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ORIGINAL ARTICLE

Application of ANFIS, ELM, and ANN models to assess water productivity indicators based on agronomic techniques in the Lake Urmia Basin

Somayeh Emami[1] · Hossein Dehghanisanij[2] · Mohammed Achite[3] · Nadhir Al-Ansari[4] · Nguyen Thi Thuy Linh[5]

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Abstract
Water productivity (WP) is one of the most important critical indicators in the essential planning of water consumption in the agricultural sector. For this purpose, the WP and economic water productivity (WPe) were estimated using agronomic technologies. The impact of agronomic technologies on WP and WPe was carried out in two parts of field monitoring and modeling using novel intelligent approaches. Extreme learning machine (ELM), adaptive neuro-fuzzy inference system (ANFIS), and artificial neural network (ANN) methods were used to model WP and WPe. A dataset including 200 field data was collected from five treatment and control sections in the Malekan region, located in the southeast of Lake Urmia, Iran, for the crop year 2020–2021. Six different input combinations were introduced to estimate WP and WPe. The models used were evaluated using mean squared error (RMSE), relative mean squared error (RRMSE), and efficiency measures (NSE). Field monitoring results showed that in the treatment fields, with the application of agronomic technologies, the crop yield, WP, and WPe increased by 17.9%, 30.1%, and 19.9%, respectively. The results explained that irrigation water in farms W1, W2, W3, W4, and W5 decreased by 23.9%, 21.3%, 29.5%, 16.5%, and 2.7%, respectively. The modeling results indicated that the ANFIS model with values of RMSE = 0.016, RRMSE = 0.018, and NSE = 0.960 performed better in estimating WP and WPe than ANN and ELM models. The results confirmed that the crop variety, fertilizer, and irrigation plot dimensions are the most critical influencing parameters in improving WP and WPe.

Keywords Crop variety · Adaptive neuro-fuzzy inference system · Irrigation · Yield

Introduction

Improving WP in the agricultural sector, as the primary sector that consumes water resources, requires special planning (Ahmadzade et al. 2015). Nowadays, a significant part of agricultural research is focused on strategies to optimize water consumption and increase productivity (Fatemi et al. 2014). Finding ways to increase WP through improving economic or crop yields in irrigated and rainfed agriculture is handled (Kassam et al. 2007). On the other

✉ Nguyen Thi Thuy Linh
nguyenthuylinh@tdmu.edu.vn

Somayeh Emami
somayehemami70@gmail.com

Hossein Dehghanisanij
h.dehghanisanij@areeo.ac.ir

Mohammed Achite
m.achite@univ-chlef.dz

Nadhir Al-Ansari
nadhir.alansari@ltu.se

[1] Department of Water Engineering, University of Tabriz, Tabriz, Iran

[2] Agricultural Research, Education and Extension Organization, Agricultural Engineering Research Institute, P.O. Box 31585-845, Karaj, Alborz, Iran

[3] Laboratory of Water and Environment, Faculty of Nature and Life Sciences, Hassiba Benbouali University of Chlef, 02180 Chlef, Algeria

[4] Department of Civil, Environmental and Natural Resources Engineering, Lulea University of Technology, 97187 Lulea, Sweden

[5] Institute of Applied Technology, Thu Dau Mot University, Binh Duong Province, Vietnam

hand, proper management of agricultural inputs, especially irrigation water, using modern technology is necessary to maximize production (Panda et al. 2003). Management factors increase WP by increasing crop yield (Tian et al. 2019, 2020, 2021; Momeni et al. 2011). All measures of actual saving and reduction of physical water loss in farm scales are considered ways to improve WP (Heidari 2012). Changing the cultivation pattern, improving irrigation management and crop varieties, and improving agricultural operations are among the most essential methods in improving WP (Neirizi and Helmi-fakhrdavoud 2004). The implementation of measures such as the use of zero tillage, deficit irrigation, modification of the cultivation pattern, and the use of improved cultivars have improved WP (Ogle et al. 2012; Yan et al. 2015; Humphreys et al. 2016). Various variables affect enhancing or increasing the WP and WPe. By examining the factors and determining the effect of each of them, solutions can be found to improve water use efficiency (WUE). The problem of feature selection is significant in many engineering problems, because many features are either useless or not very informative (Akay 2022). Population-based search approaches such as meta-heuristic algorithms are a suitable solution to reduce the number of factors (Zula et al. 2019). In recent years, the use of data mining and artificial intelligence models with the possibility of simultaneously investigating the effects of different variables on WP and crop yield has been considered (Najah et al. 2014; Palepu and Muley 2017; Ehteram et al. 2019; Khosravi et al. 2019; Dehghanisanij et al. 2021; Linaza et al. 2021; Holm et al. 2021; Saleem et al. 2021). These approaches are quantitative tools based on mathematical connections and can assess the effects of agricultural management factors on the growth and development of crops and water, soil, and climate variables (Hou et al. 2012; Zula et al. 2019). Table 1 shows some recent studies that used intelligent methods to estimate WP and crop yield parameters Artificial intelligence is vital in estimating crop yield and WP based on geography, weather, and season details. It helps grow the most suitable crop for the agricultural lands. Since the factors affecting WP differ significantly in different regions, determining the factors affecting WP will help optimize irrigation water- fertilizer consumption, additional inputs, and resources in farms. The present study was carried out to identify and determine the importance, and degree of influence, and investigate agricultural factors in improving WP and WPe.

This study was supposed out in two parts as follows:

(a) Investigating the impact of agronomic technologies on crop growth, irrigation water, and crop yield,

(b) Modeling and determination of agronomic parameters affecting WP and WPe using ANFIS, ELM, and ANN models.

The remaining sections are organized as follows: Sect. 2 introduces research areas and discusses experimental treatments and proposed methods. Section 3 presents results and a discussion on field measurements and modeling.

Table 1 Key points of intelligent methods in estimating crop yield and WP

Method	Definition
ANNs (Abrougui et al. 2019)	ANNs have good efficiency in estimating crop yield
Radial basis function (RBF) and feedforward neural (GFF) models (Emami and Choopan 2019)	The RBF model with the input parameter of irrigation water levels could better estimate the barley yield
Fuzzy logic method (Upadhya and Mathew 2020)	This method can be helpful in developing the latest irrigation methods and optimizing yield
Season's optimization algorithm (SO) and support vector regression (SVR) (Dehghanisanij et al. 2021)	The SO–SVR hybrid method has high efficiency in estimating WP and yield
Machine learning algorithms (Rashid et al. 2021)	Machine learning approaches accurately predict Palm Oil yield
A hybrid tree growth optimization algorithm (TGO) and ANFIS model (Dehghanisanij et al. 2022)	Based on the TGO-ANFIS model results irrigation with an equal ratio of the well and treated wastewater resulted in improving soil and cotton growth conditions and yield during the study
ANNs combined with sensitivity analysis (Belouz et al. 2022)	The results showed that ANNs provided more accurate predictions of greenhouse tomato yield
Hybrid particle swarm optimization–imperialist competitive algorithm–support vector regression (PSO-ICA-SVR) method (Esfandiarpour-Boroujeni et al. 2019)	The results demonstrated that the hybrid PSO-ICA-SVR algorithm estimates the apricot yield with relatively high accuracy
ANFIS (Esmaili et al. 2021)	ANFIS predicts WP and lettuce yield with acceptable accuracy
An ELM model and optimized spider monkey optimization (SMO) algorithm (Liu et al. 2022)	The SMO-ELM model has better accuracy than other models
Multiple hybrid ANFIS and multilayer perceptron (MLP) models (Bazrafshan et al. 2022)	The results indicated that multiple MLP and ANFIS model was useful for predicting tomato yield

Fig. 1 Schematic of the study area

Section 4 provides conclusions and suggestions for future improvements.

Methodology

Study area

To evaluate the application of agronomic techniques, five farms were selected in the Malekan region, located in the southeast of Lake Urmia, Iran. Malekan city is located at 37° 8'N and 46° 6'E of 1300 m above sea level. This region has a moderate climate.

The geographic site of the examination area is presented in Fig. 1.

Each farm was divided into two treatment and control sections. The experimental treatments were considered at three levels, including basin irrigation (BI), furrow irrigation (FI), and drip (tape) irrigation (DTI). The selected farms were part of a regional project conducted by the Agricultural Engineering Research Institute (AERI) during the 2020–2021 crop growing season in the Lake Urmia basin to encourage farmers to decrease applied water while the yield is constant or improved. In the AERI project, different technologies were transferred to the farmers and farmers' knowledge improved accordingly. The impact of transferred technology was studied using on-farm and weather data collections and evaluations. The factors of soil texture, meteorology, and irrigation methods were considered the same in treatment and control farms. Tables 2 and 3 show the general characteristics of farms, applied techniques, and used fertilizers.

Irrigation methods

Furrow irrigation

In the FI method, water reaches the seed area and the surface of the ridge through capillary tubes. In this method, the soil structure of the ridge surface is preserved, the ridge surface does not close, and its ventilation is desirable. The FI method is used in cases where the plant is sensitive to soil density, tuberculosis, and limited soil aeration (Sammis 1980; Dehghanisanij et al. 2022).

Drip (tape) irrigation

The DTI method is a thin-walled drip irrigation (DI) system that offers a cost-effective DI option for row crops. The DTI has drip tape sewn on the one side at a distance of 20 cm and has a discharge of 1.8 l/s. In the DTI, water is applied to the soil surface near the crop root zone to moisten a small area and depth from the soil surface (Patel and Rajput 2007).

Basin irrigation

BI is a method in which water penetrates the soil permanently or intermittently, and the soil is permanently submerged. In BI, water penetrates the crown area of the plant, and the problem of clogging heavy soils and reducing soil aeration occurs (Brouwer et al. 1988).

Irrigation scheduling

The FAO Penman–Monteith method was used to calculate potential evapotranspiration under standard conditions (ETo).

Crop coefficients were determined using the four-step process of FAO (Allen et al. 1998). The amount of irrigation water required was calculated as follows (Brouwer 1986):

$$IR = \frac{K_c * ET_o}{1 - LR} - P_e \quad (1)$$

where IR means irrigation requirement (mm), K_c demonstrates crop coefficient, P_e denotes effective rainfall, and LR reveals leaching coefficient, which depends on soil structure, crop planting, type and amount of fertilizer consumption, and soil porosity.

The WSC flume (4/5/6–Washington State College Flumes) was used to measure water consumption in the farms (in farms W1, W2, and W4). The discharge was calculated as follows:

$$Q = 0.0374H^{2.64} \quad (2)$$

$$Q = 0.0294H^{2.102} \quad (3)$$

$$Q = 0.0232H^{2.196} \quad (4)$$

Q shows the discharge (l/s), and H denotes the water height (cm). At each irrigation, the discharge entering the farms was obtained using the above equations (Chamberlain 1952). The irrigation depth was calculated as follows:

$$I = \frac{Q * t}{A} \quad (5)$$

where t indicates the duration of irrigation (sec), A shows the area (m^2), and I shows the mean irrigation depth (mm).

Table 2 Characteristics of selected farms

Farm	Area (ha)		Planting arrangement (m*m)		Irrigation method	Crop	Variety	Seeding rate (Kg/ha)
	Treatment	Control	Treatment	Control				
W1	0.4	0.42	6*52	4.5*100	FI	Wheat	Pishgam	190
W2	0.26	0.2	0.6*52	0.6*100	BI	Wheat	Pishgam	230
W3	0.3	0.4	0.4*1.8	0.3*1.4	DTI	Tomato	Super-Stone	Transplanting
W4	0.3	0.35	3*4	3*4	BI	Grape	Seedless raisin	Sapling
W5	0.23	0.2	0.4*0.6	0.6*0.6	DTI	Tomato	Super-Stone	Transplanting

Table 3 Applied techniques and fertilizers used

Farm	Treatment/ Control	Applied techniques	Fertilizers	
			Type	Value
W1	Treatment	Leveling, Bed formation + Drill Sowing (BDS)	Urea	50 kg/ha
			Superphosphate	50 kg/ha
			Sulfur	100 kg/ha
	Control	–	–	–
W2	Treatment	Bed formation + Drill Sowing (BDS)	Urea	50 kg/ha
			Sulfur	50 kg/ha
	Control	–	–	–
W3	Treatment	Reversible plow, Cultivator	Urea	250 kg/ha
			Triple Superphosphate	200 kg/ha
			Sulfur Granules	300 kg/ha
			Animal manure	20,000 kg/ha
	Control	–	–	–
W4	Treatment	Covering mulch, Compost	Ammonium sulfate	100 kg/ha
			SoluPotasse	20 kg/ha
	Control	–	–	–
W5	Treatment		Urea	300 kg/ha
			SoluPotasse	20 kg/ha
			Superphosphate	150 kg/ha
	Control	–	–	–

The water discharge in BI and FI was measured by a WSC flume and that was a volumetric flow meter for DTI. The maximum irrigation interval in DI, BI, and FI treatment was 5 and 15 days, respectively.

Application efficiency (*AE*) indicates the losses of deep infiltration and runoff in the farm. AE is calculated in each irrigation interval from the following equation:

$$\mathrm{AE} = \frac{D_z}{D_{\mathrm{app}}} \times 100 \tag{6}$$

where AE is the application efficiency (%), D_z is the average depth of stored water in the root development zone (mm), and D_{app} is the average depth of water penetrating the area under irrigation (mm).

Deep percolation loss (DP) (%) was calculated as follows:

$$\mathrm{DP} = 100 - \mathrm{AE} \tag{7}$$

WP and WPe are as follows (Howell 2001; Abbasi et al. 2017):

$$\mathrm{WP} = \frac{Y\,(\text{usually economical yield})}{\mathrm{ET}} \tag{8}$$

$$\mathrm{WP}_e = \frac{N_P}{\mathrm{ET}} \tag{9}$$

where Y shows the economic yield (kg ha^{-1}) estimated based on the yielded product to the market, ET shows the evapotranspiration (mm), and N_P represents the net profit ($) based on the difference between the costs incurred during the growing season and the revenue generated by the crop yield.

ET is calculated as follows:

$$\mathrm{ET} = I + P + D_P + R_{\mathrm{off}} \pm \Delta S \tag{10}$$

$$\mathrm{ET} = I \pm \Delta S \tag{11}$$

where P indicates a wetted area (%), R_{off} shows the surface runoff (mm), and ΔS shows a change in soil moisture (mm).

Soil properties

A sampling of disturbed and undisturbed soil was accomplished to determine physical and chemical properties, soil texture, pH, saturated moisture, field capacity, and permanent wilting point at three depths of 0–30 cm, 30–60 cm, and 60–90 cm from the selected farms. The physical and chemical characteristics of soil and water are proposed in Table 4. The data in Table 5 were used to handle the irrigation schedule. The depth of root zone in farms W1, W2, W4, W5, and W3 was considered equal to 60 cm and 100 cm, respectively. Soil moisture was measured at depths of 0–30 and 30–60 cm by gravimetric method.

The permeability of the soil was measured for BI (W2), DTI (W3 and W5), and FI (W2 and W4) irrigation using the double ring and input–output flow methods, respectively. The mapping operation was carried out to determine the slope of the farms and to prepare a suitable seed bed. According to the mapping results and farm conditions, the leveling technique was performed on the farm.

To determine the grain yield, sampling was done randomly (1 m^2) from three to six points. At each farm, 20 plants were assumed randomly assumed to determine the yield components.

Artificial neural network (ANN)

ANN is a computer model that mimics how neurons work in the human brain. ANNs use learning algorithms that can be turned on their own (Basheer and Hajmeer 2000). ANN is a multilayer, fully connected neural network. An ANN consists of an input layer, some hidden layers, and an output layer. All nodes in one layer are connected to all other nodes in the next layer. The design of ANN models follows several systematic steps. In general, there are five basic steps (Dongare et al. 2012):

- Collect data,
- Data preprocessing,
- Building a network,
- Training, and
- Model test performance.

Collecting and preparing sample data is the first step in designing an ANN model. Figure 2 shows the scheme of the ANN model.

Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS is an intelligent neuro-fuzzy technique used to model and control imprecise and uncertain systems (Walia et al. 2015). ANFIS is based on the input/output data pairs of the system under consideration. Figure 3 shows the schema of the ANFIS model. ANFIS combines the advantages of ANN and fuzzy logic (FL) into one framework. It provides accelerated learning and adaptive interpretation capabilities for complex modeling patterns and capturing nonlinear relationships. The ANFIS structure consists of five layers: fuzzy layer, product layer, normalization layer, de-fuzzy layer, and total output layer (Jang 1993).

Table 4 Physical and chemical factors of soil and water

Depth (cm)	Clay	Sand	Silt	ECsoil (dS/m)	Texture	pHsoil	TNV (%)	OC (%)	FC (cm3/cm3)	PWP (cm3/cm3)	B.D (gr/cm3)	ECwater (dS/m)	pHwater	Farm
0–30	5.6	51.2	43.2	1.09	SL	7.66	16	0.43	0.22	0.07	1.63	0.43	6.77	W1
0–30	6.2	62.6	31.2	2.61	SL	8.16	10	0.33	0.19	0.07	1.63	-	-	W2
0–30	12	40	40	0.8	L	8.29	6	0.6	0.21	0.14	1.13	1.13	6.72	W3
0–30	6	72	22	0.52	SL	7.85	6.5	0.07	0.21	0.13	1.18	1.17	7.26	W4
0–30	32	36	32	4.16	CL	8.02	10.5	0.9	0.33	0.18	1.08	1.2	7.2	W5

pH: Acidity; θ_s: saturated moisture (volumetric); *TNV*: lime; *OC*: organic carbon; *FC*: field capacity; *PWP*: permanent wilting point; B.D: soil bulk density; *SL*: sandy loam; *L*: loam; *CL*: clay loam

Extreme learning machine (ELM)

ELM is a fast and robust machine learning algorithm. It is named after the single-layer feedforward neural network (SLFN) generalized in 2006–2008 (Huang et al. 2006). Fixed-weight SLFNs possess universal fitting properties, provided that the proper function is univariate.

SLFN is formulated as follows:

$$y = g\left(b_0 + \sum_{j=1}^{h} w_{j0} v_j\right)$$
$$v_j - f_i\left(b_i + \sum_{j=1}^{h} a_i s_i x_i\right) \tag{12}$$

where V_j shows hidden layer neurons ($j = 1, \ldots, n$), a_i shows the weight of the connections between the input variable and the neuron in the hidden layer, w_{jo} expresses the importance of the relationships between neurons in the hidden layer and output neurons, b_i represents the bias of neurons in the hidden layer, b_0 shows the tendency of the output neurons, f_i and g show the activation function of neurons and output neurons, respectively, and s_i describes a binary variable.

ELM theory supports that randomness in determining input weights can be imparted to a learning model without adjusting the distribution. ELM is a particular machine learning setup that applies a single layer or multiple layers (Wang et al. 2014). An ELM contains hidden neurons with randomly assigned input weights. Figure 4 shows a schematic of the ELM model.

Data normalization

To avoid negative effect of different scales of variables on estimation models, it is necessary to correct the data through preprocessing (Fig 5). The data were normalized as follows (Larose 2005):

$$x = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{13}$$

where x_i is the observed value and x is the normal data corresponding to x_i. Modeling data were randomly split into two parts: 80% for the training and 20% for the model test. Implementation and coding were performed using MATLAB R2013a software.

Performance Measures

To evaluate ANN, ANFIS, and ELM models root mean square error (RMSE), relative root mean square error (RRMSE), and efficiency measure (NSE) were used

Table 5 Average values of irrigation parameters

AE (%)		ETa (mm)		Q (l/s)		I (mm)		Irrigation interval	Field
Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment		
54	70	293.3	289.1	12.3	12.3	542.8	412.9	5	W1
55.4	69.9	267.7	266.1	18.5	13.3	483.1	380.2	5	W2
71.2	85	677.2	569.5	10	5.3	951.6	670	21	W3
55	61	451.2	418.1	5.9	5.6	820.3	684.6	3	W4
77.6	85	423.8	451.2	9.5	9.5	545.7	530.9	14	W5

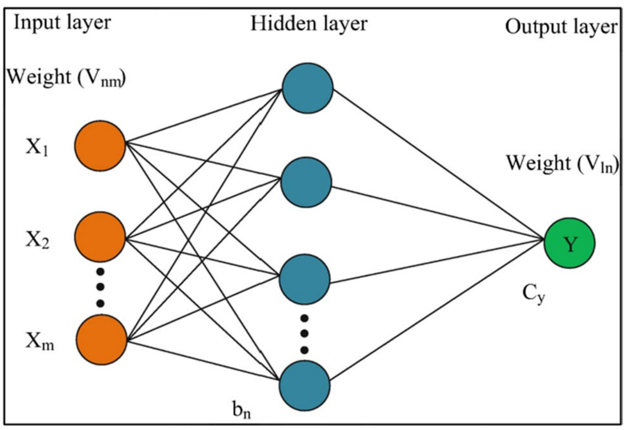

Fig. 2 Schematic of the ANN model

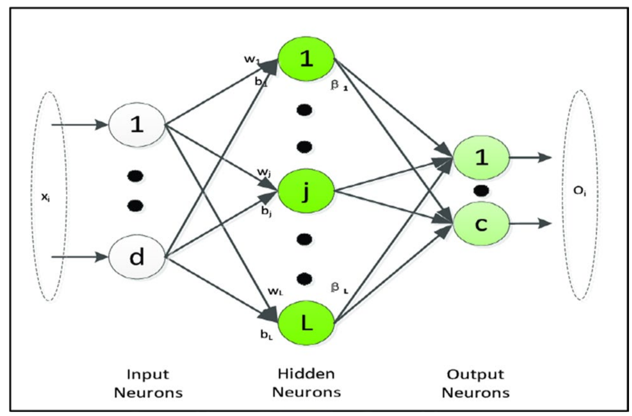

Fig. 4 Schematic of the ANFIS model

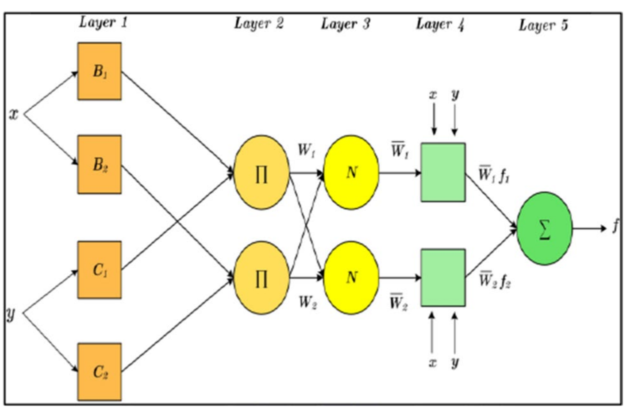

Fig. 3 Schematic of the ANFIS model

(Emami et al. 2021). The preferred criteria are provided by Eqs. 14–16.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_i - N_i)^2} \tag{14}$$

$$\mathrm{RRMSE} = \frac{\mathrm{RMSE}}{\sum_{i=1}^{n} M_i} \tag{15}$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(M_i - N_i)^2}{\sum_{i=1}^{n}(M_i - \overline{N})^2} \tag{16}$$

where M_i and N_i indicate the observed and estimated values of WP and WPe, respectively. $\overline{M}$ and $\overline{N}$ are average observed and estimated values of WP and WPe, respectively.

Results and Discussion

Field measurements

Table 5 summarizes the results of irrigation water (I), average discharge (Q), irrigation interval, actual evapotranspiration (ETa), and AE in the first to third irrigations in fields W1, W2, W3, W4, and W5.

In all treatment farms, the amount of irrigation water was reduced compared to the control. The reduction of irrigation

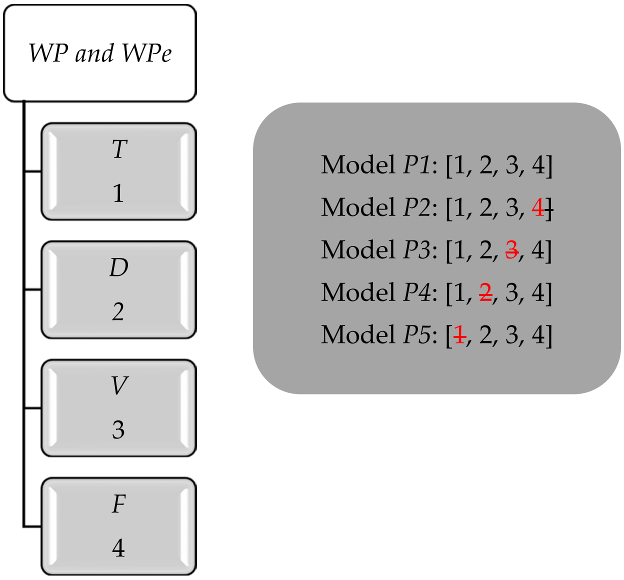

Fig. 5 Combination of input scenarios in WP and WPe modeling

water for farms W1, W2, W3, W4, and W5 was equal to 23.9%, 21.3%, 29.5%, 16.5%, and 2.7%, respectively. The average AE in fields W1, W2, W3, W4, and W5 was calculated as 22.8%, 22.8%, 20.7%, 9.8%, and 8.7%, respectively. The application of agronomic techniques improved AE by 21.80% in the treatment fields compared to the control. Reducing the dimensions of the plots in W1 and W6 farms and using compost and leveling in W3, W4, and W5 farms played a significant role in reducing irrigation water and increasing AE. Land leveling allows for the large development of surface irrigation through high WUE, land, labor, fertilizers, and energy resources managed (Miao et al. 2021). Precision land leveling saved irrigation water in corn. Precision land leveling along with irrigation management has a direct effect on the WP and WPe of corn (Miao et al. 2021). Okasha et al. (2013) showed that the zero % slope method increased irrigation water.

The use of animal manure in W3 farms played a significant role in reducing water consumption and increasing AE. The monitoring of soil moisture samples showed that animal manure had a considerable effect on water retention compared to the control. The uniformity and AE increase by reducing the length of the furrow and field (Savva et al. 2002). Abd El-Mageed et al. (2018) concluded that organic compost and soil mulch significantly improved seed and fodder production under low irrigation conditions. Eid and Negm, (2018) listed farm leveling and DTI systems as factors for improving water use efficiency. El-Kader et al. (2010) observed that the okra crop yield with animal manure was higher than with plant residues. Ding et al. (2021) found compost rate to be effective on WP and wheat yield. Hati et al. (2006) reported that the use of 10 mg of animal manure increases WUE by 103%. The use of animal manure leads to a higher yield (Loss et al. 2019). Palangi et al., (2020) reported that the treatments with animal manure have a significant difference of 5% in terms of volumetric soil moisture compared to the control. Afshar et al. (2011) reported that the increase in animal manure led to an increase in tuber yield, tuber weight, and WUE in potatoes. Sadeghipour (2015) showed that the effect of animal manure on yield and WUE was statistically significant. Total tomato yield increased by 63% in animal manure treatment (Antonious 2018). Das et al. (2018) reported that the plots under permanent broad bed had 29% higher corn grain yield than conventional tillage. Ahmadabadi and Ghajarsepanlou, (2012), Wang and Yang, (2002), and Karlen and Camp, (1985) concluded that organic fertilizers increase soil moisture retention.

The amount of ETa improvement in the treatment farms W1, W2, W3, W4, and W5 was 1.4%, 0.6%, 15.9%, 7.3%, and 6.5%, respectively, compared to the control. Applied agronomic technologies such as modifying the dimensions of the plots and proper leveling were potentially effective in reducing ETa values in the treatment section compared to the control. In Table 6, the calculated ETa values are compared with those reported by researchers in other regions of Iran for the wheat crop. The difference between the results of this research and the results reported by other researchers is due to ETa being affected by climatic conditions (Allen et al. 1998).

In W1 and W2, grain yield increased in treatment farms compared to control. The yield increase in W1, W2, W3, W4, and W5 was 11.1%, 12.9%, 24.6%, 10%, and 30.9%, respectively, compared to the control. To measure WPe, the costs of different stages of planting and purchasing crops in the crop year 2020–2021 were calculated. In Table 7, the net profit of the examined crops (the difference between the gross income and the total costs of the crop area) is presented. In Table 8, the values of yield, WP, and WPe in the treatment and control sections are shown.

The results showed that modifying the fertilization schedule and changing the crop variety effectively increased yield. Tabatabaei et al. (2015) reported that the highest seed yield was obtained in the treatment of animal manure. The effect of the animal manure factor on relative yield, WUE, and fertilizer consumption was significant (Sadeghipour 2015). The results showed that with decreasing water consumption, WP increases, which is consistent with the results of research by Afshar et al. (2020) and Dehghanisanij et al. (2022). WP has a real relationship with yield and an inverse relationship with water consumption (Rockström and Barron 2007). Researchers have reported that agronomic management and fertilizer use play a significant role in increasing WP (Oweis 1999; Kumruzzaman and Sarker 2017; Noor et al. 2020; Munyasya et al. 2022). Researchers regarded

Table 6 Comparison of calculated wheat evapotranspiration values with different regions of Iran

Study	Region	Eta (mm)
Lashkari et al. (2010)	Sarpol-e Zahab	678
	Ravansar	581
	Islamabad-e-Gharb	581
Present study (2022)	Malekan (W1)	291.2
	Malekan (W2)	266.9

that the optimal use of nitrogen fertilizer in citrus increased WP by 15% (Qin et al. 2016). Tillage affected increasing crop yield and WP. Researchers reported that intermittent tillage improves the physical and chemical characteristics of the soil, and increases the yield and WP (Hou et al. 2012).

Modeling results

Dataset

A dataset of five farms, including agronomic technologies such as changes in tillage methods (T), irrigation plot dimensions (D), crop varieties (V), and fertilizer (F) schedule. WP and WPe were used as the main outputs of the model. The agronomic technologies considered earlier are presented in Table 1 (https://zoom.earth/#view=37.7191,46.80333,9z/map=live). Table 9 shows four scenarios to determine the most suitable input variables for WP and WPe estimation. In selecting of variables, first, all the factors were considered as inputs to the models, then one of the input factors was removed, and ANN, ANFIS, and ELM models were re-implemented (Emami et al. 2021; Haghiabi et al. 2017).

The comparisons between the models show that the ANFIS and ELM models have a reasonable estimate of WP and WPe. In Table 10, ANFIS, ELM, and ANN models are compared in estimating WP and WPe. The analysis of the results showed that the ANFIS model with RMSE = 0.016 in scenario *P5* has a higher efficiency in evaluating WP and WPe compared to the ELM and ANN models.

Table 9 Different variables in estimating WP and WPe

Inputs parameters	Scenarios
T, D, V, F	P1
T, D, V	P2
T, D, F	P3
T, V, F	P4
D, V, F	P5

In Fig. 6a, b, the R^2 and RMSE of ANFIS, ELM, and ANN models in estimating WP and WPe are compared. The results of the evaluation indices showed that the ANFIS is in a more appropriate and acceptable range compared to the ELM and ANN methods.

Different scenarios in WP and WPe estimation using the ANFIS model are evaluated in Table 11. Variable selection results show that the model *P5* using the ANFIS method with values of RMSE = 0.016, RRMSE = 0.018, and NSE = 0.960 has a significant impact on WP and WPe estimation. Scenario *P5* estimates WP and WPe values based on crop variety, fertilizer, and irrigation plot dimensions. Scenario *P5* confirms that WP and WPe are positive with the moisture content at the field capacity (FC) and negative with the moisture content at the permanent wilting point (PWP). By increasing the moisture content at the FC point, the water maintaining capacity in the soil increases. Dehghanisanij et al. (2021) concluded that crop variety is the most critical factor in estimating WP in tomato crops. Taliei and Bahrami, (2002) showed that the soil moisture level at the time of planting is one of the determining factors in estimating the WP of dryland wheat. Scenario *P1* (T, D, V, F) is in the second category,

Table 7 Costs of different stages of planting and the guaranteed purchase price of crops (unit 10 Rials)

Crop	Farm preparation	Planting	Growth	Harvest	Total costs	Price (Per Kg)
Wheat	155,250	250,500	328,000	150,000	883,750	1500
Tomato	105,000	115,000	235,000	130,000	585,000	500
Grape	195,000	262,500	385,000	475,000	1,317,500	1700

Table 8 Yield, WP, and WPe values in treatment and control sections

Farm	Yield (kg/ha)		WP (kg/m^3)		Improved WP (%)		WPe (Rial/m^3)	
	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control
W1	6300	5600	2.1	1.9	–	10.5	2179	1909
W2	6200	5400	2.3	2	–	15	2329	2017
W3	50,443	38,000	8.8	5.6	–	57.1	3542	2244
W4	10,000	9000	2.4	1.9	–	26.3	2960	2473
W5	7600	5250	1.7	1.2	–	41.6	3737	2955

Table 10 Comparison of ANFIS, ELM, and ANN in estimating WP and WPe

Model	Train			Test		
	RMSE	RRMSE	NSE	RMSE	RRMSE	NSE
ANFIS	0.011	0.013	0.975	0.016	0.018	0.960
ELM	0.028	0.031	0.953	0.035	0.038	0.941
ANN	0.057	0.061	0.910	0.065	0.070	0.883

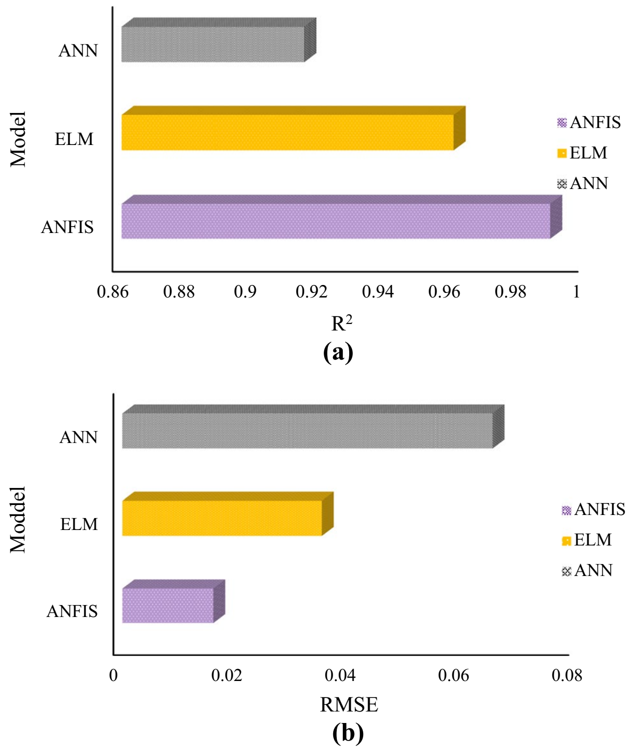

Fig. 6 **a**, **b** Comparison of ANFIS, ELM, and ANN models in estimating crop WP and WPe

which shows that tillage methods have a more significant impact on WP. Keshvari (2018) reported that conservation tillage increases WP by 10.5% compared to conventional tillage. Khorramian and Ashraeizadeh (2020) concluded that using new crop varieties and tillage improves WP by 3% to 4%. Conservation tillage leads to a 16% reduction in water consumption (Keshvari 2018).

In Figs. 7 and 8, the estimated results (WP and WPe) are compared with the observed data, and R^2 values are calculated.

The results showed that the ANFIS model is highly effective in estimating WP and WPe with $R^2 = 0.980$ values. The scenario *P5*, with inputs of crop variety, irrigation plot dimensions, and fertilizer, has the most optimal values of statistical indicators. Richards et al. (2010) and Tatari et al. (2008) stated that WP is directly related to soil moisture content at FC pint. The results of the present study with the outcomes of the investigations of Sangtarashan et al. (2021), Hill and Cruse (1985), and Hu et al. (2018) are consistent.

Figure 9 shows the effectiveness of agronomic technologies in farms W1, W2, W3, W4, and W5 based on WP and WPe indicators.

The results showed that the agronomic techniques applied in the treatment fields W1, W2, W3, W4, and W5 led to an increase in WP and WPe indices by 40%, 20%, 35%, 13%, and 23%, respectively. Several types of research emphasize the increase of WP and WPe indices by applying agronomic techniques, and the results of this study are consistent (Hill et al. 1985; Hu et al. 2018). Sangtarashan et al. (2021) reported that the agronomic technologies led to an increase in WP, WUE, and WPe indices by 38%, 31%, and 56%, respectively.

Conclusion

In this paper, the physical and economic WP was estimated using ANFIS, ELM, and ANN models. The results showed that the use of agronomy techniques improved AE by 21.80% in treated farms compared to the control. Also, reducing plot dimensions and using animal manure in the

Table 11 Evaluation of the different scenarios in estimating WP and WPe

Model	Train			Test		
	RMSE	RRMSE	NSE	RMSE	RRMSE	NSE
P1	0.023	0.025	0.968	0.027	0.030	0.952
P2	0.078	0.082	0.835	0.085	0.089	0.824
P3	0.033	0.036	0.956	0.040	0.042	0.937
P4	0.042	0.044	0.950	0.046	0.049	0.931
P5	0.011	0.013	0.975	0.016	0.018	0.960

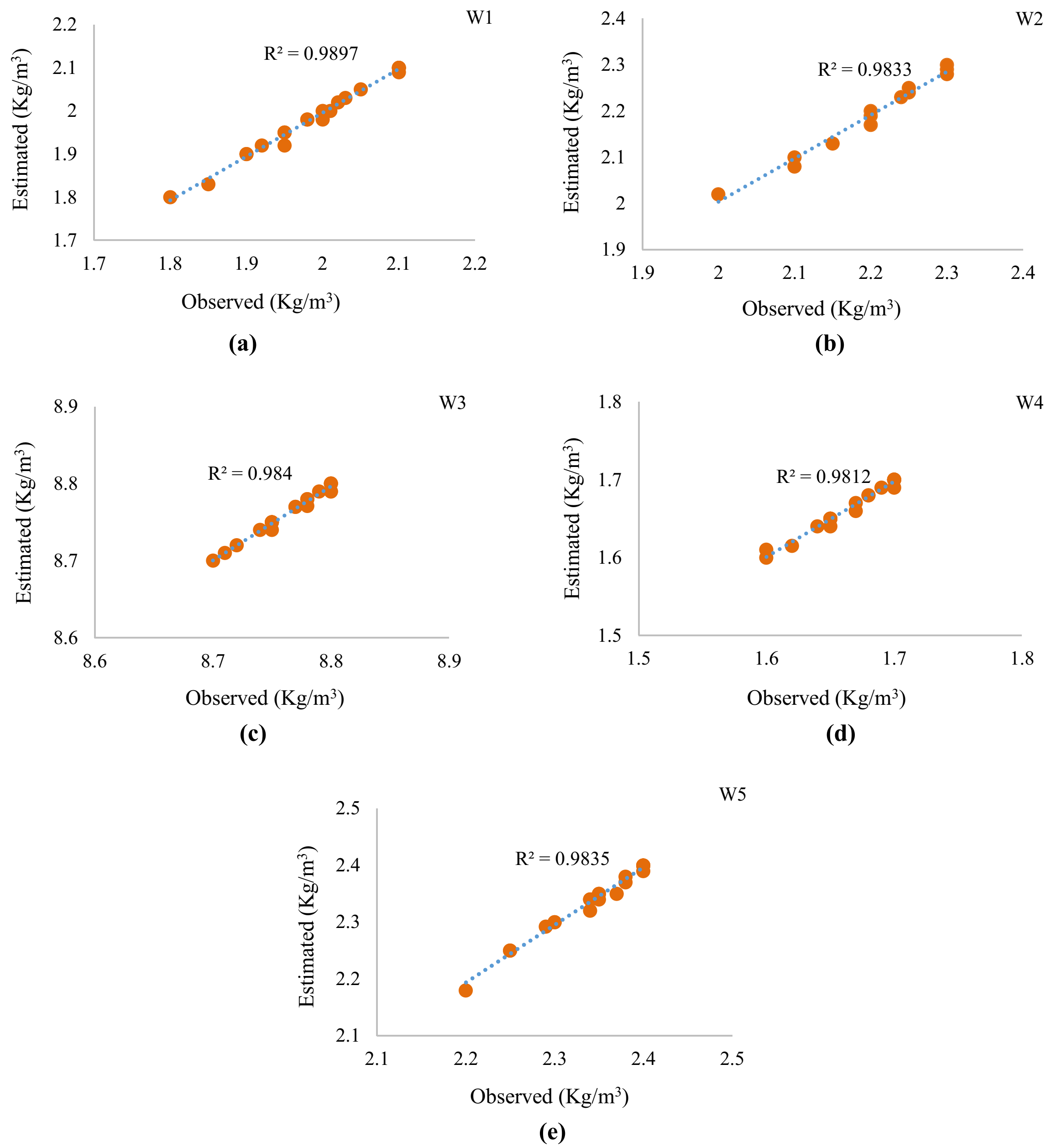

Fig. 7 (a, b, c, d) Comparison of measured and estimated WP

basin and furrow irrigation methods played a significant role in reducing irrigation water consumption and increasing AE. The results showed that WP increases as water consumption decreases. Tillage methods affected the increase in yield and WP. The modeling results showed that the ANFIS model has good efficiency in estimating WP and WPe by considering the crop variety, fertilizer, and irrigation plot dimensions as model inputs. By regarding the parameters of crop variety, fertilizer, and irrigation plot dimensions, it is possible to achieve a more accurate estimation of WP and WPe. In the agricultural sector (for farmers), it is possible to find the best effective parameters in the estimation of WP, WPe, crop yield, and irrigation agronomic plans using intelligent methods. The results demonstrated that ANFIS could be used to predict other irrigation variables. Additionally, more advanced optimization algorithms can be used to speed up the convergence rate search for the best inner ANFIS variables and optimize the training process. In general, the results of this research may help farmers with limited resources in choosing a cost-effective crop management method to increase WP, WPe, crop yield, crop nutritional composition, etc.

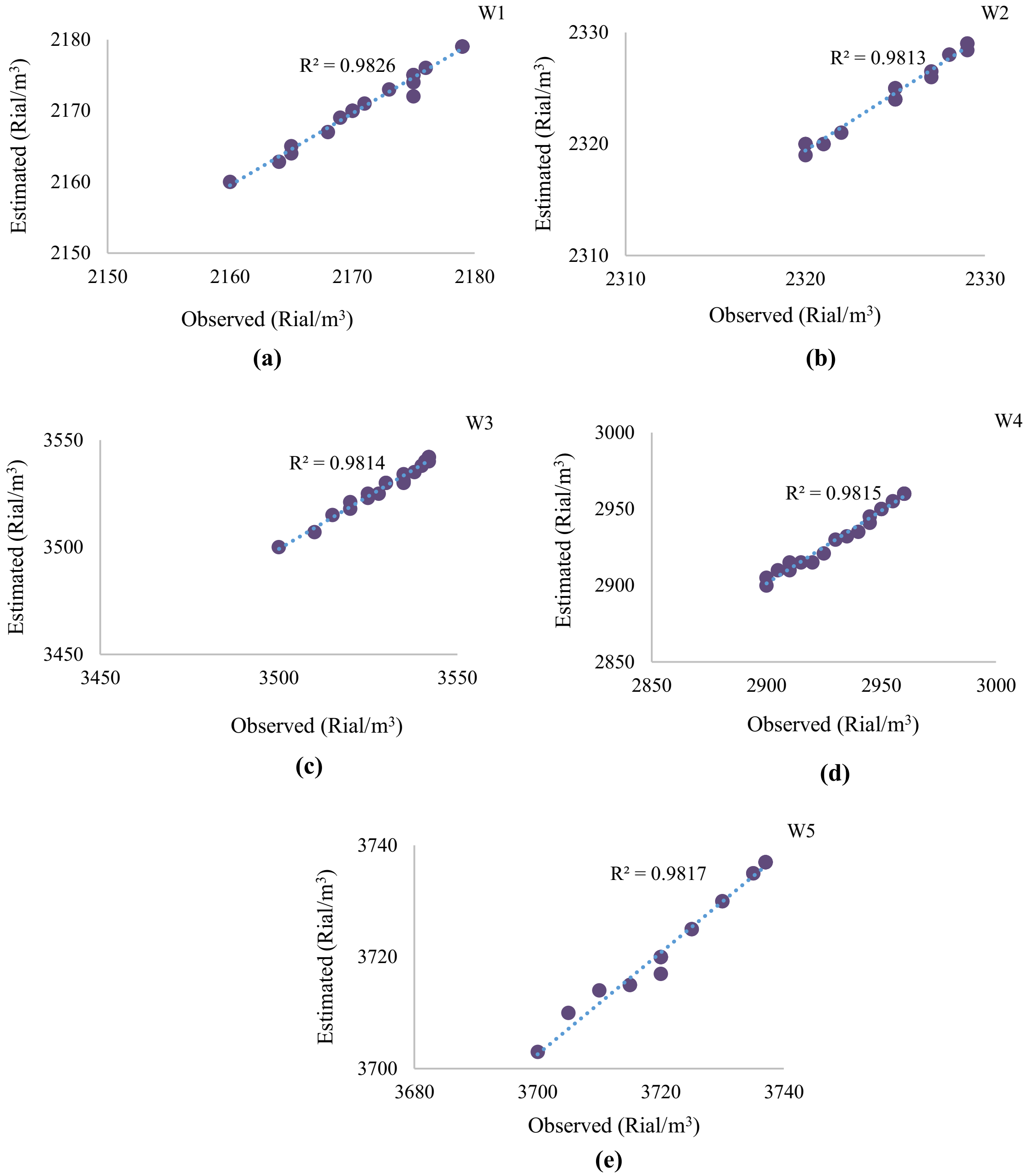

Fig. 8 (a, b, c, d, e) Comparison of measured and estimated WPe

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Author contributions HD and MA conceived the study; HD was responsible for methodology, project administration, and funding acquisition; SE was involved in software, formal analysis, investigation, resources, data curation, and visualization; MA, NT TL, and SE contributed to validation; HD, SE, and MA wrote the original draft; HD, SE, MA, and NT TL took part in writing—reviewing and editing; and HD and NAl-A participated in supervision. All authors have read and agreed to the published version of the manuscript.

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Declarations

Conflicts of interest The authors declare no conflict of interest.

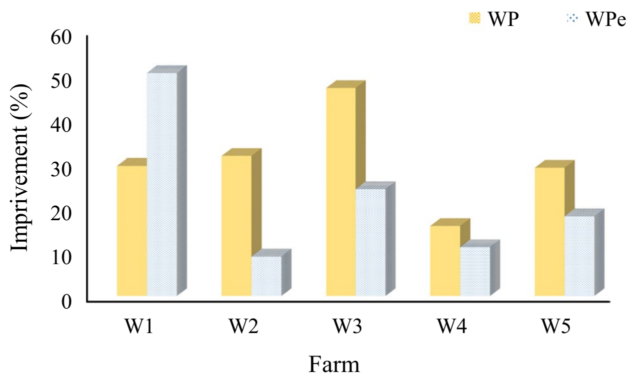

Fig. 9 Effectiveness of agronomic technologies based on WP and WPe indicators

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