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Simulating spring wheat growth under simultaneous salinity and water stress using the AquaCrop model

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ABSTRACT

Crop growth simulation models are developed to predict the effects of different factors, including water and salinity on grain, biomass yields, and water efficiency of various crops. These models are typically calibrated and validated for specific regions based on the availability of measured field data. In this research, spring wheat growth under simultaneous salinity and water stress was Simulated using the AquaCrop model. Calibration and validation were conducted using data from 2010 and 2011, respectively. Results indicate that AquaCrop accurately simulated spring wheat yield, biomass, water use efficiency, and harvest index under salinity and water-limiting conditions. The simulation of harvest index and soil salinity profiles was less precise compared to other characteristics. The mean values of NRMSE, ME, d, CRM, and R2 for grain yield were 13.3%, 36.1%, 0.95, -0.072, and 0.87, respectively in both calibration and verification. For biomass, these measures were 12.59%, 34.46%, 0.92, 0.057, and 0.77, separately. The corresponding values for the soil moisture profile were 11.84%, 25.72%, 0.93, and 0.032, while for the soil salinity profile, they were 26.25%, 58.5%, 0.91, and -0.12, respectively. The most sensitive parameters included the crop transpiration coefficient, normalized crop water productivity, reference harvest index, volumetric water content at field capacity, soil water content at saturation, and temperature.

Highlights

- The AquaCrop model accurately simulated spring wheat yield, biomass, and water use efficiency, under salinity and water stress conditions.
- The model was sensitive to parameters like crop transpiration coefficient, and normalized crop water productivity, at field capacity and saturation.
- The model's simulation of soil salinity was less precise compared to other variables.
- AquaCrop's evaluation was based on two years of field data and demonstrated its applicability for analyzing and forecasting salinity and water stress in spring wheat.
- The model's simplicity requirements make it suitable for evaluating various irrigation scenarios and optimizing water usage in spring wheat cultivation.

1. Introduction

The agricultural sector is the largest consumer of water in arid and semi-arid regions of Iran. As a result, managing water for agriculture is the most important and sensitive aspect of any integrated water conservation project. Implementing deficit irrigation (DI) and using saline water for irrigation are among the most effective strategies for addressing water shortages. However, since both saltiness and drought reduce the availability of soil water for plant roots, yield reduction must be anticipated precisely (Dominguez et al., 2011; Haghverdi et al., 2014). Additionally, salinity is a common outcome of long-term DI action in arid and semi-arid regions. Different researchers have suggested that the solution to the freshwater deficiency issue is deficit irrigation and using of saline water in Iran (e.g., Dehghanisanji et al., 2009;

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Gowing et al., 2009; Kiani and Abbasi 2009). However, there have been few studies focusing on deficit irrigation for spring wheat. Globally, spring wheat with low water requirements is harvested before the high evaporative demand of summer crops. In contrast, its water use efficiency increases since it can take advantage of spring precipitation (Lopez-Urrea et al., 2009).

Agro-hydrology simulation models that assess the influence of water on crop yield at the farm level are valuable tools for making decisions about irrigation management (Pereira et al., 2009; Shafiei et al., 2014). Consequently, to improve management practices, models based on experimental data can be developed to assess crop water requirements (CWR) and enhance irrigation management capabilities under conditions of salinity and water stress. Models allow for the combined assessment of various factors that affect productivity to determine the optimal amounts of water for different situations (Liu et al., 2007). All models should be calibrated and evaluated before use (Nain and Kersebaum 2007). During calibration, model parameters are modified to achieve accurate predictions based on observed data. Conversely, validation involves running the model with independent variables while keeping the parameters consistent (Nain and Kersebaum 2007; Salazar et al., 2009).

In the past few decades, several models such as SOYMOD (Meyer et al., 1981), CERES-Maize (Jones and Kiniry 1986), WOFOST (Todorovic et al., 2009), CropSyst (Stockle et al., 2003), and APSIM (Marinov et al., 2005) have been developed and employed to study irrigation management at the farm level. However, most of these models are quite complex, requiring advanced modeling skills for calibration and numerous input parameters such as Leaf Area Index (LAI). Some models are specific to certain types of plants and are not easily adaptable for general use. However, the newly developed FAO AquaCrop model (Raes et al., 2009a) is designed to be a user-friendly and practical-oriented model (Raes et al., 2009a). It strikes a good balance between accuracy, reliability, and simplicity, requiring only a few input parameters. This model can predict crop yield, water demand, water shortage, and saline water conditions (Raes et al., 2009b). It has been applied and validated for various plants such as maize (Zea mays L.) (Abedinpour et al., 2012; Mebane et al., 2013), cotton (Gossypium hirsutum L.) (Garcia-Vila et al., 2009; Hussein et al., 2011), sunflower (Todorovic et al., 2009), potato (Solanum tuberosum L.) (Vanuytrecht et al., 2011), winter wheat (T. aestivum L.) (Andarzian et al., 2011; Salemi et al., 2011; Mkhabela and Bullock 2012; Kumar et al., 2014), and quinoa (Chenopodium quinoa Willd.) (Geerts et al., 2009) in different places and conditions. All of these research studies have concluded that the model can accurately simulate crop biomass, product yield, and soil water dynamics under both full irrigation and water shortage conditions. Additionally, AquaCrop can simulate soil water content and salinity profiles using basic soil and climate data. The importance of accurately estimating soil water and salinity in agriculture cannot be overemphasized. AquaCrop accounts for various factors in adjusting water for the soil profile investigated by the root system, including evaporation, transpiration, runoff, infiltration, internal drainage, deep percolation, and root uptake (Raes et al., 2009a). Additionally, AquaCrop has been used to determine and optimize irrigation schedules under different levels of salinity and irrigation amounts (Raes et al., 2012).

In most arid and semi-arid regions, the lack of water is associated with reduced water quality, leading to increased salinity. In these areas, plants may be affected by both salinity and water stress simultaneously. The AquaCrop model has not been utilized to simulate spring wheat yield under simultaneous saltiness and water shortage conditions, and sensitivity analysis of the model has not been carried out for spring wheat. Hence, this model (v4.0) assessed synchronous saltiness and water shortage conditions in this study. This version was developed in 2012 to evaluate the impacts of saltiness (Raes et al., 2012). Therefore, the goals of this study were: i) to evaluate the ability of the AquaCrop model (v4.0) to simulate spring wheat yields, biomass, harvest Index (HI), water productivity (WP), soil water content, and saltiness profiles in synchronous saltiness and water stress conditions and ii) to conduct a sensitivity analysis of AquaCrop model for spring wheat in the semi-arid area of Mashhad, Iran.

2. Materials and Methods

2.1. Study area

This study was conducted at the research farm of Ferdowsi University of Mashhad at 36◦16′ N latitude, 59◦38 ′ E longitude in northeastern Iran. It was a two-year cropping study conducted in 2010 and 2011. The spring wheat cultivar (Triticum-aestivum) was planted on the 14th of March 2010 and the 18th of March 2011. Table 1 shows the Physical properties of the soil profile and Table 2 presents the Weather parameters during spring wheat cropping seasons (i.e., from March to July), 2010 and 2011, in the experimental location, Mashhad region of Iran.

Table 1. Soil information in the study area (Haghverdi et al., 2014).

Soil properties	Depth (cm)			
	0-20	20-40	40-70	70-100
Texture	loam	loam	loam	clay loam
θ_{FC} (cm^3cm^{-3})	0.3	0.32	0.32	0.32
θ_{PWP} (cm^3cm^{-3})	0.14	0.15	0.16	0.16
θ_{sat} (cm^3cm^{-3})	0.44	0.40	0.44	0.44
K_{sat} ($cm\ h^{-1}$)	182.6	120.4	81.8	81.8
Bulk density ($g\ cm^{-3}$)	1.35	1.4	1.48	1.48
ECe ($dS\ m^{-1}$)	2	2	2.1	2.1

Table 2. Weather parameters during spring wheat cropping seasons 2010 and 2011

Weather parameters	2010	2011
Average of minimum daily temperature (ºC)	13.57	12.99
Average of maximum daily temperature (ºC)	26.96	26.51
Average of monthly precipitation (mm)	24.93	56.94
Average of minimum daily relative humidity (%)	27.81	35.87
Average of maximum daily relative humidity (%)	64.75	59.90

The typical irrigation interval in this area is 12 days. However, for this study, a 10-day irrigation interval was used throughout the irrigation season to prevent any water stress. The irrigation water (IW) amount was precisely measured using a volumetric water flow meter with a sensitivity of 0.1 L. Two different sources of water with different electrical conductivity (EC) levels, 0.5 and 10 dS m-1, were available for use. The farm had not previously been irrigated with saline water before the experiment in 2010, so there were no issues with saltiness in the first year of the research.

In the second year, the plot area was adjusted so that the plots previously irrigated with saline water were excluded from the experiment. Salinity and DI treatments were applied to all crops after the third leaves had emerged in both cropping seasons. Earlier, all plots were fully irrigated with the same amount of non-saline water. Plant disease and pest management, fertilizer application, and tillage practices were consistent across all plots. The first cropping season was harvested on June 23, 2010, and the second on July 3, 2011.

The harvesting involved hand-harvesting utilizing the center of each plot (i.e., 1 m2) to avoid the possible edge impact of neighboring plots.

2.2. Experimental designs

The information on spring wheat was collected from farm experiments carried out in the study area, as mentioned in Haghverdi et al. (2014). Two different experimental plans were used in the first and second years. In the first year, a four-factor, two-level factorial plan (Myers et al., 2009) was used, while in the second year, a five-factor, five-level central composite plan (CCD; Myers et al., 2009) was employed.

The study examined different levels of available water (IW) at various wheat growth stages: seedling growth-tillering, stem elongation-booting, heading-flowering, and dough stage-ripening. In the first year, the IW levels were 20%, 60%, and 100%, while in the second year, they were 30%, 40%, 65%, 90%, and 100%. The salinity levels were 0.5 and 10 dS m-1 in the first year, and 0.5, 1.8, 5.25, 8.6, and 10 dS m-1 in the second year. Different levels of salinity were achieved by mixing two different water sources with salinity levels of 0.5 and 10 dS m-1 in storage tanks. The growth stages were determined weekly using the Zadoks et al. (1974) growth stages code (Table 3). In the first and second years, there were 36 and 45 plots, each measuring 2 m×2.1 m. These plots were arranged in 4 rows with 2 m spacing between rows and 1 m spacing between plots within each row, except for the side effects.

The detailed information about the first and second years of the experiment is presented in Tables 4 and 5. They include the levels of each treatment applied. During the first year, the Irrigation Water (IW) was calculated using time-domain reflectometry (TDR) readings from TRASE Model 6050X1 probes (Soil Moisture Equipment, Santa Barbara, CA, USA). Before applying treatments, four moisture probes were placed at 20, 40, 70, and 100 cm soil depths in each plot.

The soil moisture from the 100% IW treatment, which was irrigated with non-saline water, was used to calculate the irrigation amounts for all treatments.

Soil moisture was measured the day before irrigation, and the irrigation water (IW) requirement was calculated as the difference between the actual water content and the Field Capacity (FC) in the root zone. Based on previous local observations, the maximum root zone depth for spring wheat was assumed to be 1 m at the last irrigation, approximately two weeks before harvesting, with a linear growth rate during the cropping season.

Because of having many plots and limiting financial and labor resources, TDR probes were not used in the second year. Instead, volumetric sampling was achieved the day before each irrigation event from the main plot, which was fully irrigated with non-saline water to calculate the amount of IW.

The distribution of salt in the root zone was monitored by measuring the salinity of saturated paste from samples collected randomly from different plots at different growth stages in two depths (0–30 cm and 30–60 cm) throughout the second year. Initial random sampling before applying treatments showed that the soil profile salinity level of the entire experimental area was consistent and negligible.

Table 3. Growth stages of spring wheat in Mashhad region and corresponding irrigation water (Haghverdi et al., 2014).

Growth stages	Symbol	Zadoks growth stages	1st year irrigation (mm)[b]	2nd year irrigation (mm)
Beginning	0	Emergence-seedling growth	40, 40	40, 40
Beginning[a]	1	Seedling growth-tillering	36, 52	36, 54
Middle	2	Stem elongation-booting	44, 84	63, 87
Middle	3	Heading-flowering	62, 112	96, 122
End	4	Dough stage-ripening	148	150

[a] Beginning of the deficit and saline treatments.

[b] b Irrigation values belong to the full irrigation treatment applied using both non-saline (0.5 dS m^{-1}) and saline (10 dS m^{-1}) water resources.

Table 4: Detailed information on experimental plots and variable levels during the first cropping season (Haghverdi et al., 2014).

Plot	Variable					Plot	Variable				
	1	2	3	4	EC		1	2	3	4	EC
1	F[a]	0.2F	F	0.2F	0.5	19	0.2F	F	F	F	10
2	0.2F	F	0.2F	0.2F	0.5	20	F	F	F	F	10
3	F	F	0.2F	F	0.5	21	0.2F	0.2F	F	0.2F	10
4	0.6F	0.6F	0.6F	0.6F	0.5	22	0.2F	F	F	0.2F	10
5	0.2F	0.2F	0.2F	F	0.5	23	0.6F	0.6F	0.6F	0.6F	10
6	F	F	F	0.2F	0.5	24	0.2F	0.2F	0.2F	F	10
7	F	0.2F	F	F	0.5	25	0.2F	0.2F	0.2F	0.2F	10
8	0.2F	F	F	F	0.5	26	F	0.2F	F	0.2F	10
9	0.6F	0.6F	0.6F	0.6F	0.5	27	0.2F	F	0.2F	F	10
10	0.2F	F	F	0.2F	0.5	28	F	F	0.2F	F	10
11	0.2F	F	0.2F	F	0.5	29	F	F	0.2F	0.2F	10
12	F	0.2F	0.2F	0.2F	0.5	30	F	F	F	0.2F	10
13	0.2F	0.2F	F	0.2F	0.5	31	0.6F	0.6F	0.6F	0.6F	10
14	F	F	0.2F	0.2F	0.5	32	0.2F	F	0.2F	0.2F	10
15	0.2F	0.2F	0.2F	0.2F	0.5	33	0.2F	0.2F	F	F	10
16	F	F	F	F	0.5	34	F	0.2F	F	F	10
17	F	0.2F	0.2F	F	0.5	35	F	0.2F	0.2F	F	10
18	0.2F	0.2F	F	F	0.5	36	F	0.2F	0.2F	0.2F	10

[a] F: Full irrigation; 1, 2, 3, 4: irrigation water (% of full irrigation treatment) at different growth stages (identical to Table 3), EC: irrigation water salinity (dS m^{-1}).

Table 5. Detailed information on experimental plots and variable levels during the second cropping season (Haghverdi et al., 2014).

	Variable					Plot	Variable				
	1	2	3	4	EC		1	2	3	4	EC
1	F[a]	F	F	F	0.5	24	0.3 F	0.65F	0.65F	0.65F	5.25
2	0.65F	0.65F	0.65F	0.65F	0.5	25	0.65F	0.65F	0.65F	0.3F	5.25
3	0.9F	0.9F	0.9F	0.9F	1.89	26	0.65F	0.3F	0.65F	0.65F	5.25
4	0.9F	0.9F	0.9F	0.4F	1.89	27	0.65F	0.65F	0.3F	0.65F	5.25
5	0.4F	0.9F	0.9F	0.9F	1.89	28	0.9F	0.9F	0.9F	0.9F	8.61
6	0.9F	0.4F	0.9F	0.9F	1.89	29	0.4F	0.9F	0.9F	0.9F	8.61
7	0.4F	0.9F	0.9F	0.4F	1.89	30	0.9F	0.9F	0.9F	0.4F	8.61
8	0.4F	0.4F	0.9F	0.9F	1.89	31	0.9F	0.4F	0.9F	0.9F	8.61
9	0.9F	0.9F	0.4F	0.9F	1.89	32	0.4F	0.9F	0.9F	0.4F	8.61
10	0.9F	0.4F	0.9F	0.4F	1.89	33	0.9F	0.4F	0.9F	0.4F	8.61
11	0.9F	0.9F	0.4F	0.4F	1.89	34	0.9F	0.9F	0.4F	0.9F	8.61
12	0.4F	0.9F	0.4F	0.9F	1.89	35	0.4F	0.4F	0.9F	0.9F	8.61
13	0.4F	0.4F	0.9F	0.4F	1.89	36	0.9F	0.9F	0.4F	0.4F	8.61
14	0.9F	0.4F	0.4F	0.9F	1.89	37	0.4F	0.9F	0.4F	0.9F	8.61
15	0.4F	0.9F	0.4F	0.4F	1.89	38	0.9F	0.4F	0.4F	0.9F	8.61
16	0.9F	0.4F	0.4F	0.4F	1.89	39	0.4F	0.4F	0.9F	0.4F	8.61
17	0.4F	0.4F	0.4F	0.9F	1.89	40	0.4F	0.9F	0.4F	0.4F	8.61
18	0.4F	0.4F	0.4F	0.4F	1.89	41	0.9F	0.4F	0.4F	0.4F	8.61
19	0.65F	0.65F	F	0.65F	5.25	42	0.4F	0.4F	0.4F	0.9F	8.61
20	0.65F	F	0.65F	0.65F	5.25	43	0.4F	0.4F	0.4F	0.4F	8.61
21	F	0.65F	0.65F	0.65F	5.25	44	F	F	F	F	10
22	0.65F	0.65F	0.65F	0.65F	5.25	45	0.65F	0.65F	0.65F	0.65F	10
23	0.65F	0.65F	0.65F	F	5.25						

[a] F: Full irrigation; 1, 2, 3, 4: irrigation water (% of full irrigation treatment) at different growth stages (identical to Table 3), EC: irrigation water salinity (dS m^{-1}).

2.3. Model description

The AquaCrop model needs a few easily accessible parameters grouped into four categories: climatic, crop, soil, and field management data. This model estimates daily water balance, including all incoming and outgoing water fluxes (infiltration, runoff, deep percolation, evaporation, and transpiration) and changes in soil water content. To run AquaCrop, five weather input variables are needed: daily maximum and minimum air temperatures (T), daily rainfall, daily reference evapotranspiration (ETo), and mean annual CO2 concentration in the atmosphere. The first four variables can be obtained from typical agrometeorological stations, while the CO2 concentration data is sourced from records at the Mauna Loa Observatory in Hawaii. AquaCrop simulates the attainable yields of major herbaceous crops based on water consumption under different conditions such as rainfed, extra, shortage, and full irrigation. This is water-driven crop growth model that depends on the conservative behavior of biomass per unit transpiration (Tr) relationship (Raes et al., 2009a). The model calculates transpiration and separates soil evaporation from crop transpiration using canopy ground cover instead of leaf area index (LAI) as a basis. Crop yield depends on above-ground dry biomass and harvest index (HI). The model simulates crop responses to water deficits based on the differing sensitivity to water stress of four key plant processes: canopy expansion, stomatal control of transpiration, canopy senescence, and HI. The harvest index (HI) can be adjusted negatively or positively depending on the level of stress, its timing, and its duration. Soil salinity stress can have an impact on crop production. AquaCrop uses 4 stress coefficients (KsCCx, Ksexp,f, fCDecline, and Kssto, salt) to describe the effect of soil salinity stress on crop development and production. These coefficients account for factors such as maximum canopy cover, canopy expansion, decline coefficient of canopy cover, and stomatal closure. Also, biomass production can be influenced by soil salinity stress, which is quantified using the soil salinity stress coefficient (Kssalt) (Raes et al., 2012). The average electrical conductivity of saturation soil-paste extract (ECe) from the root zone is an important indicator of soil salinity stress. While AquaCrop provides default values for various crop parameters used in simulating different crops like wheat, some of these parameters need to be adjusted to fit local conditions, crop varieties, and management practices.

A method described in BUDGET is utilized to simulate the movement and retention of salt in the soil in AquaCrop (Raes et al., 2006). To represent the movement and retention of soil water and salt, AquaCrop divides the soil profile into multiple compartments (12 by default) with a thickness of Δz. To simulate the movement and diffusion of salts, each soil compartment is further divided into several cells where salts can be stored. The number of cells, ranging from 2 to 11, depends on the soil type of the soil layer. A clayey layer will typically have more cells than a sandy layer due to the strong attachment of salts to clay particles. The electrical conductivity of saturated soil paste extract (ECe) at a specific soil depth (soil compartment) can be estimated using Equations 1 to 3 (Raes et al., 2012):

$$W_{cell} = 1000\frac{\theta_{sat}}{n}\Delta z \quad (1)$$

$$Salt_{cell} = 0.64 W_{cell} EC_{cell} \quad (2)$$

$$EC_e = \frac{\sum_{j=1}^{n} Salt_{cell,j}}{0.64(1000\theta_{sat}\Delta z)} \quad (3)$$

In the equation, $Salt_{cell}$ represents the salt content in grams per square meter of soil surface. The value 0.64 is a conversion factor (1 dS m^{-1} = 0.64 g l^{-1}). W_{cell} stands for the volume of the water in the cell, measured in millimeters. θ_{sat} is the soil water content at saturation (m3 m-3) of the soil horizon. The variable n represents the number of cells, and Δz denotes the thickness of the soil compartment (m).

2.4. Sensitivity analysis

Before applying a model, it's important to understand how it behaves and is sensitive to different input parameters. Sensitivity analysis (SA) helps to identify which parameters have a significant impact on the model's output (Cao and Petzold, 2006). SA, developed in the late 1990s, is a relatively new method for understanding how mathematical and computer models respond to changes in input parameters. If variations in input parameter values only have a minor impact on model predictions, then the input data have an insignificant effect on the results. It means that errors in the field measurements may be negligible. The inputs for SA in the present study are agronomic, soil, meteorological, and irrigation management data. The model was first run with corresponding data of full irrigation treatment with EC equal to 0.5 dS m^{-1}. The results (wheat grain yield, average soil water content, and EC_e) were considered "basic outputs". In subsequent model runs, each step involved modifying one of the inputs while keeping the other inputs constant. The range of variation for the inputs was selected to be between -25% and +25% of their median value (Geerts et al., 2009). After adjusting the input parameters, the model outputs were compared to the "basic outputs" using the sensitivity coefficient (Sc) (Geerts et al., 2009).

$$Sc = \left|\frac{P_m - P_b}{P_b}\right| \times 100 \quad (4)$$

Where Pm represents the output after changing the input value and Pb represents the output before changing the input value. In general, Sc would be used before the calibration stage. Sensitivity classes were categorized as high, moderate, and low, based on the model's response to changes in inputs: greater than 15%, between 15% and 2%, or smaller than 2%, respectively (Geerts et al., 2009).

2.5. Calibration and validation

The model was calibrated using data from the first cropping season field experiment. Initially, the agronomical parameters of spring wheat from Table 6 were used as model inputs for full irrigation non-saline treatment (FI0.5). Then, the maximum canopy cover (CCX), canopy decline coefficient (CDC), normalized water productivity (WP*), and maximum effective rooting depth (Zx) were adjusted through trial and error for this treatment until the lowest relative error (RE) between simulated and measured grain yield and biomass was achieved. The soil moisture data for the first and second years were used to calibrate and validate soil parameters, respectively. During the second year, soil salinity profiles were monitored, and this data was used for validation. The parameters θ_{sat}, θ_{FC}, θ_{PWP}, and K_{sat} were calibrated using trial and error with the soil moisture data from the first year. The calibration process continued until the lowest root mean squared error (RMSE) between simulated and measured soil moisture was achieved. At the same time, efforts were made to minimize the difference between simulated and measured grain yield and biomass. Then, the model was adjusted for the saline full irrigation treatment with an electrical conductivity of 10 dS m^{-1} (FI10). This adjustment used the observed green canopy cover (CC), biomass production, upper threshold for electrical conductivity (p-upper) (dS m^{-1}), lower threshold for electrical conductivity (p-lower) (dS m^{-1}), and the salinity stress curve shape. The reference treatment with no soil salinity stress (FI0.5) and the stressed treatment with soil salinity stress (FI10) were considered according to Raes et al. (2012). The model was calibrated by adjusting the coefficients of water stress and salinity (i.e. soil water depletion threshold for stomatal control (p-upper), shape factor for water stress coefficient for stomatal control, soil water depletion threshold for canopy senescence (p-upper), and shape factor for water stress coefficient for canopy senescence) for 12 treatments in the first year (plots 1, 2, 3, 9, 15, 16, 20, 23, 25, 26, 28, and 32) until the RMSE of the measured and simulated grain yield and biomass were minimized. These 12 treatments were selected from a high number of treatments to represent the range of applied water stresses. The default values from the AquaCrop manual appendix (Raes et al., 2009b) were used for certain parameters like soil water depletion threshold for canopy expansion (p-upper), soil water depletion threshold for canopy expansion (power), and shape factor for water stress coefficient for canopy expansion. These parameters were considered to be broadly applicable and not specific to a particular crop variety (Raes et al., 2009b). After adjusting the model, it was tested with data from the second year to forecast grain yield, biomass, WP, and soil moisture and salinity profiles.

Table 6. Selected non-conservative (cultivar specific) and conservative input for spring wheat (Raes et al., 2009b).

Parameter description	Value	Unit or meaning
Conservative parameters		
Base temperature	0	˚C
Cut-off temperature	26	˚C
Canopy cover per seeding at 90% emergence (CC_0)	2	cm^2
Crop coefficient for transpiration at CC = 100%	1.1	Full canopy transpiration relative to ET_o
Soil water depletion threshold for canopy expansion (*p-upper*)	0.2	As fraction of TAW, above this leaf growth is inhibited
Soil water depletion threshold for canopy expansion (*p-lower*)	0.65	Leaf growth stops completely as this p
Shape factor for water stress coefficient for canopy expansion (f_{shape})	5	Moderately convex curve
Soil water depletion threshold for stomatal control (*p-upper*)	0.65	Above these stomata begin to close
Shape factor for water stress coefficient for stomatal control (f_{shape})	2.5	Highly convex curve
Soil water depletion threshold for canopy senescence (*p-upper*)	0.70	Above this early canopy senescence begins
Shape factor for water stress coefficient for canopy senescence (f_{shape})	2.5	Moderately convex cure
Coefficient inhibition of leaf growth on HI	Small	HI increased by inhibition of leaf growth at anthesis
Coefficient inhibition of stomata on HI	Moderate	HI reduced by inhibition of stomata at anthesis
Non-conservative parameters		
Tim from sowing to emergence	7	day
Time from sowing to start senescence	90	day
Time from sowing to maturity	102	day
Time from sowing to flowering	74	day
Length of flowering stage	10	day
Minimum effective rooting depth, Z_x	0.3	m
Time from sowing to maximum rooting depth	59	day
Reference harvest index, HI_o 40% Common for good condition	39	Common for good condition
Building up of HI, days (CDD)	34	day

2.6. Model evaluation

During the validation process, the simulation results for wheat grain yield, biomass, HI, WP, and soil water content and salinity were compared with the observed/measured values. Various statistical indices such as coefficient of determination (R2), regression line of best agreement, normalized root mean square error (NRMSE, Eq. 5), index of agreement (d, Eq. 6), and coefficient of the residual mass (CRM, Eq. 7) (Willmott 1982) were used to compare the simulated and observed data.

$$\mathrm{NRMSE} = \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}\right]^{0.5} \times \frac{100}{\overline{O_i}} \quad (5)$$

$$d = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(\left|P_i - \overline{O_i}\right| + \left|O_i - \overline{O_i}\right|)^2} \quad (6)$$

$$\mathrm{CRM} = \frac{\sum_{i=1}^{n} O_i - \sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} O_i} \quad (7)$$

where Pi and Oi are predicted and observed data, respectively, is the mean value of Oi, and n is the number of observations.

A simulation is considered perfect if the NRMSE is less than 10%, acceptable if it falls between 10% and 20%, fair if it ranges from 20 to 30%, and poor if it exceeds 30% (Jamieson et al., 1991). The value "d" is dimensionless and falls within the range of 0 to 1.0, where 0 and 1.0 represent complete disagreement and complete agreement, respectively. The CRM indicates a model tendency to either overestimate or underestimate measured parameter values.

3. Results and Discussion

3.1. Sensitivity analysis

The model's sensitivity to certain parameters can indicate over-parameterization or high dependence on specific calculation procedures. Sensitivity analysis helps identify which parameters require accurate field measurements and model calibration. In a simulation of soil moisture and salinity profiles, it was found that for simulating soil moisture, θFC and θPWP had moderate sensitivity, while θsat and Ksat had low sensitivity. For simulating soil salinity, moderate sensitivity was attributed to θPWP, θFC, and *Ksat*, while θsat had low sensitivity. Therefore, precise determination of $\theta FC$and θsat is crucial for modeling.

The sensitivity analysis of AquaCrop input parameters for simulating grain yield is presented in Table 7. The results showed that the crop coefficient for transpiration (KcTr), WP*, and reference harvest index (HIo) were key parameters for the model, as they exhibited high sensitivity to these parameters. The time from sowing to maximum canopy cover is crucial because rapid canopy development leads to higher biomass and yield due to increased transpiration. Additionally, parameters such as soil water depletion threshold for stomatal control (p-upper), shape factor for water stress coefficient for stomatal control (shape), soil water depletion threshold for canopy senescence (p-upper), and shape factor for water stress coefficient for canopy senescence (shape) require attention, as the model is calibrated under deficit irrigation conditions using these parameters. For these parameters, the sensitivity of the model increases for the most stressed treatments (Geerts et al., 2009). The model was not sensitive to plant density, CGC, emergence, length of the flowering stage, upper temperature, K_{sat}, θ_{PWP}, θ_{sat}, initial soil salinity, and rainfall. However, the sensitivity of the model to input parameters may depend on the type of crop and climate of the study region. For instance, Salemi et al. (2011) demonstrated that winter wheat in Ahvaze, Iran, with a hot climate was sensitive to WP* and KcTr, while the maximum temperature was moderate. In contrast, sensitive parameters for quinoa (Chenopodium quinoa Willd) in the Bolivian Altiplano, with an arid climate, were WP*, HIo, θ_{FC}, θ_{PWP}, soil water depletion threshold for canopy senescence (p-upper), soil water depletion threshold for canopy expansion (p-upper), maximum rooting depth, and rainfall (Geerts et al., 2009).

Table 7. Sensitivity coefficient (Sc) of AquaCrop for winter wheat in Mashhad, Iran.

	Input parameter	S_c (+25%)	S_c (-25%)	Sensitivity level
		%		
Agronomic parameters	Crop coefficient for transpiration (Kc_{Tr})	0.29	20.33	Moderate
	plant density	1.27	1.7	Low
	CGC	1.80	1.74	Low
	WP^*	23.62	25.26	High
	HI_o	20.05	25.52	High
	emergence	1.97	1.12	Low
	Time from swing to maximum canopy cover	3.04	7.69	Moderate
	Time from swing to flowering	9.6	1.10	Moderate -Low
	Length of flowering stage	0.11	1.07	Low
	Upper temperature	0.0	0.0	Low
	maximum rooting depth (Zr_X)	0.24	1.32	Low
	Soil water depletion threshold for canopy expansion (*p-upper*)	0.33	0.42	Low
	Soil water depletion threshold for canopy expansion (*p-lower*)	0.89	1.67	Low
	Shape factor for water stress coefficient for canopy expansion (f_{shape})	0.40	0.85	Low
	Soil water depletion threshold for stomatal control (*p-upper*)	3.71	4.43	Moderate
	Shape factor for water stress coefficient for stomatal control (f_{shape})	2.02	1.99	Moderate
	Soil water depletion threshold for canopy senescence (*p-upper*)	2.74	2.12	Moderate
	Shape factor for water stress coefficient for canopy senescence (f_{shape})	2.01	2.23	Moderate
Soil parameters	θ_{FC}	17.88	0.63	High- Low
	θ_{sat}	0.33	1.16	Low
	θ_{PWP}	1.90	1.79	Low
	K_{sat}	0.0	0.0	Low
Initial conditions	Soil moisture	0.96	14.73	Low- Moderate
	Soil salinity	0.0	0.0	Low
Climate parameters	Maximum temperature	0.75	2.3	Low- Moderate
	Rainfall	0.63	0.78	Low

3.2. Soil water content and salinity

The soil hydraulic parameters were adjusted to ensure that the simulated soil water content closely matched the observed values (Table 8). Upon reviewing the table, it was noted that all of the adjusted soil hydraulic parameters, except θ_{PWP}, were higher compared to the measured values (Table 2). This indicates that the RETC model may have underestimated these parameters. The model performed well in simulating soil water content and salinity, as shown in Table 9, which demonstrates good agreement with the observed values. Specifically, during the validation phase, the average NRMSE, CRM, and d values for soil water content were 11.27, 0.002, and 0.94, respectively. For soil salinity, the corresponding values were 26.5, -0.12, and 0.91, as shown in Table 9. The evaluation of the model revealed that it underestimated soil water content (positive CRM values) and overestimated soil salinity (negative CRM values), although these discrepancies were relatively minor. Based on Table 9, it was observed that the model exhibited higher accuracy in simulating soil water content compared to simulating soil salinity. It is important to note that as the salinity of irrigation water increases, soil salinity also increases, but the distribution across the soil profile is not uniform. Consequently, simply averaging soil salinity at different soil layers (0-30 and 30-60 cm) for any salinity treatment may not accurately represent the salinity distribution. Therefore, the model may have a greater error in simulating soil salinity compared to simulating soil water content. The statistical metrics used to assess model performance in simulating soil water content during calibration and validation phases exhibited nearly the same. The root mean square error (RMSE) values for soil water content during calibration and validation were recorded as 12.41% and 11.27%, respectively. It is noteworthy that the model was calibrated solely based on soil water content data. Furthermore, the model's ability to accurately simulate soil salinity also supports the claim that it has been effectively calibrated.

Table 8. Calibrated soil hydraulic parameters for simulating soil water content and salinity during spring wheat cultivation.

Depth of soil (cm)	θ_{FC}	θ_{PWP}	θ_{sat}	K_{sat}
		(%)		(Cm h^{-1})
0-20	31	13.8	45.9	185
20-40	30.8	13.4	45.6	140
40-70	32.6	15.7	46.0	87
70-90	32.5	15.7	45.5	86

Table 9. Statistical comparison of observed and predicted soil water content (first-year data for calibration, second-year data for validation) and salinity (second-year data for validation at 0-30 cm and 30-60 cm depths).

Parameter	Method	NRMSE (%)	*d*	CRM
soil water content	calibration	12.41	0.93	0.06
	Validation	11.27	0.94	0.002
soil salinity	Validation	26.25	0.91	-0.12

In Figure 1, both simulated and measured values of soil water content and salinity are presented. The results show significant values (0.77 for soil water content and 0.81 for soil salinity), indicating a strong correlation between the simulated and measured values. These findings align with existing literature. Mkhabela and Bullock (2012) found RMSE, R2, and d values of 49.4 mm, 0.9, and 0.99, respectively, when using AquaCrop to simulate soil water content in a combination of clay and silt loam in Western Canada under dry and humid continental climate conditions for spring wheat. In a study by Mebane et al. (2013), RMSE values ranged from 0.015 to 0.098 m3 when using AquaCrop to simulate soil water content for six different soil depths in a silt loam combination in Pennsylvania with a humid continental climate for rained maize. The model's accuracy in simulating soil water content seems to be influenced by the specific soil type, crop, and regional climate, with variations observed in different soils and climates.

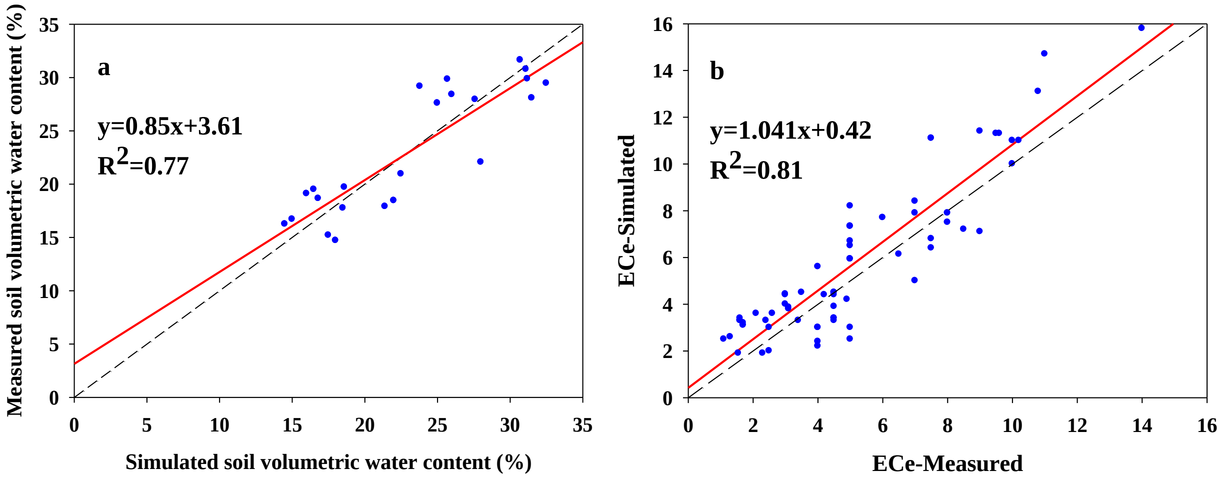

Figure 1. Simulated and measured values of soil water content (a) and salinity (b) during the second growing season.

According to various researches, it has been observed that other models, such as the SWAP model demonstrate a behavior similar to the AquaCrop model. This behavior results in varying soil salinity estimates across different regions. The authorities (Jiang et al., 2011; Kumar et al., 2015; Mohammadi et al., 2016) do not provide a clear explanation for this behavior. The differences in soil characteristics, irrigation methods, and the chemical composition of irrigation water (specifically anions and cations) in different areas are cited as potential reasons for the model's varying behavior. These parameters were found to vary across different sources. Notably, The

AquaCrop model, like the SWAP model, does not consider the dissolution process and sedimentation in the transfer of solutes. In most soils under irrigation, chemical reactions that lead to dissolution or sedimentation (involving anions and cations) may result in salt being added to or removed from the soil solution. Therefore, since these processes are not considered in the model, the calculated salinity may underestimate, accurately estimate, or overestimate the expected salinity. In arid and semi-arid regions, most water resources are saturated with calcium carbonate and some others also contain large amounts of sulfate ions. The presence of this anion in some water sources results in sedimentation as gypsum in the soil. It's important to note that the effects of salinity can be mitigated by water containing high levels of sedimentation anions as well as high concentrations of calcium and magnesium. However, the AquaCrop model does not account for the chemical reactions that lead to solubility in the soil. Therefore, the chemical composition of irrigation water significantly influences the model's behavior across different regions. Additionally, the model's behavior in simulating soil salinity in diverse regions may be influenced by the assumption of a constant diffusion factor. However, in real conditions, the heterogeneity of soil, along with the unsaturation of all soil layers due to seams, cracks, and water courses, can lead to differences between predicted and measured soil salinity values after leaching.

The lower accuracy of the AquaCrop model in simulating salinity could potentially be attributed to the simplification of solute transport equations. The movement of salts in the soil is influenced by a multitude of factors, such as mass transfer, diffusion, water propagation, salt adsorption, salinity degradation, and sedimentation. While the AquaCrop model accounts for mass transfer and diffusion processes in solute transport, it overlooks the influence of other pertinent mechanisms. Notably, studies referenced in the literature (Jiang et al., 2011; Kumar et al., 2015; Mohammadi et al., 2016) have demonstrated that the estimation of soil moisture content varies in different regions. Therefore, it can be concluded that simulating soil moisture content using the AquaCrop model depends not only on different levels of irrigation water but also on the climate and type of soil in the area. The variation in salinity of irrigation water across different regions can be another factor leading to different simulations of soil moisture. The model's underestimation of moisture content may be due to the water balance equation not accounting for certain factors affecting water movement, such as preferential flows and hysteresis. AquaCrop, like most soil water simulation models, assumes that saturated soils drain to field capacity within a short period. Additionally, AquaCrop currently does not have a mechanism to handle input from a rise in the water table, such as a capillary rise from a shallow water table (Raes et al., 2011).

3.3. Grain yield, biomass, HI, and WP

The calibrated crop parameters for spring wheat and water stress coefficients can be found in Table 10. These parameters include Ksto (soil salinity stress coefficient for stomatal closure), EC threshold (p-upper) (dS m^{-1}), EC threshold (p-lower) (dS m^{-1}), and salinity stress curve shape. These parameters were obtained after calibrating the model for salinity conditions. It's worth noting that the water stress coefficients, WP*, and EC thresholds can vary from AquaCrop default values due to factors such as crop type, climate, water stress conditions, and salinity levels of irrigation water. Notably, research has demonstrated that these coefficients and thresholds differ from the default values in various regions and for different crops, such as wheat in New Delhi, India, and rainfed wheat in Western Canada, as well as maize. Kumar et al. (2014) reported that water stress coefficients and EC thresholds under irrigated saline regimes for wheat in New Delhi, India were found to be different than AquaCrop default values. Mkhabela and Bullock (2012) reported water stress coefficients and WP* for rainfed wheat in Western Canada were different than AquaCrop default values. Similar reports were obtained for maize as well (Abedinpour c2012).

Table 10. Calibrated crop-type AquaCrop parameters and water stress coefficients corresponding to the best calibration process for simulating grain yield and biomass of spring wheat.

Parameter	Value	Parameter	Value
CC_X (%)	96	EC threshold (*p- lower*) (dS m^{-1})	4
CDC (%)	9	salinity stress curve shape	2
Zr_X (m)	1.07	Soil water depletion threshold for stomatal control (*p-upper*)	0.44
$K_{sto,salt}$	0.6	Shape factor for water stress coefficient for stomatal control (f_{shape})	1.7
WP^* (g m^{-2})	19	Soil water depletion threshold for canopy senescence (*p-upper*)	0.83
EC threshold (*p-upper*) (dS m^{-1})	13	Shape factor for water stress coefficient for canopy senescence (f_{shape})	2.3

The data in Table 11 shows a comparison between the measured and simulated yield, biomass, harvest index (HI), and water productivity (WP) for spring wheat. The d values were very close to one, except for HI, indicating that the simulated grain yield, biomass, and WP were similar to the measured values. In most cases, the values were sufficiently high, and the CRM values were close to zero, confirming a good correlation between simulated and measured values. The NRMSE values in most cases were lower than 15%, which is considered good. However, the model accuracy for simulating yield and biomass was better than the simulation of WP and HI. It's important to note that Hussein et al. (2011) also reported a less accurate simulation of HI (d=0.66) compared to the simulation of grain yield (d=0.99), biomass (d=0.99), and WP (d=0.99) for cotton Andarzian et al. (2011) conducted a study where they found that the AquaCrop model effectively simulated soil water content in the root zone, as well as crop biomass and grain yield for both fully and deficit-irrigated wheat production in Ahvaz, Iran. Additionally, Mkhabela and Bullock (2012) confirmed the capability of AquaCrop to simulate wheat grain yield accurately. The comparison between the modeled and observed wheat grain yield demonstrated a satisfactory agreement, with statistical indices including R2 of 0.66, d of 0.99, RMSE of 743, and MAE of 611 kg ha−1. Notably, the statistical indices for model calibration and validation were found to be consistent, indicating a well-calibrated model (Table 11).

Table 11. Statistical comparison of measured and simulated yield, biomass, HI, and WP for spring-winter wheat calibration and validation in Mashhad, Iran.

Parameter	Process	NRMSE (%)	*d*	CRM	R^2
Yield	Calibration	11.82	0.98	-0.08	0.94
	Validation	14.79	0.92	-0.064	0.79
Biomass	Calibration	13.28	0.94	0.07	0.84
	Validation	11.91	0.90	0.045	0.69
WP	Calibration	11.93	0.91	-0.08	0.81
	Validation	15.77	0.82	-0.083	0.61
HI	Calibration	21.2	0.70	-0.149	0.51
	Validation	16.77	0.69	-0.135	0.49

The accuracy of the AquaCrop model decreases in high salinity and low irrigation conditions (Figures 2 to 5). Heng et al. (2009) found that the model's accuracy in simulating corn yield under high stress is reduced, but it is acceptable under low and medium stresses. They suggested that the model needs to be reviewed and refined to address this issue. Additionally, Gertz et al. (2009) reported that the model overestimates the yield of Quinoa under full irrigation conditions, as it assumes a fixed amount of normalized water productivity under both full irrigation and deficit irrigation conditions. If the normalized water productivity decreases by 9% and is used for simulation under full irrigation conditions, the results will be improved. Therefore, one reason for reduced model accuracy under both wet and dry conditions is the model's use of a constant value for this parameter. The authors also identified the simulation of the harvest index as a factor contributing to the differences in model accuracy in biomass and yield simulation. They recommended that the model should be adjusted and improved to account for the impact of waterlogging on the harvest index. Todorich et al. (2009) reported that the simplifications adopted in AquaCrop and also in CropSyst could be a limiting factor of both models when severe water stress conditions need to be analyzed. This is particularly due to the lack of a more complex plant physiological submodel to account for water stress's impact on biomass growth and its partitioning into yield. Additionally, Homaei et al. (2002) pointed out that multiplicative models lack a physical basis and cannot differentiate between the various components of soil water energy and their individual effects. Moreover, in the AquaCrop model, the impact of salinity stress on vegetation growth, transpiration, and ultimately crop yield is considered by multiplying it in terms of drought stress (Raes et al., 2012). Therefore, this method is identified as another factor contributing to reduced model accuracy under conditions of salt and drought stress.

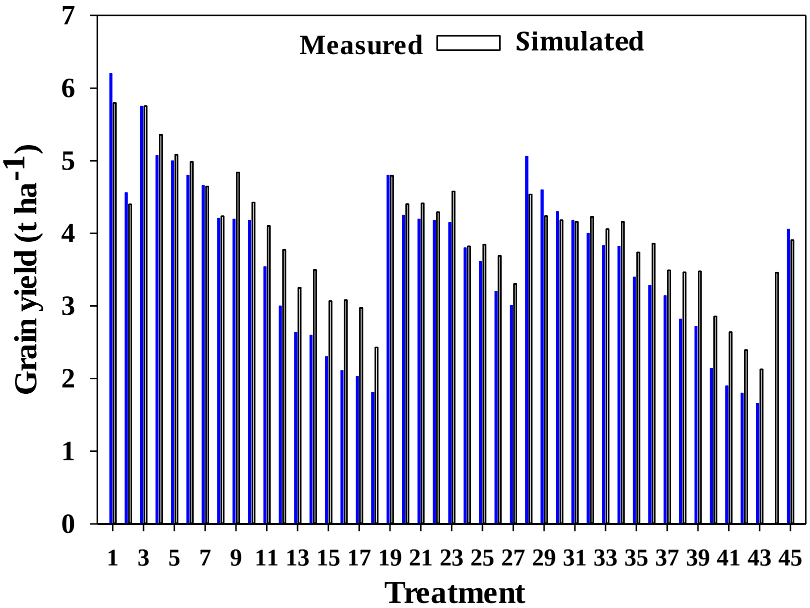

Figure 2. Measured and simulated grain yield of spring wheat in Mashhad. Plot numbers are based on Table 5.

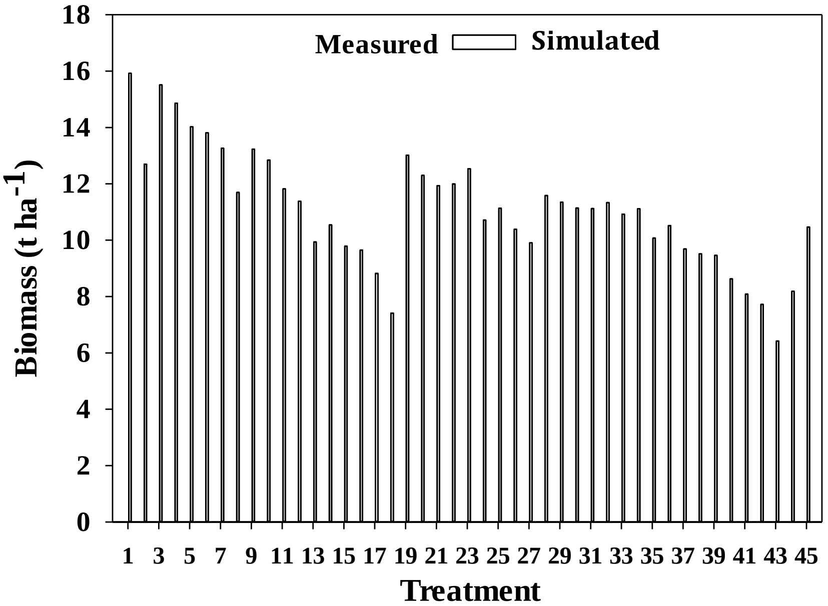

Figure 3. Measured and simulated biomass of spring wheat in Mashhad. Plot numbers are based on Table 5.

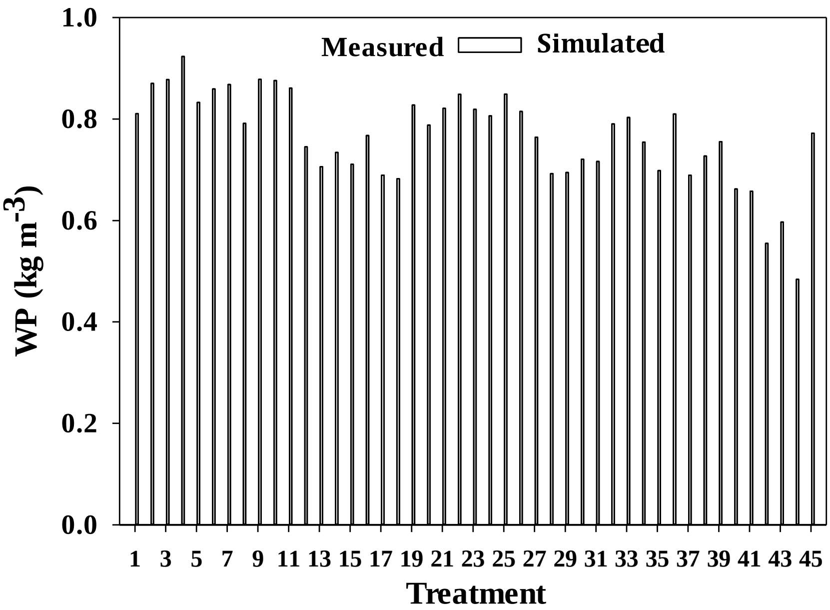

Figure 4. Measured and simulated WP of spring wheat in Mashhad. Plot numbers are based on Table 5.

4. Conclusion

AquaCrop is a simulation model designed to evaluate how water and salinity levels affect crop yield. It uses a basic set of crop parameters and input data, including climate, soil, field, and irrigation management information. Even though it has a simple model structure, AquaCrop is essential for simulating key processes related to crop productivity and how crops respond to water from both physiological and agronomic perspectives. Thus, the evaluation of AquaCrop is especially important for strategic crops such as spring wheat.

In the present study, AquaCrop's efficacy was evaluated based on two years of field-measured data for spring wheat in Mashhad. The primary objective was to ascertain the model's applicability as a tool for analyzing and forecasting salinity and water stress conditions. Sensitivity analysis indicated moderate sensitivity to θ_{FC} and θ_{PWP} for simulating soil water content and moderate sensitivity to θsat for simulating soil salinity. However, for simulating grain yield, the model showed high sensitivity to K_{cTr}, WP*, HIo, and θ_{FC}. AquaCrop was calibrated and validated separately and simultaneously for all salinity treatments. The evaluation of the AquaCrop model showed that it accurately simulated grain yield, biomass, HI, WP, soil water content, and salinity. However, the simulation of HI and soil salinity was less accurate compared to yield and biomass. The model's accuracy in simulating yield and biomass was better than that for WP and HI. The agreement between modeled and observed wheat grain yield, biomass, and WP was satisfactory, with R2 values close to one in most cases, NRMSE values ranging between 10 and 20%, and CRM values close to zero. In the validation phase, the average value of NRMSE, CRM *d*, and R2 for soil water content were 11.27, 0.002 0.94, and 0.77, respectively, and for soil, salinity was 26.5, -0.12, 0.91, and 0.81, respectively.

The AquaCrop model is simple and requires minimal data, making it suitable for use with a wide range of available measurements. As a result, it can be used to evaluate different irrigation scenarios involving varying water qualities, including increased salinity. This application aims to optimize water usage and improve irrigation management for spring wheat cultivation in the Mashhad region.

Data Availability Statement

All data, models, and code generated or used during the study appear in the submitted manuscript.

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