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Investigation of the Dust Effect on the Technical Efficiency of Irrigated Wheat Production in Five Selected Provinces in Iran

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Abstract

This research investigates the impact of dust on the technical efficiency of wheat production in Iran's major wheat-producing provinces from 2010 to 2018. Using a non-parametric Window Data Envelopment Analysis (WDEA) with five-year windows and a panel Tobit model, the study evaluated efficiency trends across provinces. Kermanshah demonstrated the highest average efficiency (0.92), while Khuzestan and Lorestan had the lowest in different windows. Among the four functional forms tested—Cobb-Douglas, generalized quadratic, transcendental, and translog—the transcendental function was selected for the Tobit model based on goodness-of-fit. Findings show that an increase in the number of dusty days negatively affects irrigated wheat production efficiency. The study recommends adopting smart agriculture technologies, reforming agricultural insurance laws, and increasing investment in the agricultural insurance fund to address these challenges.

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INTRODUCTION

Dust storms are one of the major factors affecting agricultural production (Boroughani et al., 2022). This phenomenon has numerous destructive impacts on the agriculture sector (Zarei et al., 2022; Hatami et al., 2018; Hatami et al., 2017), human health (Ostro et al., 2021; Jeong et al., 2022), and the climate (Azad et al., 2022; Barnaba et al., 2022; Eskandari et al., 2022). Dust storms frequently occur in the western regions of Iran (Azizi et al., 2011) and have become the country's most significant environmental problem (Zeinali, 2016). In response, the government of Iran has introduced regulations to address the adverse impacts of dust across various provinces[1].

The severity of dust storms has steadily increased over time, resulting in significant monetary losses and rising mortality rates. The impact of this phenomenon has expanded beyond the western regions and is now felt in central provinces as well (Ghaderi and Azizi, 2020). In response, the National Committee for Coping with the Dust Problem, along with the Department of Environment, has launched a 10-year program aimed at addressing this issue. The program focuses on implementing effective solutions and strengthening collaboration among stakeholders, particularly at the provincial level. The five provinces examined in this study—Khuzestan, Ilam, Kermanshah, Hormozgan, and Lorestan—collectively produce approximately 25–30% of Iran's total wheat output (Borzou et al., 2021; Dargahian and Razavizadeh, 2021).

According to FAO data, Iran ranked as the eighth-largest wheat importer in 2020, with annual imports exceeding four million tonnes to meet domestic demand. This underscores the critical importance of domestic wheat production for national food security. Dust storms, which are particularly frequent during spring and summer, pose a serious threat to wheat output, especially in major producing regions. Data from the Ministry of Agriculture indicate that the main wheat growing season in the provinces of Ilam, Lorestan, Kermanshah, and Khuzestan aligns with the peak period of dust activity. Consequently, agricultural productivity in these provinces is highly vulnerable to environmental disruptions caused by dust. This study seeks to examine the impact of dust on the technical efficiency of irrigated wheat production in Khuzestan, Ilam, Kermanshah, Hormozgan, and Lorestan, considering wheat's vital role in ensuring both national and international food security.

This research aims to evaluate the technical efficiency of irrigated wheat production in the provinces of Khuzestan, Ilam, Kermanshah, Hormozgan, and Lorestan. The analysis focuses on how efficiently resources are utilized in wheat cultivation and examines the impact of the number of dusty days on production efficiency. By applying the Window Data Envelopment Analysis (WDEA) method, the study seeks to understand the extent to which environmental stressors like dust influence agricultural performance. The findings are expected to offer critical insights for both agricultural and environmental policy, identifying areas for improvement in farming practices and informing strategies to mitigate the adverse effects of dust. Ultimately, the study contributes to enhancing productivity and sustainability in Iran's dust-affected agricultural regions.

Environmental pollution, dust, and climate change have been widely examined in the context of agriculture. Several studies have employed efficiency analysis methods to evaluate the impact of these factors. Dridi et

[1] Iranian organizations and ministries including the Department of Environment, Planning and Budget Organization, Ministry of Agriculture, Organization of Forests, Rangelands, and Watersheds, Ministry of Energy, Ministry of Petroleum, Ministry of Roads and Urban Development, Meteorological Organization, Crisis Management Organization, Ministry of Foreign Affairs, Ministry of Defense, Ministry of Science, Technology, and Research, Ministry of Health and Medical Education, Ministry of Industry, Mine, and Trade, Geological Organization, Ministry of Education, Science and Technology Deputy of Presidential Office, and Islamic Republic Iran's Broadcasting Organization.

al. (2023) applied the DEA approach to analyze the economic efficiency of farmers in the irrigated region of Nabeul, Tunisia. Their study assessed the potential improvements in Total Factor Productivity (TFP), benefits from horizontal integration, and producer efficiency. Results showed a 2 percent increase in productivity through TFP, and land consolidation strategies contributed to overall efficiency gains. The DEA method also identified crops that had a positive impact on efficiency, and they concluded that higher agricultural productivity could lead to improved water use efficiency. Similarly, Kyrgiakos et al. (2023) highlighted specific methodological considerations required for applying the DEA approach in agricultural settings, emphasizing its suitability for capturing sector-specific dynamics.

A total of 120 papers from the Web of Science and Scopus databases were reviewed using the PRISMA methodology. The findings indicate that applying DEA in the agricultural sector requires appropriate weighting to enhance explanatory power. Azizi et al. (2022) employed panel data and the dynamic ordinary least squares (DOLS) method to assess the effects of climate change on irrigated barley yields across 28 Iranian provinces from 1999 to 2015. Their results revealed that increases in temperature and rainfall negatively affected barley yields, depending on the provinces' threshold levels. Sefeedpari et al. (2021) examined technical efficiency as an indicator of energy use in dairy farming systems, applying WDEA to data from 25 Iranian regions over a 22-year period (1994–2016). Using milk production as output and energy use as input, they found an average efficiency score of approximately 0.85. Habibpour et al. (2020) studied the effect of dust on soybean foliage yield, showing that dust exposure led to varying yield losses depending on coverage timing, likely due to impacts on seed mass, stomatal conductance, and grain development. Zhang et al. (2021) assessed the efficiency of maternal and childbirth hospitals in Shanxi Province, China. DEA models were used to evaluate scale, technical, and pure technical efficiency for 33 district- and 84 county-level hospitals. Efficiency scores were then regressed using bootstrap truncated regression, revealing district-level hospitals scored 0.7433, 0.8633, and 0.9335 for scale, technical, and pure technical efficiency, respectively.

Even though more than half of the hospitals achieved scale efficiency, they all exhibited low overall efficiency. Mousaei (2021) examined factors influencing wheat farmers' capacity to adapt to climate change. Multivariate regression results showed that social capital, income from agriculture, and wheat yield per hectare explained 39.77 percent of the variation in adaptation capacity. Sardar Shahraki et al. (2018) applied WDEA to assess the economic efficiency of wheat production in Iran's Sistan region from 2014 to 2016, reporting average efficiency scores of 0.96 in Zabol, 0.95 in Zehak, and 0.96 in Hirmand, indicating efficient performance in these areas. Hatami et al. (2017) demonstrated that dust exposure significantly reduced wheat harvest index, biological yield, and grain yield. Similarly, Hatami et al. (2018) found that desert dust negatively affected cowpea productivity. Widiarto et al. (2017) analyzed 628 not-for-profit microfinance organizations across 87 countries using a Non-oriented DEA model with a regional meta-frontier framework and Tobit regression. Their results underscored the need for region-specific performance assessments due to geographic variability in efficiency outcomes. Gholami et al. (2015) studied IT investment impacts on the quality and operational efficiency of U.S. hospitals using a two-stage double bootstrap DEA and Tobit model. They found that service quality significantly moderates operational efficiency, IT investments enhance healthcare service quality, and a threshold exists beyond which additional IT investment yields diminishing returns.

Studies investigating efficiency in the agricultural sector commonly apply non-parametric models—particularly various forms of Data Envelopment Analysis (such as window, multi-period, grid-based, and fuzzy DEA)—alongside Tobit and truncated regression models to analyze climatic and non-climatic variables. These studies also highlight that dust has a significantly destructive impact on agriculture by reducing yields, jeopardizing the health of farmers and the labor force, and causing environmental degradation.

METHODOLOGY

Efficiency measurement

Efficiency can be measured using either parametric methods, such as the Stochastic Frontier Approach (SFA) developed by Aigner et al. (1977), or non-parametric methods, such as Data Envelopment Analysis (DEA) introduced by Charnes et al. (1978). SFA accounts for random errors and separates them from inefficiency, providing a more accurate analysis by distinguishing noise from inefficiency. On the other hand, DEA incorporates noise into its efficiency scores, which can compromise the accuracy of the results. Additionally, SFA is generally less sensitive to outliers compared to DEA, making it more robust in datasets with irregular observations. This distinction arises from the methodological foundations of each approach—SFA utilizes regression analysis, whereas DEA relies on linear programming (Kyrgiakos et al., 2023). Ndauka and Matotola (2023) introduced an innovative method for evaluating economic efficiency in agriculture using Window Data Envelopment Analysis (WDEA). This approach offers a dynamic perspective by assessing efficiency over multiple periods, making it a valuable tool for tracking progress and trends. WDEA allows researchers and policymakers to observe changes in efficiency over time, providing critical insights into performance fluctuations. The method enhances the capacity to detect both horizontal and vertical variations in the efficiency of Decision-Making Units (DMUs), and it strengthens discriminatory power, especially when the number of DMUs is limited (Peykani et al., 2021). This can significantly inform agricultural strategies, resource allocation, and policy development aimed at boosting productivity and sustainability. In the WDEA model, assuming N number of decision-making units in the T period, it is observed that in all these observations r input units are used to produce s output units. As a result, the sample will include □ observations. indicates a in the period of t with an input vector of r-dimensional and an output vector of s-dimensional, as shown below (Júnior et al., 2019; Sokhanvar et al., 2019).

$$X_t^n = \begin{bmatrix} X_{1t}^{\acute{n}} \\ X_{2t}^{n} \\ \vdots \\ X_{rt}^{n} \end{bmatrix} \tag{1}$$

$$y_t^n = \begin{bmatrix} y_{1t}^{\acute{n}} \\ y_{2t}^{n} \\ \vdots \\ y_{rt}^{n} \end{bmatrix} \tag{2}$$

Assuming that the WDEA approach starts from time k and the length of the window is W, the matrix of inputs and outputs for evaluation by this approach is as follows (Sefeedpari et al., 2020; Khalili and Alinejad, 2015).

$$X^{k+w} = \begin{bmatrix} x_1^k & x_2^k & \cdots & x_n^k \\ x_1^{k+1} & x_2^{k+1} & \cdots & x_n^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{k+w} & x_2^{k+w} & \cdots & x_n^{k+w} \end{bmatrix} \tag{3}$$

$$Y^{k+w} = \begin{bmatrix} y_1^k & y_2^k & \cdots & y_n^k \\ y_1^{k+1} & y_2^{k+1} & \cdots & y_n^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{k+w} & y_2^{k+w} & \cdots & y_n^{k+w} \end{bmatrix} \tag{4}$$

The problem of input-oriented WDEA under the hypothesis of constant returns to scale is as follows (Charnes et al., 1985).

$$Min\ \theta$$
$$St{:}\ \theta \acute{X}_t - \lambda X_{kw} \geq 0$$
$$\lambda Y_{kw} - \acute{Y}_t \geq 0$$
$$\lambda_n = 1 \quad (n = 1.\ 2.\ \cdots.\ N \times w) \tag{5}$$

Where θ is a scalar that determines the rate of decline in inputs. If θ=1, the decision-making unit is efficient compared to other units. Denotes the input matrix in WDEA in time K and length w. indicates the output matrix in the WDEA model in time k and length w. indicates the vector consisted of constant numbers or the weights of the reference set (Karimi et al., 2007; Mohammadi and Dastyar, 2013).

Tobit model

On the other hand, considering that the nature of the data is a combination of time series and cross-section, the panel Tobit model is used in this article to evaluate the number of dusty days on the irrigated wheat production efficiency variable (Gholami et al., 2015; Widiarto et al., 2017; Zhang et al., 2021; Salas-Velasco, 2019). In the panel Tobit model (Wang and Du, 2023; Ghorbani and Radmehr, 2019):

$$y_{it}^{*} = \beta x_{it} + \varepsilon_{it} \qquad i = 1,2,3,\ \ldots,$$
$$y_{it} - y_{it}^{*} \qquad if\ \ y_{it}^{*} > 0 \tag{6}$$
$$y_{it} = 0 \qquad if\ \ y_{it}^{*} \leq 0$$

Which is y_{it}^{*} the observed variable, y_{it} represents the latent or unobserved variable, x_{it} indicates the vector of independent variables, β represents the parameter vector, and ε_{it} is a disturbance term.

$$\varepsilon_{it} = \lambda_i + u_{it} \tag{7}$$

Where, and indicate to the number of unobserved dependent variables of fixed and random effects, respectively (Samut and Cafri, 2015). To better and more accurately examine the dust effect on the obtained technical efficiency, four Cobb-Douglas, quadratic, translog, and transcendental functions have been evaluated.

$$\boldsymbol{y} = \propto + \sum_{i=1}^{n} \boldsymbol{\beta}_i \boldsymbol{x}_i \tag{8}$$

$$\boldsymbol{y} = \propto + \sum_{i=1}^{n} \boldsymbol{\beta}_i \boldsymbol{x}_i + {}^{1}\!/_{2} \sum_{i=1}^{n} \boldsymbol{\gamma}_{ii} (\boldsymbol{x}_i)^2 + \sum_{i=1}^{n} \sum_{j=2}^{n} \boldsymbol{\gamma}_{ij} (\boldsymbol{x}_i)(\boldsymbol{x}_j) \tag{9}$$

$$y = \propto + \sum_{i=1}^{n} \beta_i x_i + {}^{1}\!/_{2} \sum_{i=1}^{n} \gamma_{ii} (lnx_i)^2 + \sum_{i=1}^{n} \sum_{j=2}^{n} \gamma_{ij} (lnx_i)(lnx_j) \qquad ,\ i \neq j \tag{10}$$

$$\boldsymbol{y} = \propto + \sum_{i=1}^{n} \boldsymbol{\beta}_i \boldsymbol{x}_i + \sum_{i=1}^{n} \boldsymbol{\gamma}_{ii}\ \boldsymbol{lnx}_i \tag{11}$$

In which A, K, L, α, β, γ, and μ are constant coefficients, X = the independent variable, and Y is the amount of production (Nguyen et al., 2022).

Data

Given the problem's environmental and agricultural dimensions, this study adopted a methodological approach aligned with prior research. It utilized data from 2010 to 2018 to estimate the technical efficiency of irrigated wheat production. The selected provinces—Khuzestan, Ilam, Kermanshah, Hormozgan, and Lorestan—are not only major wheat-producing regions but also heavily affected by dust storms. These dual characteristics make them suitable for analyzing both production efficiency and the adverse effects of environmental stressors such as dust. Geographically, the provinces span

Figure. 1. The Location of the Studied Provinces in Iran (Source: Statistical Center of Iran).

the western and southern regions of Iran, as illustrated in Figure 1.

Ilam province spans 20,133 km^2 in western Iran's hilly, semi-arid region. Kermanshah, also in the west, covers 24,434 km^2. Lorestan province occupies 29,308 km^2, comprising about 1.7 percent of Iran's total area. Khuzestan lies in the southwest with an area of 63,213 km^2, representing 3.9 percent of the country's land. Hormozgan, in southern Iran, is about 68,000 km^2, making it the eighth largest province.

Based on prior studies (Mohammadian and Samdaliri, 2020; Naghdyzadegan Jahromi et al., 2023; Praveen et al., 2022), variables such as water consumption, chemical fertilizers, chemical toxins, labor, and machinery hours were selected to estimate the efficiency of irrigated wheat production. Due to data limitations and the slow pace of technical change in the sector, the Window Data Envelopment Analysis (WDEA) method was applied. Table 1 presents the statistical characteristics of the variables used.

The variables of water, pesticides, chemicals, fertilizer, labor, machinery, number of training classes, and irrigated wheat production were collected after data validation. Although seeds play a critical role in crop production—contributing over 50 percent to output—the study excluded them from the production input set. This omission may lead to underestimating the impact of other inputs, as crops cannot be cultivated without seeds. Additionally, data on the number of dusty days was accurately recorded at meteorological stations in the studied provinces.

In Table 2, data sources and units for each variable are reported separately. The variables—water consumption, chemical fertilizers, chemical pesticides, labor and machine hours, number of training classes, insured irrigated wheat cultivated area, and total wheat production—were evaluated annually for each crop year. Additionally, data on the number of dusty days during the wheat growing season were obtained directly from the Iran Meteorological Organisation for the relevant districts under study.

RESULTS AND DISCUSSIONS

For efficiency evaluation using windowed

Table 1

Statistical Information of the Input and Output Variables of the Agricultural Sector over the Period 2010-2018

Variables	Unit	Average	Maximum	Minimum	S.D.
Irrigated wheat production	Ton	407.24	1771.01	27.26	462.66
Water	Million square meters	560.92	2347.89	87.99	701.50
Fertilizer	Thousand tons	41.59	177.39	3.55	52.03
Chemical pesticides	Ton	177.74	805.99	16.00	206.73
Labor	One thousand persons/day	12900.11	7615.10	63.70	1580.53
Machine	Thousand hours	353.33	15019.64	0.11	1924.72
Dusty days	Day	92.69	181	20	36.23
Number of training classes	Person/day	26421.1	224676	165	45281.7
The percentage of the insured irrigated wheat cultivated area	-	33.318	84.9	6.36	24.72

Table 2

Sources of Collected Data.

Variable	Comments	Source
Irrigated wheat production	Wheat yield in tons	Ministry of Agriculture Jihad
Machine	Machinery per one thousand hour	Ministry of Agriculture Jihad
Water	Amount of water consumed in a million cubic meters	Ministry of Agriculture Jihad
Labor	Labor per one thousand persons a day	Ministry of Agriculture Jihad
Fertilizer	Fertilizer used in one thousand-ton	Ministry of Agriculture Jihad
Chemical pesticides	Chemical pesticides used per ton	Ministry of Agriculture Jihad
Number of training classes	Classes and training courses held by Ministry of Agriculture Jihad	Ministry of Agriculture Jihad
The percentage of the insured irrigated wheat cultivated area	The ratio of the insured irrigated wheat cultivated area to the total irrigated wheat cultivated area	Ministry of Agriculture Jihad
Number of dusty days	Number of dusty during the growth period of the wheat crop	Iran Meteorological Organization

data overlay analysis, there is no specific theory and basis for the window size or the number of decision-making units, but according to Mohammadi and Dastiyar (2013), Júnior et al. (2019), Cooper et al. (2007), the following formula is suggested to determine the number of windows:

$$W=K-P+1 \tag{12}$$

The number of receiver units per window=n*P (13)

Where W: number of windows, K: number

of periods, P: length of windows, n: number of decision-making units (investigated provinces). Based on equation (12), the efficiency of five provinces with nine years and a window length of 5 years will include five windows. Since operators and producers have more control over inputs than outputs, an input-based WDEA model was used in this study. The amount of water consumed, chemical fertilizers, chemical pesticides, labor force, and machine hours are input variables, whereas the amount of irrigated wheat production is considered an output variable. In the following, the provinces' irrigated wheat crop production efficiency is annually estimated in each window. Then, the average obtained in the window of each decision-making unit during specific periods is the basis for evaluating and investigating the performance of operators and producers. Results are reported in Table 3.

As shown in Table 3, window (4) has the highest average technical efficiency, with a value of 0.90, and is associated with Khuzestan province. This window covers the period from 2012 to 2016. The minimum average technical efficiency for windows in Khuzestan province is found in window (2), with a

Table 3

Irrigated Wheat Crop Efficiency of Khuzestan, Kermanshah, Ilam, Lorestan, and Hormozgan Provinces, Iran, During the Years 2017-2018 Using Window Data Envelopment Analysis Approach.

Province	Efficiency	2010	2011	2012	2013	2014	2015	2016	2017	2018	Average	S.D.
	Window (1)	0.66	0.56	0.71	0.95	0.82					0.74	0.15
	Window (2)		0.56	0.67	0.95	0.81	1				0.80	0.18
Khuzestan	Window (3)			0.64	0.95	0.80	0.97	0.97			0.87	0.15
	Window (4)				0.95	0.83	1	1	0.74		0.90	0.11
	Window (5)					0.85	1	1	0.79	0.61	0.85	0.16
	Annual average	0.66	0.56	0.67	0.95	0.82	0.99	0.99	0.77	0.61	0.78	0.17
	Window (1)	0.92	0.67	1	1	1					0.92	0.14
	Window (2)		0.67	1	1	1	0.93				0.92	0.14
Kermanshah	Window (3)			1	1	0.98	0.93	0.95			0.97	0.03
	Window (4)				1	1	0.93	0.95	0.91		0.96	0.04
	Window (5)					1	1	1	0.95	0.81	0.95	0.08
	Annual average	0.92	0.67	1	1	1	0.95	0.97	0.94	0.81	0.92	0.11
	Window (1)	1	0.67	0.93	0.95	0.96					0.90	0.13
	Window (2)		0.59	0.91	0.81	0.75	1				0.81	0.15
Ilam	Window (3)			0.88	0.76	0.75	1	1			0.88	0.12
	Window (4)				0.76	0.75	1	1	0.79		0.86	0.13
	Window (5)					0.77	1	1	0.79	0.99	0.91	0.12
	Annual average	1	0.63	0.91	0.82	0.80	1	1	0.79	0.99	0.88	0.13
	Window (1)	0.89	0.54	0.71	0.97	0.92					0.81	0.18
	Window (2)		0.54	0.71	0.80	0.78	0.89				0.74	0.13
Lorestan	Window (3)			0.71	0.80	0.78	0.89	0.76			0.79	0.07
	Window (4)				0.80	0.78	0.89	0.76	0.81		0.81	0.05
	Window (5)					0.81	0.89	0.79	0.83	0.75	0.82	0.05
	Annual average	0.89	0.54	0.71	0.84	0.82	0.90	0.78	0.82	0.75	0.78	0.11
	Window (1)	0.87	0.74	0.76	0.94	0.87					0.84	0.08
	Window (2)		0.74	0.76	0.94	0.87	0.78				0.82	0.08
Hormozgan	Window (3)			0.76	0.94	0.87	0.78	1			0.87	0.10
	Window (4)				0.97	0.87	0.78	1	0.86		0.90	0.09
	Window (5)					0.90	0.93	1	0.87	0.71	0.88	0.11
	Annual average	0.87	0.74	0.76	0.95	0.88	0.82	1	0.87	0.71	0.84	0.10

value of 0.80. In 2011, the cases investigated in both windows (1) and (2) had the lowest technical efficiency. The highest technical efficiency in this province occurred in 2014 and 2015, with a value of 0.99. In 2010, Kermanshah province had the lowest technical efficiency during the investigated years. The highest average technical efficiency in Kermanshah can be seen in window (3), which covers 2012 to 2016. The lowest average technical efficiency in Kermanshah is also associated with windows (1) and (2), both of which have a value of 0.92. These two windows also have the highest standard deviation. In Ilam province, window (5) has the highest average technical efficiency, equal to 0.91. The lowest average technical efficiency is found in window (2), with a value of 0.81. The highest technical efficiency in this province occurred in 2010, 2015, and 2016, while the lowest was in 2011. In Lorestan province, the highest and lowest technical efficiencies are found in windows (2) and (5), respectively. Window (1) has the highest standard deviation, while windows (4) and (5) have the lowest standard deviations for this province throughout 2010 to 2018. In Hormozgan province, window (4) has the highest average technical efficiency, equal to 0.90, while window (2) has the lowest, with a value of 0.82. Table 4 compares the average efficiency of windows by province.

According to Table 4, the highest average efficiency of windows in the WDEA model over the period 2010–2018 belongs to Kermanshah province, which is consistent with Shahnavazi and Ashrafi (2022). Kermanshah province demonstrated optimal use of primary inputs and resources (Mohammadian and Samdeliri, 2019). The lowest average efficiency for windows (1) and (2) to (5) belongs to Khuzestan and Lorestan provinces, respectively. Generally, the highest to lowest average technical efficiency among the investigated provinces is as follows: Kermanshah, Ilam, Hormozgan, and Khuzestan and Lorestan provinces (with Khuzestan and Lorestan sharing the same value). Additionally, the results of this study align with those of Sadeghian et al. (2022) and Esfahani (2022). According to Ghosheh et al. (2016), the highest efficiency of water consumption in Khuzestan ranges from 4300–4200 and 4000–3900 cubic meters per hectare, whereas the water consumption of irrigated wheat farmers in this province, based on the statistics, ranges from 4212–4768 cubic meters. This suggests that excessive water consumption is one of the main reasons for the low efficiency of wheat production in Khuzestan province. Furthermore, Ajabshirchi Oskui et al. (2012) reported that the lack of optimal use of fertilizers, pest control, and weed and disease management—relative to farm scale—contributes to the low efficiency of wheat production in Lorestan province. Next, we compare the average number of dusty days with the average technical efficiency in each window of the wheat crop (Figure 2).

As shown in Figure 2, the average dust variable affects the average technical efficiency differently across provinces. In Hormozgan province, the average technical efficiency increases with the number of dusty days, whereas in the other provinces, the opposite trend is observed, with the average technical efficiency decreasing. The reduction in average efficiency in relation to the increase in the number of dusty days in Khuzestan province is particularly notable. Next, the panel Tobit model was employed to investigate the effects of the number of dusty days on the average efficiency of wheat production. In this model, the average technical efficiency of wheat production served as the dependent variable, while the number of dusty days, the number of training classes, and the percentage of insured irrigated wheat cultivated areas were used as independent variables. Previous studies by Russo et al. (2022), Tleubayev et al. (2022), and Hoang-Khac et al. (2020) have explored the influence of educational and promotional activities, human

Table 4

The Average Efficiency of Irrigated Wheat Crops in Five Studied Provinces Without Considering the Number of Dusty Days Over the Period 2010-2018 Using the Wdea Approach.

Efficiency	Khuzestan	Kermanshah	Ilam	Lorestan	Hormozgan
Window (1)	0.74	0.92	0.90	0.81	0.84
Window (2)	0.80	0.92	0.81	0.74	0.82
Window (3)	0.87	0.97	0.88	0.79	0.87
Window (4)	0.90	0.96	0.86	0.81	0.90
Window (5)	0.85	0.95	0.91	0.82	0.88
Average windows	0.78	0.92	0.88	0.78	0.84

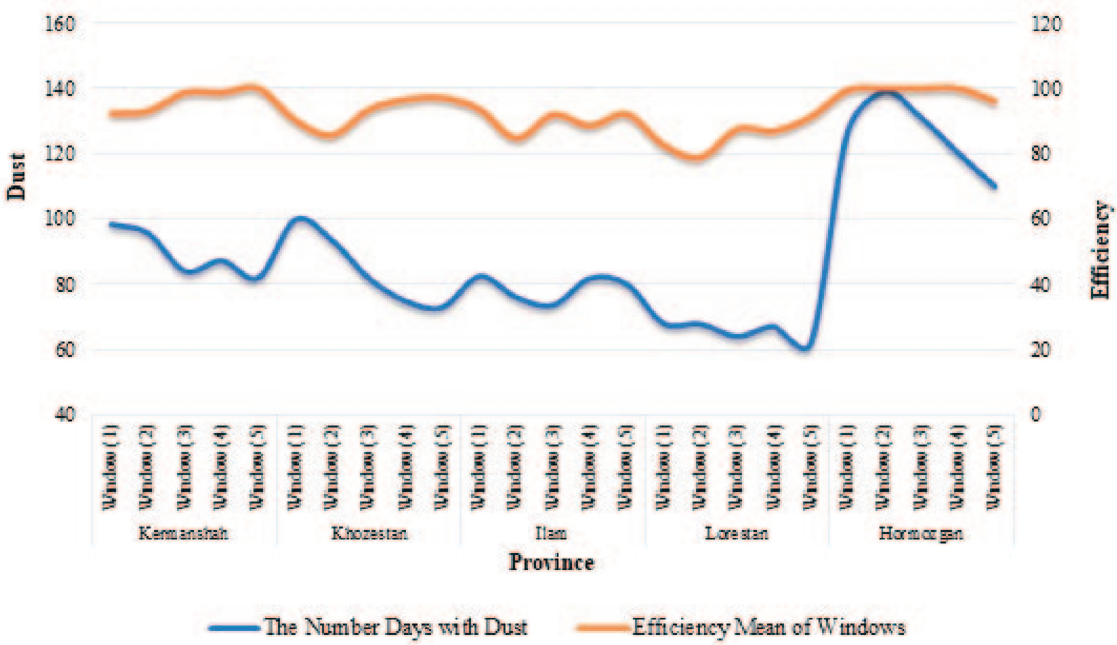

Figure. 2. Comparison of the Average Number of Dusty Days with the Average Technical Efficiency in Each Irrigated Wheat Crop Production Window in the Period of 2010-2018.

capital, and insurance variables on the technical efficiency of wheat production. The first step in estimating this model was testing the reliability of the data. The Levin-Lin-Chu (LLC) and Breitung tests were used to assess the nature of the data series used for the analysis (Table 2).

All variables were stationary at the I(0) level according to the LLC and Breitung tests. After conducting the unit root test for the variables, data collinearity was assessed. The VIF test results showed that the values were all less than 5, with the mean VIF also falling within acceptable limits. This indicates that there was no significant collinearity among the variables in the irrigated wheat production function (Table 5).

A probability check was conducted to assess the data's suitability for panel modeling, as shown in Table 7. The F-Limar test results for the irrigated wheat functions rejected the null hypothesis, indicating that the data

Table 5
The Results of the Static Test of Irrigated Wheat.

Variables	LLC	Breitung
	Level	Level
LEF	-5.213[0.0000]	-3.064[0.0011]
DUST	-2.98[0.0015]	-2.371[0.0089]
LDUST	-1.433[0.0760]	-2.029[0.0212]
LE	-5.217[0.0000]	-2.814[0.0024]
LLE	-10.17[0.0000]	-2.551[0.0054]
IN	-15.34[0.0000]	-2.526[0.0058]
LIN	-15.34[0.0000]	-2.026[0.0214]

Table 6
Collinearity Check Results.

Variable	VIF	1/ VIF
LDUST	1.14	0.867
LLE	1.01	0.875
LIN	1.15	0.990
Mean VIF	1.10	

Table 7
Integration Test.

Test name	Statistics	Prob	Results
F Limar	74.2	0424.0	Panel data
Hausman	28.2	0655.0	Random effect

should be treated as pooled. The next step involved determining whether the panel data exhibited random or fixed effects, which was accomplished using the Hausman test. The results of this test revealed the presence of variable effects in both functions.

Before estimating the Panel Tobit models, it was necessary to determine the most appropriate functional form for the data and variables. Four functions were investigated, as described in the methodology: generalized quadratic, transcendental, translog, and Cobb-Douglas. Each of these four functions was approximated based on the available data. The selection of the optimal function was made using several criteria, including F-statistics, R-squared values, the validity of coefficient signs, and the number of significant coefficients. Additionally, the relevance of the y-intercept was also considered in the evaluation (Table 8).

The number of significant coefficients is

Table 8
Comparison of Irrigated Wheat Production Functions.

Functions	coefficients with C	significant coefficients with C	Coefficient sign	F	R^2
Cobb–Douglas	4	1	wrong	42.1	09.0
Generalized quadratic	10	2	wrong	43.1	26.0
Transcendental	7	7	Correct	2.74	30.0
Translog	10	2	wrong	30.1	25.0

** 10% level, *** 5% level.

Table 9.
The Estimation Results of the Panel Tobit Panel over the Period 2010-2018.

Variables	Coefficients	Standard deviation
DUST	-0.0057	0.0023
LE	0.0000013	0.0000006
IN	0.00379	0.00265
LDUST	0.40919	0.173
LLE	-3.71	0.0183
LIN	-0.198	0.0934
CONS	4.108	0.565
Chi2	16.55	

** 10% level, *** 5% level.

lower in the generalized quadratic, Cobb-Douglas, and Translog functions compared to the total number of coefficients. Moreover, in these functions, most of the coefficient signs are reversed. In contrast, the transcendental function has a higher number of significant coefficients relative to the total coefficients, with the correct signs for these coefficients. Therefore, the transcendental function was selected as the preferred model. After selecting the preferred function, the panel Tobit model was estimated (Table 8).

As depicted in Table 9, various variables were analyzed for their impact on the average efficiency of wheat production in the five studied provinces from 2010 to 2018. The results revealed noteworthy findings: The variable representing the number of dusty days exhibited a statistically significant negative influence on average efficiency at a 10% significance level. Conversely, the logarithm of the number of dusty days displayed a positive and statistically significant impact on the dependent variable at a 10 percent significance level. The variable associated with the number of educational classes demonstrated significance at the 10% level and had a negative effect on the dependent variable. Similarly, the logarithm of the number of training classes negatively influenced the average efficiency of wheat production. Furthermore, the variable representing the percentage of insured irrigated wheat cultivated area was found to have a positive effect on the dependent variable. However, it is noteworthy that the logarithm of this variable exhibited a negative impact. Detailed effects and coefficients are provided in the table below for further interpretation and analysis (Table 10).

According to Table 10, the final effect of all variables is significant at the 10 percent level. The final effect and logarithm of the number of dusty days are negative and positive, respectively. In addition, the final effect and logarithm of the number of training classes are positive, while their logarithm is negative. The insured cultivated area variable has a positive effect, but it is not significant at the 5 or 10 percent level, which is consistent with the results of Aghapour (2015). To interpret the results, the elasticity of the transcendental function is reported in Table 11.

Based on Table 11, the elasticity of the number of dusty days is less than zero, meaning that on average, a one percent increase in the number of dusty days results in a 0.067 percent decrease in the average efficiency of irrigated wheat production. The results of this study are consistent with studies such as Paudyal and Shakya (2016) and Zabihi Sheshpoli et al. (2021). According to Naghib Alsadati et al. (2019), the reasons for this decrease include reduced herbicide efficiency in controlling wheat weeds, a decrease in the number of seeds per spike, and impaired photosynthesis due to dust accumulation on plant leaves. This study suggests that rain irrigation can help mitigate the negative effects of dust on plants.

The number of educational classes has a positive elasticity between zero and one. A one percent increase in this variable leads to

Table 10
Estimation Results of the Panel Tobit Model over the Period 2010-2018.

Variables	Final effect	Standard deviation
DUST	-0.0046	0.0019
LE	0.0000011	0.00001
IN	0.00308	0.00216
LDUST	0.333	0.1427
LLE	-0.0443	0.0151
LIN	-0.1613	0.0765

* 15% level, ** 10% level, *** 5% level.

Table 11
Calculation of Transcendental Function Elasticity over the Period 2010-2018.

Variable name	Elasticity
Number of dusty days	-0.067
Number of training classes	0.362
The percentage of the insured irrigated wheat cultivated area	-0.0579

a 0.362 percent increase in the dependent variable's mean, which is consistent with the studies of Krasachat et al. (2023), Murshed-E-Jahan et al. (2011), Wonde et al. (2022), Barazandeh et al. (2020), Fathabadi and SufiMajidpur (2018), and Vahedi et al. (2022). Familiarity with new science, techniques, or better methods for cultivating irrigated wheat enables farmers to utilize resources more efficiently and increase production economically (Vahedi et al., 2022). Finally, the elasticity of the insured irrigated wheat cultivated area percentage is less than zero. A one percent increase in the insured irrigated wheat cultivated area leads to a 0.0579 percent decrease in the average efficiency of wheat production. This result is consistent with Torkamani and Mousavi (2010). The reasons for this decrease include farmer dissatisfaction with insurance coverage, the non-payment of compensation by the insurance fund for certain incidents, reduced fund payments relative to the damage, bureaucratic hurdles, the complexity of the agricultural insurance process, lack of awareness among producers about agricultural insurance, issues with agricultural insurance laws, and high insurance premiums (Shahnoushi et al., 2010).

CONCLUSION AND RECOMMENDATIONS

This article investigates the effect of dust on the technical efficiency of wheat production in the provinces of Khuzestan, Ilam, Kermanshah, Hormozgan, and Lorestan. Due to limitations in data access, the non-parametric WDEA approach was initially used to estimate the average efficiency of irrigated wheat production. Then, to explore the impact of dust on the average efficiency, a panel Tobit model with a transcendental function format was applied. In the WDEA approach, each window was considered to span five years, and the average technical efficiency for five windows in each province was estimated from 2010 to 2018. This model compares the technical efficiency of each window with the other windows of each province and with the respective windows in other provinces. Additionally, the input variables include water consumption, chemical fertilizers, chemical pesticides, labor, and machine-hours, while the output variable is irrigated wheat production. Data for these variables were personally collected from the Ministry of Agriculture Jihad statistics and the ministry's experts. The results of the WDEA model show that Kermanshah province had the highest average efficiency across all windows from 2010 to 2018. In contrast, the lowest average efficiency in Windows (1) and (2), (3), (4), and (5) were observed in Khuzestan and Lorestan provinces, respectively.

In summary, it can be concluded that reducing inputs such as water consumption and labor, which are considered desirable inputs, leads to an increase in the number of windows where the average technical efficiency approaches or reaches one. In the next step, LLC and Breitung tests were employed to verify the reliability of the variables for the panel Tobit model estimation, and the results indicated that all variables were stable at the I(0) level. Additionally, the VIF test was used to confirm the absence of collinearity among the variables. Following this, an integrability test confirmed that the data was panel and exhibited random effects. Given that the functional form significantly impacts model specification, this study evaluated four forms—Cobb-Douglas, generalized quadratic, transcendental, and translog functions—for the second model estimation. Based on goodness-of-fit criteria, the transcendental function was chosen as the preferred model. Finally, after estimating the panel Tobit model and calculating its final effect, the partial elasticity of the inputs was determined for the investigated variables. The results indicate that the number of dusty days negatively affects the average efficiency of irrigated wheat production. The number of training classes conducted by the Ministry of Agriculture Jihad positively impacts the dependent variable. Moreover, the percentage of insured irrigated wheat cultivated area was found to have a negative and significant effect on the average efficiency of irrigated wheat production. Given the importance of wheat as a crucial crop, both in Iran and globally, and considering the growing severity of dusty days in the country, particularly advancing to the central provinces, the following strategies are recommended to improve the efficiency of irrigated wheat production.

i. The results of the present study indicate that most irrigated wheat production units in the provinces during the investigated years were more productive and efficient, using fewer inputs. Therefore, one approach to increasing the efficiency of wheat production, as a strategic crop in the country, is to enhance the productivity of inputs and primary resources and reduce the impact of dust storms through international agreements and negotiations. Upgrading and modernizing irrigation systems, particularly in arid and semi-arid regions, and implementing subsurface irrigation can improve water use efficiency by more than 50%. Additionally, the adoption of precision and smart agriculture technologies for farm management in the provinces can reduce the consumption of resources and key inputs, such as labor and machine hours, while significantly enhancing technical efficiency in the agricultural sector.

ii. According to the results, the number of training classes has a positive effect, while the percentage of insured irrigated wheat cultivated area has a negative effect on average production efficiency. It is therefore recommended that the Ministry of Agriculture Jihad, through agricultural cooperatives in each district, simultaneously enhance both the quality and quantity of training programs. In parallel, it should address the challenges in agricultural insurance by reforming relevant laws and increasing investment in the agricultural insurance fund.

iii. As noted, the dynamic or window Data Envelopment Analysis (WDEA) approach is based on moving averages within time windows and effectively captures trends in the technical efficiency of wheat production. The results of this method can inform policy packages aimed at improving provincial efficiency, considering both productive inputs and negative factors such as dusty days. It is thus recommended to apply this method to evaluate the technical efficiency of other major crops, such as barley, corn, and soybeans.

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