, reflecting relatively sustainable production practices. Cluster 2 includes counties with moderate environmental efficiency but higher chemical input intensity. Cluster 3 is characterized by low environmental efficiency and unfavorable EPI scores, indicating environmentally intensive systems. Cluster 4 represents counties with mixed performance, often reflecting transitional production systems.

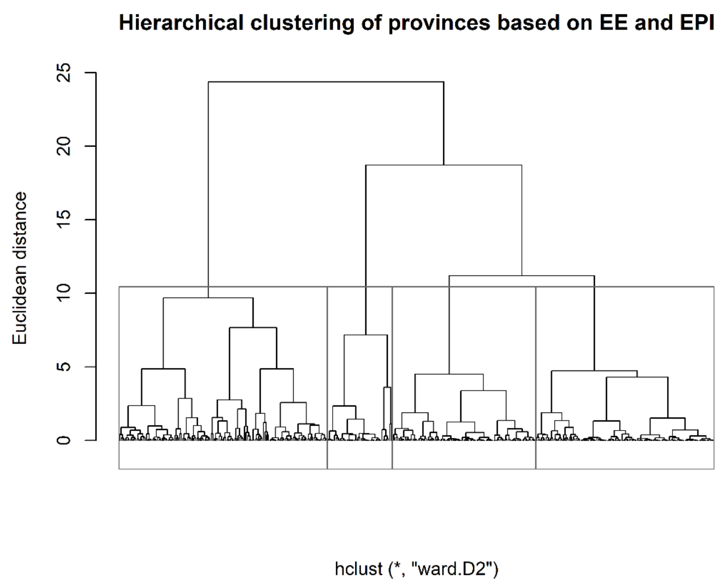

Figure 3. Hierarchical clustering dendrogram (Ward's method).

Figure 3 illustrates the hierarchical clustering of provinces based on EE and EPI. The clustering results reveal clear structural differences among counties and provide a meaningful basis for targeted policy interventions.

Statistical Differences Between Clusters

The Kruskal–Wallis tests indicate statistically significant differences among clusters for both environmental efficiency and the Environmental Performance Index ($p < 0.001$). These results confirm that the identified clusters represent distinct environmental performance regimes rather than random groupings (Table 3). Effect size estimates based on epsilon squared (ε^2) reveal large effects for both indicators, indicating that cluster membership explains a substantial proportion of the observed variability in environmental performance. Post hoc Dunn tests further show that most pairwise comparisons involving the lowest-performing cluster are statistically significant after Bonferroni adjustment, underscoring the magnitude of differences between environmentally efficient and inefficient groups (Table 4).

Table 3. Kruskal–Wallis test results and effect sizes (ε^2) for environmental indicators across clusters.

Indicator	Chi_Square	df	p_value	ε^2
EE	280.170096	3	1.95E-60	0.74377031
EPI	230.460354	3	1.10E-49	0.61085656

Table 4. Dunn's post hoc test results for pairwise cluster comparisons.

Comparison	EE Z	EE p-value	EPI Z	EPI p-value
Cluster 1 – 2	14.228***	<0.001	-1.512	0.783
Cluster 1 – 3	1.001	1	-10.510***	<0.001
Cluster 1 – 4	-12.348***	<0.001	-9.442***	<0.001
Cluster 2 – 3	-0.893	1	6.572***	<0.001
Cluster 2 – 4	-11.109***	<0.001	7.7856***	<0.001
Cluster 3 – 4	-1.615	0.638	14.240***	<0.001

Provincial-Level Environmental Performance

Aggregating county-level results to the provincial scale reveals pronounced spatial patterns in environmental efficiency and environmental performance. Provincial averages of environmental efficiency and EPI exhibit considerable variation, reflecting differences in agroecological conditions, technology adoption, and management practices (Figures 4 and 5).

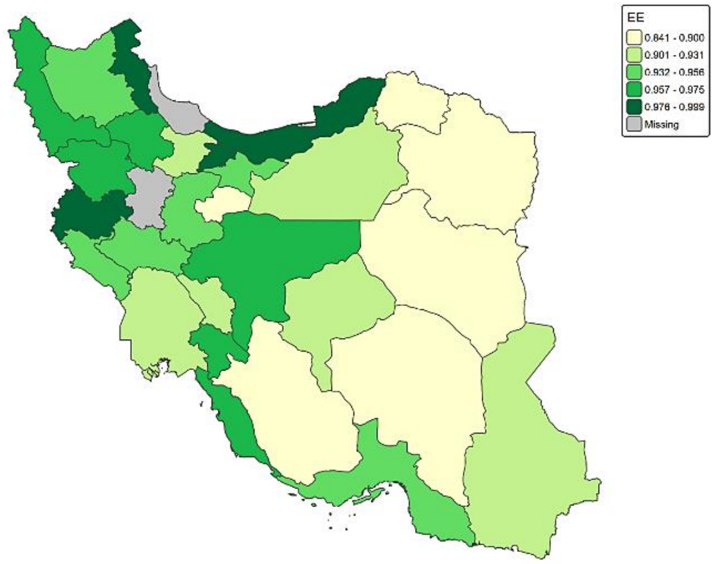

Figure 4. Spatial distribution of environmental efficiency (EE) across provinces at the provincial level.

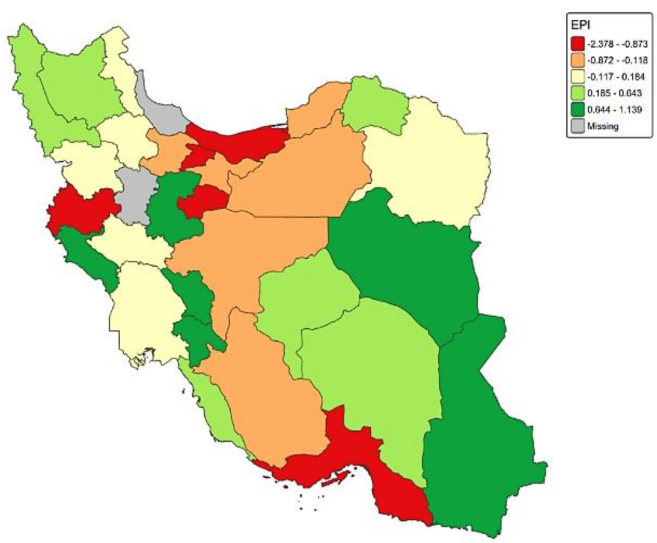

Figure 5. Spatial distribution of Environmental Performance Index (EPI) at the provincial level.

Several provinces consistently exhibit high environmental efficiency and EPI values, suggesting more sustainable wheat production systems. In contrast, other provinces rank lower, indicating a heavier reliance on chemical inputs and lower environmental efficiency. These spatial disparities are clearly visualized in the high-resolution provincial maps of EE and EPI, which reveal geographic clustering of environmentally efficient and inefficient regions (figure 6).

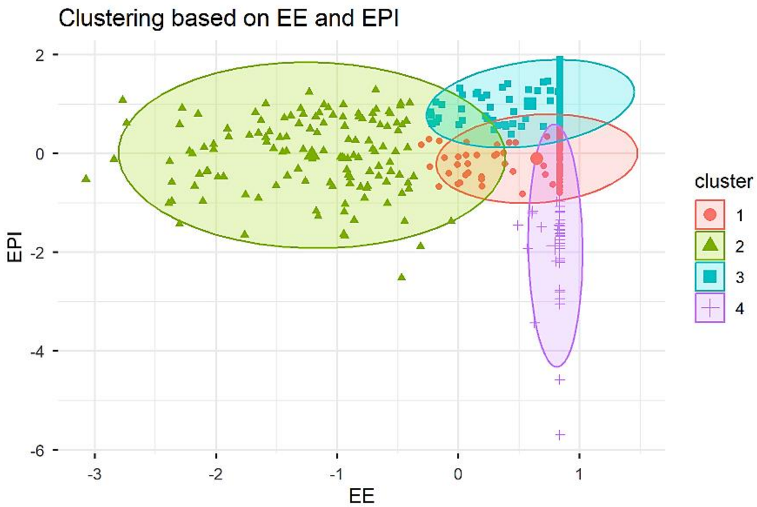

Figure 6. Spatial clustering of provinces based on EE and EPI at the provincial level.

TOPSIS-Based Provincial Ranking

To integrate these indicators into a single measure, the TOPSIS method was applied using equal weights for environmental efficiency and EPI. The resulting rankings highlight provinces that simultaneously achieve high efficiency and low environmental pressure as top performers, while provinces at the lower end of the ranking emerge as priority areas for policy intervention. (Table 5).

Table 5. Provincial ranking based on TOPSIS (EE + EPI).

Province	TE	EE	EPI	Cluster	TOPSIS	Rank
Sistan and Baluchestan	0.7921	0.9030	1.0734	2	0.9690	1
Kohgiluyeh and Boyer-Ahmad	0.8768	0.9660	0.9992	3	0.9617	2
Chaharmahal and Bakhtiari	0.8280	0.9325	1.1393	2	0.9323	3
Ilam	0.8186	0.9538	0.7481	2	0.9163	4
Markazi	0.7840	0.9325	0.6879	2	0.9006	5
South Khorasan	0.6353	0.8441	0.7994	2	0.8972	6
North Khorasan	0.6909	0.8876	0.6335	2	0.8825	7
East Azerbaijan	0.7819	0.9517	0.6260	3	0.8560	8
Bushehr	0.9618	0.9686	0.6152	2	0.8532	9
Yazd	0.7463	0.9192	0.3437	2	0.8300	10
Hamedan	0.9165	0.9730	0.2971	1	0.8264	11
Ardabil	0.7561	0.9798	0.1712	2	0.8041	12
Kerman	0.6668	0.8414	0.2044	2	0.7964	13
Kurdistan	0.7004	0.9593	0.1255	2	0.7945	14
West Azerbaijan	0.8288	0.9610	0.2753	2	0.7565	15
Khuzestan	0.6921	0.9224	-0.1109	2	0.7541	16
Fars	0.6473	0.8872	-0.1261	2	0.7489	17
Semnan	0.7428	0.9324	-0.1900	2	0.7436	18
Lorestan	0.7430	0.9557	0.1159	2	0.7110	19
Razavi Khorasan	0.6557	0.8915	0.0479	2	0.6906	20
Zanjan	0.7835	0.9694	0.0203	2	0.6840	21
Tehran	0.7133	0.9387	-0.7831	2	0.6748	22
Qom	0.4785	0.8812	-1.0999	2	0.6437	23
Qazvin	0.7683	0.9122	-0.2181	2	0.6154	24
Isfahan	0.7944	0.9749	-0.2300	2	0.6128	25
South Kerman	0.5766	0.9125	-2.2085	2	0.5838	26
Golestan	0.8753	0.9989	-0.8592	2	0.4343	27
Hormozgan	0.7483	0.9416	-0.9214	3	0.4157	28
Mazandaran	0.7677	0.9847	-1.0393	2	0.3829	29
Kermanshah	0.8132	0.9903	-2.2225	3	0.0596	30
Alborz	0.8532	0.9787	-2.3781	2	0.0367	31

Synthesis of Key Findings

Taken together, the results reveal substantial heterogeneity in technical efficiency, environmental efficiency, and environmental pressure across irrigated wheat-producing regions in Iran. While some counties and provinces achieve high productivity with relatively low environmental impact, others rely heavily on chemical inputs, resulting in pronounced environmental inefficiencies. The combined use of DEA-based efficiency measures, PCA-derived environmental indicators, clustering, and multi-criteria ranking provides a coherent and policy-relevant picture of environmental performance in Iran's irrigated wheat sector.

Discussion

The results provide clear evidence of a divergence between technical efficiency and environmental efficiency in Iran's irrigated wheat production systems. While many counties achieve relatively high output levels, this performance is often supported by intensive use of fertilizers and pesticides, particularly nitrogen-based inputs. This finding suggests that productivity gains in irrigated wheat have frequently been driven by input intensification rather than by efficient resource management, a pattern that raises concerns about long-term environmental sustainability.

The average technical efficiency score indicates that substantial reductions in conventional inputs are possible without compromising wheat yields. More importantly, the high average environmental efficiency suggests that even greater improvements can be achieved through better management of agrochemical inputs. This highlights the presence of "win–win" opportunities in which environmental pressure can be reduced while maintaining current production levels. Such opportunities are especially relevant in water-scarce and environmentally vulnerable regions where the marginal benefits of additional chemical inputs are likely to be low.

The Environmental Performance Index derived from PCA reinforces these conclusions by identifying fertilizers and pesticides as the primary drivers of environmental pressure. Nitrogen fertilizer, in particular, emerges as a dominant factor, consistent with evidence from previous studies on cereal production systems. The strong alignment between low EPI values and low environmental efficiency scores provides additional confidence in the robustness of the integrated assessment framework employed in this study.

Clustering results further reveal the existence of distinct environmental performance regimes across regions. Counties classified in the high-efficiency, low-pressure cluster demonstrate that sustainable production practices are achievable under Iranian conditions, even within irrigated systems. In contrast, environmentally intensive clusters highlight areas where policy intervention and extension efforts could yield the greatest benefits. The large effect sizes associated with cluster differences indicate that these groupings reflect structural rather than marginal variations in production practices.

At the provincial level, the TOPSIS-based ranking offers a transparent benchmark for comparing environmental performance across regions. Provinces at the top of the ranking can serve as reference points for peer learning and dissemination of best practices, while lower-ranked provinces represent priority targets for efficiency-oriented interventions. These findings suggest that uniform national policies may be less effective than region-specific strategies tailored to local agroecological and management conditions.

Overall, the results are consistent with earlier studies documenting efficiency gaps in Iranian wheat production, but extend the literature by providing a finer spatial resolution and an integrated analytical framework. By jointly considering technical efficiency, environmental efficiency, and chemical input intensity, the study advances understanding of how productivity and sustainability interact in irrigated wheat systems. From a policy perspective, the findings support a shift away from input-intensive approaches toward precision agriculture, improved nutrient management, and integrated pest management as key pathways for enhancing environmental sustainability without jeopardizing food security.

Comparison with Prior Work

These findings are broadly consistent with previous studies reporting noticeable gaps between technical and environmental efficiency in agricultural production systems. Similar patterns have been documented for wheat production in Iran (Esmaeili and Ehsani, 2019; Ehsani et al., 2020), as well as in Spain (Picazo-Tadeo and Gómez-Limón, 2012), Lithuania (Baležentis and Li, 2013), and China (Zhang et al., 2015), where excessive agrochemical use was identified as a major source of environmental inefficiency. Nevertheless, the present study extends the existing literature by integrating DEA, PCA, hierarchical clustering, spatial mapping, and TOPSIS within a unified analytical framework applied to 377 counties across Iran. This finer spatial resolution enables identification of local heterogeneity that is often masked in province-level or farm-level analyses.

Theoretical and Practical Implications

Overall, the evidence suggests that improving environmental performance in irrigated wheat systems does not necessarily require revolutionary technologies, but rather smarter management of inputs and region-specific interventions. This insight bridges the gap between theoretical efficiency gains and practical sustainability transitions in Iran's agricultural policy landscape.

Theoretically, this validates environmental DEA extensions (Seiford & Zhu, 2002; Sueyoshi & Goto, 2012) for multi-output agriculture while advancing cluster-based policy typologies (Everitt et al., 2011). Practically, TOPSIS rankings position Sistan and Baluchestan as benchmarks (score = 0.969), enabling peer-learning platforms. **The findings suggest that policymakers may consider gradually complementing existing input-support policies with measures that encourage precision agriculture, integrated pest management, and region-specific extension programs aimed at improving environmental efficiency.**

Conclusions

In conclusion, Iran's wheat sector harbors substantial "win-win" potential: chemical reductions without yield trade-offs, as evidenced by DEA frontiers and validated clusters. This spatially explicit framework helps close important gaps in sub-provincial assessment, offering policymakers a blueprint for sustainable intensification that balances food security with ecological limits—provided reforms prioritize efficiency over volume. **These findings provide empirical evidence that may inform future refinement of agricultural support and extension policies toward more efficiency-oriented and region-specific sustainability strategies.** Looking forward, future research can extend this framework by incorporating water-use efficiency, climate variability, and socio-economic drivers. Such additions would further clarify the pathways through which Iran's wheat sector can achieve genuine sustainable intensification—one that safeguards both productivity and environmental integrity for generations to come.

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ارزیابی یکپارچه کارایی فنی و زیست‌محیطی در تولید گندم آبی در ایران

فرشید اشراقی

چکیده

در مناطق خشک و نیمه‌خشک ایران، تضمین تولید گندم ضمن کاهش فشار بر منابع طبیعی، یک چالش بزرگ است. این مطالعه به ارزیابی کارایی فنی و زیست‌محیطی تولید گندم آبی در ۳۷۷ شهرستان ایران در طول فصل زراعی ۲۰۲۳ می‌پردازد. کارایی فنی با استفاده از یک مدل تحلیل پوششی داده‌ها (DEA) ورودی‌محور تحت یازده متغیر به مقیاس تخمین زده شد، در حالی که کارایی زیست‌محیطی با در نظر گرفتن نهاده‌های نامطلوب کشاورزی-شیمیایی از طریق رویکرد تبدیل معکوس ارزیابی شد. برای اندازه‌گیری فشار زیست‌محیطی مرتبط با کشاورزی-شیمیایی، یک شاخص عملکرد زیست‌محیطی (EPI)با استفاده از تحلیل مؤلفه‌های اصلی (PCA) استفاده از کود و آفت‌کش ساخته شد، که در آن مقادیر بالاتر نشان دهنده فشار زیست‌محیطی کمتر است. شهرستان‌ها با خوشه‌بندی سلسله مراتبی بر اساس کارایی زیست‌محیطی و EPI گروه‌بندی شدند و معیارگذاری استانی با استفاده از چارچوب TOPSIS با وزن برابر انجام شد. نوآوری این مطالعه در ادغام DEA ، PCA، خوشه‌بندی سلسله مراتبی، تحلیل فضایی و TOPSIS در یک چارچوب یکپارچه است که برای ۳۷۷ شهرستان به کار گرفته شده است و یکی از اولین ارزیابی‌های سراسری در سطح شهرستان از کارایی فنی و زیست‌محیطی در بخش گندم آبی ایران را ارائه می‌دهد. میانگین نمرات کارایی فنی و زیست‌محیطی به ترتیب ۰.۷۴۴ و ۰.۹۲۹ بود که نشان‌دهنده پتانسیل قابل توجه برای صرفه‌جویی در نهاده‌ها ضمن حفظ سطح تولید فعلی است. کود نیتروژن به عنوان عامل اصلی فشار زیست‌محیطی شناسایی شد و نابرابری‌های فضایی قابل توجهی در بین شهرستان‌ها مشاهده شد. به طور کلی، یافته‌ها بر اهمیت استراتژی‌های خاص منطقه که پایداری زیست‌محیطی را بهبود می‌بخشند و در عین حال بهره‌وری کشاورزی را حفظ می‌کنند، تأکید می‌کنند.