Irrigation Scheduling and Production of Wheat with Different Water Quantities in Surface and Drip Irrigation: Field Experiments and Modelling Using CROPWAT and SALTMED

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Abstract: Water is a key factor in global food security, which is critical to agriculture. The use of mathematical models is a strategy for managing water use in agriculture, and it is an effective way to predict the effect of irrigation management on crop yields if the accuracy of these models is demonstrated. The CROPWAT and SALTMED models were tested in this study, with water quantities applied to surface and drip irrigation (SI and DI) systems to estimate irrigation scheduling and wheat yield. For this purpose, field experiments were conducted for two consecutive years to study the effects of irrigation water levels of 80%, 100%, and 120% crop evapotranspiration (I80, I100, and I120) on the yield and water productivity (WP) of wheat in SI and DI systems. Irrigation treatments affected yield components such as plant height, number of spikes, spike length, and 1000-kernel weight, though they were not statistically different in some cases. In the I80 treatment, the biological yield was 12.8% and 8.5% lower than in the I100 and I120 treatments, respectively. I100 treatment under DI resulted in the highest grain yield of a wheat crop. When DI was applied, there was a maximum (22.78%) decrease in grain yield in the I80 treatment. The SI system was more water-consuming than the DI system was, which was reflected in the WP. When compared with the WP of the I80 and I100 treatments, the WP was significantly lower (p < 0.05) in the I120 treatment in the SI or DI system. To evaluate irrigation scheduling and estimate wheat yield response, the CROPWAT model was used. Since the CROPWAT model showed that increasing irrigation water levels under SI for water stress coefficient (Ks) values less than one increased deep percolation (DP), the I120 treatment had the highest DP value (556.15 mm on average), followed by the I100 and I80 treatments. In DI, I100 and I120 treatments had Ks values equal to one throughout the growing seasons, whereas the I80 treatment had Ks values less than one during wheat’s mid- and late-season stages. The I100 and I80 treatments with DI gave lower DP values of 93.4% and 74.3% compared with that of the I120 treatment (on average, 97.05 mm). The I120 treatment had the lowest irrigation schedule efficiency in both irrigation systems, followed by the I100 and I80 treatments. In both seasons, irrigation schedule deficiencies were highest in the I80 treatment with DI (on average, 12.35%). The I80 treatment with DI had a significant yield reduction (on average, 21.9%) in both seasons, while the irrigation level treatments with SI had nearly the same reductions. The SALTMED model is an integrated model that considers irrigation systems, soil types, crops, and water application strategies to simulate soil water content (SWC) and crop yield. The SALTMED model was calibrated and validated based on the experimental data under irrigation levels across irrigation systems. The accuracy of the model was assessed by the coefficients of correlation (R), root mean square errors (RMSE), mean absolute errors (MAE), and mean absolute relative error (MARE). When simulating SWC, the SALTMED models’ R values, on average, were 0.89 and 0.84, RMSE values were 0.018 and 0.019, MAE values were 0.015 and 0.016, and MARE values were 8.917 and 9.133%, respectively, during the calibration and validation periods. When simulating crop yield, relative errors (RE) for the SALTMED model varied between −0.11 and 24.37% for biological yield and 0.1 and 19.18% for grain yield during the calibration period, while in the...
validation period, RE was in the range of 3.8–29.81% and 2.02–25.41%, respectively. The SALTMED model performed well when simulating wheat yield with different water irrigation levels under SI or DI.

**Keywords:** soil water content; water productivity; yield reductions; deficit irrigation

1. Introduction

Water scarcity has become a global problem with a significant impact on agricultural production [1,2]. According to the most recent report [3], irrigation covers more than 20% of global cultivated lands and contributes to more than 40% of global total food production. Agricultural irrigation consumes the most water, but it yields the lowest return per unit of water when compared with other economic sectors [4]. However, traditional irrigation methods, such as flood irrigation, result in less water productivity (WP). There have been many irrigation methods developed to increase WP throughout the world, including furrow and drip irrigation [5]. Furrow irrigation is a finer form of surface irrigation (SI) in which ridge tillage aids root development and water infiltration while reducing deep percolation, causing an increase in WP [6–8]. Furthermore, drip irrigation (DI) has developed rapidly over the past few decades. DI has a distinct advantage over conventional irrigation in reducing water use and regulating salt through reduced evaporation and precise water use, which plays an important role in agricultural production worldwide [9,10]. Deficit irrigation is another water management technique that allows larger agricultural lands to be irrigated with scarce water resources [11,12]. Because crops respond to water stress in different ways at different stages of growth, this technique has a big impact on irrigation scheduling while having a small impact on yield. When using deficit irrigation, an important factor to consider is the timing and degree of water stress to which plants are exposed [13–15]. When crops are irrigated insufficiently, their roots grow deep into the soil and reach the soil water, resulting in significant water savings without reducing crop yield, while increasing WP and increasing net farm income [16–20].

Wheat (*Triticum aestivum* L.) has been adopted mostly as a food crop worldwide and is the world’s most widely distributed cereal after maize, ranking eighth in the world. However, growers are concerned about its long-term production and yield in water-stressed conditions [21]. Wheat farmers are currently facing a number of challenges, including water shortages and uncertain water delivery schedules [22]. At all growth stages, wheat needs sufficient soil moisture for normal growth and development, which can be achieved by precise irrigation scheduling that minimizes overwatering [23]. Excessive use of water can lead to waterlogging and nutrients leaching outside the root zone. To improve WP, it is necessary to schedule proper irrigation with an adequate amount of water, as flooding can reduce WP and crop yield [24]. Previous studies [25,26] have suggested that using deficit irrigation to save water in wheat can be beneficial. Several studies have looked at how different irrigation schedules affect wheat growth, yield, and WP [27–30]. Panda et al. [27] reported that wheat WP was highest when irrigation was applied when the available soil moisture was 45% depleted. According to Jalota et al. [28], reducing the number of irrigations to maximize WP and using less irrigation water would conserve wheat grain yield in semi-arid environments. When compared with full wheat-crop irrigation, Wang et al. [29] and Rao et al. [30] found that deficit irrigation improved WP by 11–40%. As a result, developing water-saving farming techniques that decrease irrigation water consumption while increasing WP to produce great and consistent yields similar to those produced with reduced irrigation is critical for achieving sustainable agricultural development [31–33]. Furthermore, decision-makers saved time by using mathematical models to manage irrigation water and forecast production under various conditions [34]. These models are an important tool for scientifically documenting irrigation scheduling with the
goal of reducing water consumption and facilitating horizontal agriculture expansion by utilizing limited irrigation water resources.

The use of CROPWAT to decide on an irrigation regime is one of the most popular approaches to assessing irrigation performance and WP in irrigated areas. CROPWAT is an irrigation management and planning application software established by a group of experts [35–38]. CROPWAT model’s calculations are based on guidelines for calculating crop water requirements [39] and the yield response to water requirements [40]. The CROPWAT model can be considered as a valuable method for calculating water irrigation requirements for developing irrigation schedules based on the crop parameters and daily soil moisture balance at maximum root depth, which can be used to estimate evapotranspiration using different water source options and irrigation management conditions for a variety of crops under various environmental conditions [41–48].

SALTMED is an integrated model that uses well-known physically based equations to simulate soil water profiles, salinity distribution and nitrogen in the soil, leaching requirements, crop growth and yield, taking into account water application strategies, soil types, irrigation systems, crops, and various water qualities [49,50]. The SALTMED model can be used to assess the future effect on irrigation management and predict water distribution under automatic irrigation scheduling by running different scenarios under different conditions and crop parameters [51]. Some research has been conducted on the SALTMED model, which has shown that it can be used to manage water, crops, and soil under a variety of irrigation applications and environmental conditions [34,52–58].

Therefore, our study aims to (1) compare changes in yield and water productivity of wheat exposed to different water quantities under surface and drip irrigation systems; (2) explore the CROPWAT model’s ability to evaluate irrigation scheduling and performance during the wheat-growing stages; and (3) simulate soil water content (SWC), dry matter, and grain yield of wheat using the SALTMED model and compare it with observed data from field experiments.

2. Materials and Methods

2.1. Field Study Site

Field experiments were conducted during the two successive seasons of 2018/2019 and 2019/2020 in the Qarun Kebili region, El Fayoum, Egypt. This region has an altitude of 17 m above sea level at 29°21′55″ N latitude and 30°27′11″ E longitude. The experimental site has a semi-arid climate, as shown in Figure 1, with air temperature (T), relative air humidity (RH), rainfall, and reference evapotranspiration (ET0). From November to April, the average T and RH concentrations were 16.2 °C and 54.9% in the first growing season, respectively, and 17.9 °C and 58.9% in the second growing season, respectively. The rainfall received in the first growing season was 20 mm, while in the second growing season it was 12.2 mm. In the first and second growing seasons, ET0 was 490.7 mm and 459 mm, respectively. In Table 1, the physical (i.e., texture, bulk density, field capacity, wilting point, and saturated hydraulic conductivity) and chemical (i.e., electrical conductivity, pH, organic matter, and soluble cations and anions) soil properties of the site were determined at two soil depths (10–30 and 30–60 cm) after eliminating the top soil, by standard procedures according to Page et al. [59] and Klute [60]. The soil of the experimental site had a loamy sand texture. The water used to irrigate the experimental site had a pH of 5 and an electrical conductivity of 2 dS m⁻¹ for the experimental period.
Figure 1. Daily values of climatic data at the experimental site throughout the two growing seasons.

Table 1. Physical and chemical properties of the soil at the experimental site.

<table>
<thead>
<tr>
<th>Soil’s Physical Properties</th>
<th>Depth (cm)</th>
<th>Particle Size (%)</th>
<th>Texture</th>
<th>$\rho_b$ (g cm$^{-3}$)</th>
<th>FC (%)</th>
<th>WP (%)</th>
<th>$\theta_s$ m$^3$ m$^{-3}$</th>
<th>TAW m$^3$ m$^{-3}$</th>
<th>$K_s$ (mm h$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0–30</td>
<td>72.1 11.9 16.0</td>
<td>Loamy sand</td>
<td>1.57</td>
<td>20.0</td>
<td>12.0</td>
<td>0.44</td>
<td>0.08</td>
<td>32.5</td>
</tr>
<tr>
<td></td>
<td>30–60</td>
<td>73.4 12.0 14.6</td>
<td>Loamy sand</td>
<td>1.51</td>
<td>19.5</td>
<td>11.5</td>
<td>0.43</td>
<td>0.08</td>
<td>33.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Soil’s Chemical Properties</th>
<th>Depth (cm)</th>
<th>$E_{C_e}$ (dS m$^{-1}$)</th>
<th>pH</th>
<th>OM</th>
<th>Soluble Cations (meq L$^{-1}$)</th>
<th>Soluble Anions (meq L$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0–30</td>
<td>4.42</td>
<td>7.87</td>
<td>0.7</td>
<td>Ca$^{2+}$ 27.8</td>
<td>CO$_3^{2-}$ 2.98</td>
</tr>
<tr>
<td></td>
<td>30–60</td>
<td>5.56</td>
<td>7.47</td>
<td>0.8</td>
<td>Mg$^{2+}$ 7.74</td>
<td>HCO$_3^{−}$ 22.00</td>
</tr>
</tbody>
</table>

$p_b$: bulk density; FC: field capacity; WP: wilting point; $\theta_s$: saturated moisture content; TAW: total available water; $K_s$: saturated hydraulic conductivity; $E_{C_e}$: electrical conductivity; OM: organic matter.
2.2. Experimental Layout and Design

The soil was plowed and leveled after the removal of plant debris prior to the establishment of the experimental layout. Before sowing wheat, all areas where corn was the previous crop received 357 kg ha\(^{-1}\) P\(_2\)O\(_5\) and 120 kg ha\(^{-1}\) K\(_2\)O as fertilizer, which was mixed using the disc harrow. After that, the soil was furrowed with 1.2 m spacing, and flatbeds with 1 m width and 0.10–0.15 m height were the result. Wheat (\textit{Triticum aestivum} L. cv. Masr2) seeds were manually sown in the flatbeds at a rate of 110 kg ha\(^{-1}\) on 17 November 2018 for the first season and 15 November 2019 for the second season. Four NH\(_4\)NO\(_3\) fertilizer doses (286 kg ha\(^{-1}\)) were applied at 20, 30, 65, and 45 days after sowing (DAS), with Fe-, Zn-, and Mn- fertilizer sprayed at 53 DAS. Herbicides were sprayed at a rate of 19 g ha\(^{-1}\) and 333 g ha\(^{-1}\) on 24 and 33 DAS, respectively. The wheat crop was harvested at 160 DAS (i.e., 25 April 2019 and 23 April 2020).

The total study area was divided into four fields, representing replications. Each field contained two irrigation systems that were SI and DI, which represented the main blocks. Each block had three plots which were irrigation water levels, namely, full [100% crop evapotranspiration (ET\(_c\)), I\(_{100}\)], deficit [80% ET\(_c\), I\(_{80}\)], and over [120% ET\(_c\), I\(_{120}\)] irrigation. It was maintained at a distance of 1 m between adjacent plots to prevent the potential impact of water leakage. The randomized complete block design (RCBD) was used.

In surface irrigated plots, the water was supplied through perforated PVC pipe with a 63 mm outside diameter along the plot width. In drip-irrigated plots, surface laterals were installed with inline emitters at 50 cm spacing on the lateral line and a 3.5 L h\(^{-1}\) flow rate at an operating pressure of 100 kPa. The laterals were placed in the center of the flatbeds and furrow bottoms (i.e., lateral spacing of 60 cm). The irrigation interval time for SI and DI treatments was selected to be 12 and 4 days, respectively. All plots were irrigated based on the crop evapotranspiration (ET\(_c\)) under standard conditions, which was calculated according to the following equation [39]:

\[
ET_c = K_c \times ET_0
\]  

(1)

where \(K_c\) is the crop coefficient and ET\(_0\) is the reference evapotranspiration (mm day\(^{-1}\)).

On the basis of field observations of crop stages using the FAO-56 data [39], \(K_c\) was determined to be 0.35 for the initial stage (up to 20 DAS), 1.15 during the mid-season stage of 51 to 115 DAS, and 0.25 during the late-season stage of 116 to 160 DAS, and the development stage was from 21 to 50 DAS. The Penman–Monteith FAO-56 equation [39] was used to calculate ET\(_0\) on a daily basis from the measured climatic data:

\[
ET_0 = \frac{0.408\Delta (R_n - G) + \gamma \frac{900}{T_\text{a} + 273} u_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34u_2)}
\]  

(2)

where \(R_n\) is net radiation (MJ m\(^{-2}\) day\(^{-1}\)), G is the soil heat flux (MJ m\(^{-2}\) day\(^{-1}\)), \(\gamma\) is the psychrometric constant (kPa °C\(^{-1}\)), \(T_a\) is the mean air temperature at 2 m height (°C), \(u_2\) is the wind speed at 2 m height (m s\(^{-1}\)), \(e_s\) is the saturation vapor pressure (kPa), \(e_a\) is the actual vapor pressure (kPa), and \(\Delta\) is the slope of the saturation vapor pressure–temperature curve at mean air temperature (kPa °C\(^{-1}\)).

2.3. Measurement of Soil Water Content

In the irrigation level plots, time domain reflectometry (TDR) probes (Trime FM; IMKO GmbH; Germany-76275 Ettlingen) were installed for continuous monitoring of the SWC over the two growing seasons. In each plot, a 60 cm-long probe was installed after the measurements of the TDR sensors were calibrated. A data logger was used to record SWC data.
2.4. Measurements of Yield Components, Grain Yield, and Water Productivity

Prior to harvesting and at the maturity stage of wheat, sheaves were randomly selected from each treatment area to measure the following data: plant height (cm), spike length (cm), spikes per unit area (m$^{-2}$), 1000-kernel weight (g), grain yield (GY, Mg ha$^{-1}$), and biological yield (Mg ha$^{-1}$).

Plant length and spike length were measured at each plot. The number of spikes was calculated by cutting them from sheaves, counting them, and recalculating the m$^2$ area. 1000-kernel weight (g) were determined by rubbing out grains from randomly selected 20 plants in each treatment, counting, and weighing them by scales Kern KB 1200-2 [61]. The GY (Mg ha$^{-1}$) was calculated from each treatment’s area by weighting grain samples after air drying and reaching a water content of 14% (g H$_2$O g$^{-1}$ fresh weight) [62] and then biological yield was measured. To avoid border effects, flatbeds on every side of each plot were not considered at harvest. The harvest index (HI) was determined by dividing grain yield by biological yield. According to Kijne et al. [63], the WP (kg m$^{-3}$) is defined as the ratio of GY (Mg ha$^{-1}$) to the amount of applied water (W, m$^3$ ha$^{-1}$) (irrigation water + effective rainfall) as follows:

$$ WP = \frac{GY}{W} $$ (3)

2.5. Maximum Grain Yield

The relationship between GY and W is called the grain water production function (GWPF). As some of the excess applied water is drained or lost, the GWPF becomes curvilinear. It expresses the benefit of applied water in terms of grain yield or biological yield. Helweg’s [64] quadratic polynomial function was written as follows:

$$ GY = b_0 + b_1 W + b_2 W^2 $$ (4)

where $b_0$, $b_1$, and $b_2$ are fitting coefficients for a specific irrigation system.

When at the maximum GY (GY$_{max}$) value, the slope of the GWPF against W goes to zero, therefore differentiating Equation (4) and equalizing by zero.

$$ \frac{dGY}{dW} = b_1 + 2b_2 W = 0 $$ (5)

The maximum applied water ($W_{max}$) was calculated as follows:

$$ W_{max} = \frac{-b_1}{2b_2} $$ (6)

Then the predicted GY$_{max}$ was calculated by substituting the $W_{max}$ in Equation (4) [56].

$$ GY_{max} = b_0 + b_1 W_{max} + b_2 W_{max}^2 $$ (7)

2.6. CROPWAT Model

The United Nations Food and Agriculture Organization (FAO) [35–38] developed the CROPWAT version 8.0 model [65], which is a software package. The CROPWAT model is frequently used for planning and managing irrigation projects based on the method described in Allen et al. [39]. The CROPWAT model was used to calculate crop water requirements and evaluate irrigation schedules for different irrigation strategies in this study. Climatic, crop, and soil variables are included in the CROPWAT model’s input data.

- The daily ET$_0$ values were calculated using the Penman–Monteith FAO-56 equation (Equation (2)), which was based on climatic data from the Central Laboratory for Agricultural Climate’s Meteorological Data, as well as the daily rainfall data, for the seasons of 2018/2019 and 2019/2020. The actual crop evapotranspiration was estimated by multiplying ET$_0$, $K_c$, and 0.8, 1, or 1.2. The efficiencies of SI and DI were estimated through field investigation, which was about 69% and 93%, respectively.
Irrigation application depth was then estimated at irrigation events for SI and DI, as shown in Figure 2.

- Planting and harvesting dates, duration and water stress coefficient (K_s) of crop growth stages, and root depth were all included in the crop data. In addition, according to Allen et al. [39], the depletion fraction (p) (0.65 for initial and mid-season stages, and 0.57 for late-season stage) were calculated using the following equation:

\[ p = p_{ETS} + 0.04(5 - ET_c) \]  

where \( p_{ETS} \) is the depletion fraction at \( ET_c = 5 \) mm/day, which is equivalent to winter wheat as 0.55 [39].

- Total available soil water from measured data (Table 1), maximum rooting depth and maximum rain infiltration rate from FAO, and initial soil moisture depletion from the CROPWAT program were among the soil data.

![Figure 2](image)

Figure 2. Applied irrigation water at the timing intervals for different treatments in both growing seasons. \( I_{80} = 80\% \) crop evapotranspiration (ET_c), \( I_{100} = 100\% \) ET_c, \( I_{120} = 120\% \) ET_c, SI = surface irrigation, and DI = drip irrigation.

Accordingly, irrigation schedules were developed for 80% ET_c, 100% ET_c, and 120% ET_c with the irrigation systems, namely, SI and DI. The CROPWAT model produces a variety of parameters that can be used to compare irrigation schedules. The output parameters are: root zone depletion (D_r), deep percolation (DP), efficiency of the irrigation schedule (EIS), deficiency of the irrigation schedule (DIS), and yield reduction (Y_R).

Due to the fact that soil water budget parameters are often expressed as depths of water, the D_r is useful since it makes adding and subtracting losses and gains straightforward.
The soil water balance was performed in the schedule module of CROPWAT according to Swennenhuis [65] to estimate the daily $D_r$ (Equation (9)).

$$D_{ri} = D_{ri-1} + (\text{ET}_{ci})_{\text{actual}} - P_i - I_i + RO_i + DP_i$$  \hspace{1cm} (9)

where $D_{ri}$ and $D_{ri-1}$ are on days $i$ and $i - 1$; $P_i$ is the total rainfall over day $i$; $I_i$ is net irrigation on day $i$; $RO_i$ is water loss by runoff from the soil surface on day $i$—since the ends of the plots in SI system were closed in our study, the $RO$ was zero; and $DP_i$ is water loss by deep percolation on day $i$. If irrigation was used, the $D_r$ was calculated before it was applied.

The readily available water (RAW) is the $p$ fraction of total available water (TAW) that a crop can extract from the root zone without being stressed by water. At a given soil depth, RAW is expressed as a percentage or in mm, as follows:

$$\text{RAW} = p \times \text{TAW}$$  \hspace{1cm} (10)

When daily $D_{ri}$ is less than $\text{RAW}_i$, daily $K_{s,i}$ = 1. Under soil water limiting conditions, $D_{ri}$ is greater than $\text{RAW}_i$ and $K_{s,i} < 1$ and is given by Allen et al. [39] as:

$$K_{s,i} = \frac{\text{TAW}_i - D_{ri}}{\text{TAW}_i - \text{RAW}_i}$$  \hspace{1cm} (11)

Irrigation water reaching the root zone, $I_i$, is not always advantageously used by the crop due to irrigation losses such as $DP_i$ in our study. Therefore, the EIS evaluates how advantageously the $I_i$ contributions are used by the crop over the growing period, as follows [65]:

$$\text{EIS} = \frac{\sum (I_i - DP_i)}{\sum I_i} \times 100$$  \hspace{1cm} (12)

The relationship between seasonal potential water use by crop ($\text{ET}_c$ under standard conditions) and seasonal actual water use by crop is expressed by the DIS that was calculated by [65]:

$$\text{DIS} = \frac{\text{Seasonal (ET}_c)_{\text{potential}} - \text{Seasonal (ET}_c)_{\text{actual}}}{\text{Seasonal (ET}_c)_{\text{potential}}} \times 100$$  \hspace{1cm} (13)

Due to soil water stress, $Y_R$ was also used in the scheduling performance analysis. $Y_R$ was estimated as a percentage of the maximum crop yield achievable in the case of full satisfaction of crop water needs ($GY_{max}$) [37], as follows:

$$Y_R = \left( 1 - \frac{GY_a}{GY_{max}} \right) = K_y \left( 1 - \frac{(\text{ET}_c)_{\text{actual}}}{(\text{ET}_c)_{\text{potential}}} \right)$$  \hspace{1cm} (14)

where $GY_a$ is the grain yield achievable under actual conditions, and $K_y$ is the yield response factor. For initial, development, mid-season, and late-season stages, as well as the total growing period, $K_y$ is set to 0.4, 0.6, 0.8, 0.4, and 1.0, respectively [40]. As a result, the best irrigation schedules are those that combine an irrigation interval and depth that result in a low DP and a reasonable $Y_R$.

2.7. SALTMED Model

The SALTMED model version 3.03.21 [49,50] was used for the simulation of SWC, total dry matter (biological yield), and grain yield of wheat by considering irrigation systems and different irrigation water quantities during the two seasons of 2018/2019 and 2019/2020. The data required depends on two main components: the first is for selected application options (global model parameters) and the second is for the interest of the user (field data). The user is not required to provide all of the data in the model tabs. For some applications,
the model has multiple options. The user only needs to provide data for the options that are required. The data requirements for the SALTMED model may be directly measured in laboratory and field conditions, or default values may be provided from the SALTMED database for different plant species and soil types. In our study, the data requirements were as follows:

1. Climate data, including the daily data of maximum and minimum temperatures, wind speed, sunshine hours, rainfall, relative humidity, total solar radiation, and net radiation. The Penman–Monteith FAO-56 equation (Equation (2)) was used to calculate the daily ET$_0$ values.

2. Irrigation management data, including applied irrigation water amounts, dates of irrigation events, and irrigation water quality, were based on field measurement data.

3. Soil parameters, including saturated SWC, initial soil moisture, saturated hydraulic conductivity, and salinity, were based on measurements either in the laboratory or in the field. Soil evaporation coefficient (K$_e$) values were taken from Allen et al. [39]. The Richards equation was used in the model to simulate two-dimensional water flow in the soil. The analytical functions of van Genuchten [66] in the model were used for determining soil hydraulic properties (i.e., the soil water pressure head and hydraulic conductivity relationships).

4. Crop parameters, including plant height, maximum and minimum root depth, leaf area index, length of the growth stage, and sowing and harvesting dates, were obtained from field measurements. From Allen et al. [39], K$_c$ and fraction cover (F$_c$) for the initial, middle, and late growth stages were taken. Basal crop coefficient (K$_{cb}$) values were then estimated as:

\[ K_{cb} = K_c - K_e \]  

(15)

To simulate crop yield, there are two options in the model: the first by calculating the harvest index and the daily biomass production; and the second, which was used in our study, by using the relative yield index (RY), which is a ratio between the sum of the actual water uptake over the season and the maximum water uptake. Actual yield (AY) can then be calculated as follows:

\[ AY = RY \times GY_{max} \]  

(16)

The SALTMED model was calibrated and validated for values of SWC, total dry matter (biological yield), and grain yield. The SALTMED model was calibrated for the 2018/2019 growing season by using default values of soil and crop parameters, as well as other measured values of these parameters from the field and laboratory, without any adjustments. Then, to achieve the best agreement between the measured and simulated parameters, a trial-and-error method was used to adjust both soil and crop parameters of the relevant model, namely soil pore-size distribution index, air-entry value, K$_c$, K$_e$, F$_c$, leaf area index, and photosynthesis efficiency. In the validation process, the SALTMED model used data collected during the 2019/2020 growing season to compare observed and simulated SWC, as well as biological and grain yields data of treatments.

2.8. Performance Accuracy Criteria

Five criteria indicators, namely the coefficient of correlation (R), the root mean square error (RMSE), mean absolute error (MAE), mean absolute relative error (MARE), and the relative error (RE), were selected to assess the accuracy of the proposed models. These criteria can be expressed as follows:

\[ R = \frac{\sum_{i=1}^{n} (O_i - \bar{O}) (S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n} (O_i - \bar{O})^2 \cdot \sum_{i=1}^{n} (S_i - \bar{S})^2}} \]  

(17)
\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}}
\]

(18)

\[
\text{MAE} = \frac{\sum_{i=1}^{n}|S_i - O_i|}{n}
\]

(19)

\[
\text{MARE} = \frac{1}{n} \left( \frac{\sum_{i=1}^{n} \left| S_i - O_i \right|}{\overline{O}} \times 100 \right)
\]

(20)

\[
\text{RE} = \left( \frac{S_i - O_i}{O_i} \right) \times 100
\]

(21)

where \( O_i \) and \( S_i \) are observed and simulated values, respectively, \( \overline{O} \) and \( \overline{S} \) are the average observed and simulated values, respectively, and \( n \) is the number of observations.

The degree of correlation between the observed and simulated values is measured by \( R \). RMSE expresses the error in the same units as the variable and measures how close simulated values are to observed values \([67]\). MAE is a measure of how close the predicted values to the experimental values \([68]\). An acceptable goodness of fit is indicated by an \( R \) value close to 1, and RMSE, MAE, and MARE values close to 0. RE describes bias as a percentage provided by models.

2.9. Statistical Analysis

Using CoStat software (Version 6.303, CoHort, Monterey, CA, USA, 1998–2004) \([69]\), the data from the two growing seasons were subjected to ANOVA analysis following a RCBD with four replicates of each treatment. The significant differences between the two treatment means of the measured parameters of GY, its components, and WP were evaluated using the least significant difference (LSD) method at a 5% significant level \([70]\).

3. Results and Discussion

3.1. Irrigation Water Applied

Irrigation water applied to wheat for the 2018/2019 and 2019/2020 growing seasons was presented in Figure 2. The amount of irrigation water applied in the first growing season was higher than in the second. It is possible that this is due to climatic differences. The air temperature was lower in 2019/2020 than in 2018/2019, while rainfall and relative humidity were higher in 2019/2020 than in 2018/2019 (Figure 1). In both growing seasons, increasing the irrigation level increased the total water applied, as expected. Regarding the irrigation system in Figure 2, the total water applied increased with the SI system in both growing seasons. The highest total irrigation water applied value was obtained in the \( I_{120} \) treatment under the SI system, which was 930 mm in the first growing season and 871 mm in the second growing season, while under the DI system it was 492 mm and 450 mm, respectively. In this study, full-irrigated (\( I_{100} \)) wheat plants had a similar total irrigation water applied value to those obtained by Moussa and Abdel-Maksoud \([71]\) and Abdelkhalek et al. \([72]\).

3.2. Yield Components and Grain Yield

Table 2 shows the analysis of variance for wheat yield components and grain yield in the 2018/2019 and 2019/2020 growing seasons. Plant height and spike length were not significantly \((p > 0.05)\) affected by the systems and levels of irrigation and the interaction between them in both seasons. The values of plant height ranged from 95.25 cm to 100.25 cm in the 2018/2019 season and from 95.75 cm to 100 cm in the 2019/2020 season. While the spike length was between 9.25 cm and 10 cm in the first and second seasons, there was a significant difference in the number of spikes \((p < 0.05)\) between different irrigation levels only in the second season, whereas there were no significant differences \((p > 0.05)\) between the spikes number values in the first season. The \( I_{100} \) and \( I_{120} \)-treated plants in 2019/2020 showed no significant differences in the number of spikes (Figure 3), while the \( I_{80} \)-treated number of spikes was significantly reduced by 17.86% and 14.48%, respectively, compared
with the I100 (396 spikes) and I120 (380 spikes) plants. Irrespective of the irrigation systems, the irrigation level treatments showed a significant effect on the 1000-kernel weight and biological yield in both seasons (Table 2). Figure 4 showed that the 1000-kernel weight and biological yield decreased with decreasing or increasing water levels than I100, but the decrease was more pronounced under I80 than under I120. In 2018/2019, the 1000-kernel weight values of I80 and I120 were decreased, compared with I100 (47.5 g), by 22.24% and 12.11%, respectively, while the value (38.88 g) for I80 was decreased by 17.07% in 2019/2020. The same trend applied to biological yield; the average value for I80 and I120 was 16.38 Mg ha\(^{-1}\) in 2018/2019. The corresponding I100 value was 18.13 Mg ha\(^{-1}\). In 2019/2020, the I80 treatment had the lowest biological yield of 14.78 Mg ha\(^{-1}\) (a 13.99% decrease from the I100 value). According to Pandey et al. [73], as the amount of irrigation water applied increased, the growth rate and biological yield of wheat increased as well. Therefore, Table 2 shows that yield components of the wheat had non-significant differences between irrigation systems in both seasons. This is consistent with the findings of Eissa [74] and Noreldin et al. [75], who found that the irrigation system had no significant effect on the wheat plant characteristics studied.

Table 2. Statistical analysis results for grain yield and yield components of wheat under different treatments in both growing seasons.

<table>
<thead>
<tr>
<th>Treatments</th>
<th>df</th>
<th>(p^*) Value</th>
<th>LSD</th>
<th>(p^*) Value</th>
<th>LSD</th>
<th>(p^*) Value</th>
<th>LSD</th>
<th>(p^*) Value</th>
<th>LSD</th>
<th>(p^*) Value</th>
<th>LSD</th>
<th>(p^*) Value</th>
<th>LSD</th>
<th>(p^*) Value</th>
<th>LSD</th>
</tr>
</thead>
<tbody>
<tr>
<td>2018/2019</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Irr. syst.</td>
<td>1</td>
<td>0.1417</td>
<td>ns</td>
<td>0.2680</td>
<td>ns</td>
<td>0.3037</td>
<td>ns</td>
<td>0.1063</td>
<td>ns</td>
<td>0.0747</td>
<td>ns</td>
<td>0.0188</td>
<td>0.51</td>
<td>0.4502</td>
<td>ns</td>
</tr>
<tr>
<td>Irr. lev.</td>
<td>2</td>
<td>0.9522</td>
<td>ns</td>
<td>0.4414</td>
<td>ns</td>
<td>0.1998</td>
<td>ns</td>
<td>&lt;0.001</td>
<td>1.58</td>
<td>0.0239</td>
<td>1.48</td>
<td>0.0008</td>
<td>0.63</td>
<td>0.1491</td>
<td>ns</td>
</tr>
<tr>
<td>Irr. syst. (\times) Irr. lev.</td>
<td>2</td>
<td>0.2830</td>
<td>ns</td>
<td>0.4651</td>
<td>ns</td>
<td>0.9103</td>
<td>ns</td>
<td>0.3825</td>
<td>ns</td>
<td>0.2375</td>
<td>ns</td>
<td>0.0405</td>
<td>0.89</td>
<td>0.1187</td>
<td>ns</td>
</tr>
<tr>
<td>CV, %</td>
<td>3.78</td>
<td>19.44</td>
<td>6.05</td>
<td>3.53</td>
<td>8.17</td>
<td>8.26</td>
<td>6.86</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2019/2020</td>
<td></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Irr. syst.</td>
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<td>0.4590</td>
<td>ns</td>
<td>0.2852</td>
<td>ns</td>
<td>0.9403</td>
<td>ns</td>
<td>0.2042</td>
<td>ns</td>
<td>0.0919</td>
<td>ns</td>
<td>0.0476</td>
<td>0.52</td>
<td>0.2376</td>
<td>ns</td>
</tr>
<tr>
<td>Irr. lev.</td>
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<td>0.3757</td>
<td>&lt;0.001</td>
<td>21.99</td>
<td>0.3518</td>
<td>ns</td>
<td>0.0022</td>
<td>3.93</td>
<td>&lt;0.001</td>
<td>0.57</td>
<td>&lt;0.001</td>
<td>0.64</td>
<td>0.0853</td>
<td>ns</td>
<td></td>
</tr>
<tr>
<td>Irr. syst. (\times) Irr. lev.</td>
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<td>0.0829</td>
<td>ns</td>
<td>0.5231</td>
<td>ns</td>
<td>0.4794</td>
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<td>0.3828</td>
<td>ns</td>
<td>0.3245</td>
<td>ns</td>
<td>0.4472</td>
<td>ns</td>
<td>0.3028</td>
<td>ns</td>
</tr>
<tr>
<td>CV, %</td>
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<td>5.63</td>
<td>6.91</td>
<td>8.57</td>
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</tbody>
</table>

Irr. syst.: irrigation systems; Irr. lev.: irrigation levels; df: degrees of freedom; LSD: least significant difference; ns: non-significant; CV: coefficient of variation.

Figure 3. Number of wheat spikes under three irrigation levels in the 2019/2020 growing season (values are averages of two irrigation systems). According to the least significant difference test at \(p < 0.05\), the same letters indicate statistically no significant differences. I80 = 80% crop evapotranspiration (ET\(_c\)), I100 = 100% ET\(_c\), and I120 = 120% ET\(_c\). Vertical lines give the means ± SE of the mean (\(n = 8\)).
Figure 4. 1000-kernel weight and biological yield in wheat under three irrigation levels in each growing season (values are averages of two irrigation systems). According to the least significant difference test at $p < 0.05$, the same letters within a growing season indicate statistically no significant differences. $I_{80} = 80\%$ crop evapotranspiration ($ET_c$), $I_{100} = 100\%$ $ET_c$, and $I_{120} = 120\%$ $ET_c$. Vertical lines give the means ± SE of the mean $(n = 8)$.

As shown in Table 2, irrigation level treatments had a significant ($p < 0.05$) effect on grain yield regardless of the irrigation system in both seasons. The average values of grain yield under DI were 7.46 and 7.03 Mg ha$^{-1}$, respectively, in 2018/2019 and 2019/2020, whereas the values under SI were significantly ($p < 0.05$) decreased by 8.50% and 7.50%, compared with those of DI (Figure 5a). Irrespective of the irrigation systems, the value of grain yield for $I_{100}$ (7.89 and 7.52 Mg ha$^{-1}$) was significantly ($p < 0.05$) the highest, followed by $I_{120}$ (decreasing by 10.05% and 5.29%, respectively) and later by $I_{80}$ (decreasing by 18.34% and 24.58%, respectively) in 2018/2019 and 2019/2020 (Figure 5b). According to Mugabe and Nyakatawa [76], applying 75% of the wheat crop’s water requirements reduced yields by 12% in two years. Low yields in the case of deficit irrigation, especially in cases of water limitation, may be offset by increasing production with additional water supply through deficit irrigated areas [77]. Table 2 shows that the interaction between irrigation systems and irrigation levels was significant ($p < 0.05$) in 2018/2019 but not significant ($p > 0.05$) in 2019/2020. In 2018/2019 (Figure 6), the $I_{100}$ with DI treatment (8.21 Mg ha$^{-1}$) had the highest grain yield, but without significant differences with the $I_{120}$ with DI and $I_{100}$ with SI treatments. The $I_{80}$ with DI treatment (6.34 Mg ha$^{-1}$) had the lowest value, but without significant differences with the $I_{120}$ with SI and $I_{80}$ with SI treatments. Finally, there were non-significant effects ($p > 0.05$) on the harvest index (Table 2).
Figure 5. Grain wheat yield in each growing season under (a) two irrigation systems (values are averages of three irrigation levels, n = 12), and (b) three irrigation levels (values are averages of two irrigation systems, n = 8). According to the least significant difference test at p < 0.05, the same letters within a growing season indicated statistically no significant differences. I₈₀ = 80% crop evapotranspiration (ETₑ), I₁₀₀ = 100% ETₑ, I₁₂₀ = 120% ETₑ, SI = surface irrigation, and DI = drip irrigation. Vertical lines give the means ± SE of the mean.

Figure 6. Grain yield in wheat under irrigation levels across irrigation systems in 2018/2019 growing season. According to the least significant difference test at p < 0.05, the same letters indicate statistically no significant differences. I₈₀ = 80% crop evapotranspiration (ETₑ), I₁₀₀ = 100% ETₑ, I₁₂₀ = 120% ETₑ, SI = surface irrigation, and DI = drip irrigation. Vertical lines give the means ± SE of the mean (n = 4).
3.3. Grain Yield–Water Relationship

From the regression analysis of the crop water production function in Figure 7, it is shown that the \( GY_{\text{max}} \) values for plants treated with SI were 7.57 and 7.48 Mg ha\(^{-1} \), respectively, in the first and second seasons, and the corresponding calculated \( W_{\text{max}} \) values were 7738 m\(^3\) and 7379 m\(^3\). While the corresponding values for plants treated with DI were 8.33 and 7.84 Mg ha\(^{-1} \), respectively, the \( W_{\text{max}} \) values were 4343.9 m\(^3\) and 4086.8 m\(^3\). Thus, it was found that the highest \( Y_R \) values (13.52–27.02%) were achieved with deficit irrigation (I\(_{80}\)) under the two irrigation systems in both seasons, except in the first season under SI, where the plants treated with I\(_{120}\) gave a slightly greater \( Y_R \) than those with I\(_{80}\). The least \( Y_R \) (0.06–2.77%) was for the full irrigation (I\(_{100}\)) plants.

The results in Figure 8 showed that the SI system was the most water-consuming, followed by the DI system, which was the least water-consuming system. In terms of WP, the DI of the I\(_{100}\) treatment was found to be the best. No significant (\( p > 0.05 \)) WP decrease was observed when using the DI of I\(_{80}\) treatment, where the WP decreased from 2.01 to 1.94 kg m\(^{-3}\) in the first season and from 2.05 to 1.97 kg m\(^{-3}\) in the second season for I\(_{100}\) and I\(_{80}\), respectively. The I\(_{120}\) with either the SI or DI system was the most affected as WP decreased significantly (\( p < 0.05 \)); however, it increased the water amount. Deficit irrigation, according to Geerts and Raes [78] and Pereira et al. [79], can increase WP by reducing the water loss from unproductive evaporation, increasing harvest index, and controlling pests and diseases during crop growth. Due to the relatively small increase in grain yield with increased evapotranspiration, Maurya and Singh [80] reported a decrease in WP with increased irrigation levels.

![Figure 7. Relationship between grain yield (GY) and applied water (W) under different irrigation systems. SI = surface irrigation, and DI = drip irrigation. Vertical lines give the means ± SE of the mean (n = 4).](image-url)
Figure 8. Water productivity in wheat under different irrigation levels across irrigation systems in each growing season. According to the least significant difference (LSD) test at \( p < 0.05 \), the same letters within an irrigation system indicate statistically no significant differences. Different letters between brackets represent significant differences between irrigation systems based on the LSD test with \( p < 0.05 \) within growing season. \( I_{80} = 80\% \) crop evapotranspiration (ET\(_c\)), \( I_{100} = 100\% \) ET\(_c\), \( I_{120} = 120\% \) ET\(_c\), SI = surface irrigation, and DI = drip irrigation. Vertical lines give the means ± SE of the mean (\( n = 4 \)).

3.4. CROPWAT Model

Figure 9 shows the soil water balance for wheat in the 2018/2019 and 2019/2020 growth seasons with the CROPWAT model under irrigation levels across irrigation systems. Irrigation scheduling was evaluated by the crop’s daily water requirements, the soil’s properties (particularly its TAW or water-holding capacity), and the root’s effective depth. The TAW evolved in two phases: a filling phase when reserves reached 40 mm at 50 DAS, and a continual stabilization phase from that day through the conclusion of the cycle. The RAW went through a filling phase when reserves reached 20 mm at 50 DAS and then stayed in a steady phase till the cycle ended. The CROPWAT model directly calculates the root growth increase from the first day of vegetation [81]. The same behavior of soil depletion was found in the irrigation-level treatments under SI, where the soil depletion approached the lower limit of RAW at 75 DAS in the 2018/2019 season, while the crop entered stress at 87 DAS in the 2019/2020 season (Figure 9). The crop reached peak stress at 126 DAS and 114 DAS with depletion values of 34.4 mm and 31.7 mm (TAW = 40 mm), respectively, in both seasons. Figure 9 shows that the shape of the depletion curves for irrigation level treatments with DI was very similar in the first 20 days. There were considerable differences in irrigation schedules, as the depletion values for the \( I_{100} \) and \( I_{120} \) treatments were between the FC and the RAW throughout the growth seasons. The drip-irrigated plot with a water saving of 20% (\( I_{80} \)) gave water stress during the mid- and late-season stages, where the maximum depletion was at 106 DAS (31.9 mm) in the 2018/2019 season and 142 DAS (28.7 mm) in the 2019/2020 season. When soil water is extracted through evapotranspiration, depletion increases, and stress occurred when \( D_r \) equaled RAW. The \( D_r \) exceeded RAW (the water content fell below the threshold), which limited evapotranspiration to less than potential ET\(_c\) values, and the crop consumption decreased proportionally to the amount of water retained in the root zone [65]. Accordingly, Figure 10 shows that the lowest \( K_x \) values (0.28 and 0.48) in SI treatments were achieved at 126 DAS and 114 DAS (late-season stage). While in DI treatments, the \( K_x \) values were not less than one throughout the growing seasons in the \( I_{100} \) and \( I_{120} \) treatments (Figure 10),
while the $K_s$ values were less than one in the $I_{80}$ treatment from 75 DAS ($K_s$ of 0.92) in the 2018/2019 and 87 DAS ($K_s$ of 0.9) in the 2019/2020 (i.e., mid-season) to the end of the season.

Figure 9. Water balance of wheat during each growth season under different irrigation levels across irrigation systems. $I_{80} = 80\%$ crop evapotranspiration ($ET_c$), $I_{100} = 100\%$ $ET_c$, $I_{120} = 120\%$ $ET_c$, SI = surface irrigation, and DI = drip irrigation.
On the other hand, the DP (i.e., irrigation losses) with irrigation levels occurred throughout the seasons. In SI, the I_{120} treatment had the highest DP values (596 and 516.3 mm in both seasons), while the I_{100} and I_{80} treatments gave 26% and 52% lower values.
in 2018/2019, respectively, and 28.1% and 55.2% in 2019/2020, respectively, compared to the \( I_{120} \) treatment (Figure 11). Hence, the EIS values were the highest with the \( I_{80} \) treatment (on average 56.7%), followed by the \( I_{100} \) and \( I_{120} \) treatments (on average 45.5% and 37.8%, respectively).

Figure 11. Total irrigation losses, actual water use by crop, efficiency and deficiency of irrigation schedule (EIS and DIS), and yield reduction (\( Y_R \)) under different irrigation levels across irrigation systems in each growing season. \( I_{80} = 80\% \) crop evapotranspiration (\( ET_c \)), \( I_{100} = 100\% \) \( ET_c \), \( I_{120} = 120\% \) \( ET_c \), SI = surface irrigation, and DI = drip irrigation.

In DI, the DP occurred in \( I_{80} \) and \( I_{100} \) treatments in about the first 45 DAS, where total DP values were 7.4 and 28.8 mm for \( I_{80} \) and \( I_{100} \) treatments, respectively, in 2018/2019 and 5.4 and 21 mm, respectively, in 2019/2020 (Figure 11). While \( I_{120} \) treatment had DP over both seasons, the total values were 101 mm and 93.1 mm in 2018/2019 and in 2019/2020, respectively. The EIS values for the \( I_{80} \) and \( I_{100} \) treatments were high at 90%, whereas the \( I_{120} \) treatment had an EIS value of 79% in both seasons (Figure 11).

The \( (ET_c)_{\text{potential}} \) with the CROPWAT model was estimated at 370.8 mm in the 2018/2019 season and 336 mm in the 2019/2020 season. The \( (ET_c)_{\text{actual}} \) values’ SI treatments were higher in the 2018/2019 season (on average, 325 mm) than in the 2019/2020 season (on average, 313.3 mm) (Figure 11). Knežević et al. [81] reported that \( (ET_c)_{\text{actual}} \) values of winter wheat in Serbia were 345.4 mm and 463.3 mm on soils with a medium and high TAW, respectively, obtained with the CROPWAT model under rainfed conditions. In the \( I_{80} \) treatment, the obtained \( (ET_c)_{\text{actual}} \) values with DI were around 5 mm and 13 mm in the first and second seasons, respectively, which were lower than those obtained with SI. The \( I_{80} \) treatment with DI had the highest values of DIS (13.8% and 10.9%) in both seasons. On the contrary, in the \( I_{100} \) and \( I_{120} \) treatments, the \( (ET_c)_{\text{actual}} \) values for DI were greater, on average, by 13.8% and 7.1%, than those for SI. Therefore, the \( I_{100} \) and \( I_{120} \) treatments with DI had the lowest values of DIS (on average, 0.5% and 0.4%, respectively).

Figure 11 indicates the effect of irrigation scheduling on grain yield potential. During the \( I_{80} \) treatment with DI in the 2018/2019 and 2019/2020 seasons, tests of irrigation levels across irrigation systems showed significant yield reduction results (24.5 and 19.3%, respectively), while yield reductions across the irrigation level treatments under SI were similar in each season (21.7% in 2018/2019 and 12.2% in 2019/2020). The relative yield obtained with the simulations was compared with the measured yield. The \( GY_{\text{max}} \) ranged
from 7.48 Mg ha\(^{-1}\) with SI in the 2019/2020 season to 8.33 Mg ha\(^{-1}\) with DI in 2018/2019 (Figure 7). The highest relative yields were achieved with irrigation-level treatments under DI (RE between \(-0.78\%\) and 7.65\%) in both seasons. In SI, the highest relative yield (99\%) was estimated in 2019/2020 with \(I_{120}\) treatment (RE of \(-1\%)\), while the lowest relative yield (78.35\%) was estimated in 2018/2019 with \(I_{100}\) treatment (RE of \(-21.65\%)\). According to the results of the CROPWAT model in study of Zhou and Zhao [82], an appropriate SI schedule for wheat in sandy soil included more frequent irrigation and lower application depth; this schedule can reduce deep percolation and save approximately 10–20\% of irrigation water without affecting crop yield.

The CROPWAT model’s outputs show that irrigation is crucial in the middle and late stages of wheat production to avoid yield reductions. Deficit irrigation may be used in areas where water is a limited resource for crop production. Deficit irrigation reduces irrigation water in certain crop growth stages that are thought to be the least sensitive to water stress, without affecting yields, to deal with water issues in areas where supply is limited [83,84]. A well-designed irrigation schedule can improve water productivity over a large area when full irrigation is not possible. However, because of the relationship between ET\(_c\) and crop yield, a yield reduction is expected [47,84,85].

### 3.5. SALTMed Model

The ability of the SALTMed model to represent the experimental data was examined during the periods of calibration (growing season 2018/2019) and validation (growing season 2019/2020) under different irrigation treatments. The SALTMed model was able to simulate SWCs with relatively high accuracy during the calibration period, based on the criteria indices presented in Table 3. In this period, the model for \(I_{80}\) in SI had the lowest RMSE, MAE, and MARE values, and vice versa in DI. The differences between measured and simulated SWCs were greatest in the SI for the \(I_{100}\) and \(I_{120}\) treatments, which had the highest RMSE, MAE, and MARE values. This can be explained by the fact that water infiltrated deeper into the soil during individual irrigation events in full and over-irrigation (\(I_{100}\) and \(I_{120}\)) treatments compared with water-saving irrigation (\(I_{80}\)) treatment. Furthermore, when simulating SWCs under the DI, more precise results were obtained, with lower RMSE, MAE, and MARE values for irrigation-level treatments than with SI. This is due to lower SWC differences in DI as a result of limited irrigation and root water uptake [86].

<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>MAE</td>
<td>MARE, %</td>
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<td>0.016</td>
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<tr>
<td></td>
<td>(I_{100})</td>
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</tr>
<tr>
<td></td>
<td>(I_{120})</td>
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</tr>
<tr>
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<td>0.015</td>
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<td>0.016</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>(I_{120})</td>
<td>0.015</td>
<td>0.009</td>
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</table>

Figure 12 shows scatter plots comparing the SALTMed model estimates for SWC to the SWC-measured data. In addition, linear regression is used to evaluate the model statistically. As shown in Figure 12, the results of the model show that points for irrigation level treatment under SI are located above the 1:1 line (perfect line), whereas in the DI, many points are located above and below this line. The fit line equations also show that under SI or DI, the \(I_{120}\) treatment had the lowest slope and the highest intercept. This indicates that the \(I_{120}\) treatment produced a lower R value.
Figure 12. The observed and the SALTMED-simulated soil water content (SWC) for different irrigation levels across irrigation systems during the calibration period (i.e., the 2018/2019 growing season). $I_{80} = 80\%$ crop evapotranspiration (ET$_c$), $I_{100} = 100\%$ ET$_c$, $I_{120} = 120\%$ ET$_c$, SI = surface irrigation, and DI = drip irrigation.

In the validation period (the 2019/2020 growing season), the RMSE, MAE, MARE, and R values varied between 0.017–0.023, 0.01–0.019, 6.0–11.3%, and 0.62–0.95. The lowest RMSE, MAE, and MARE values (Table 3), were found in the SALTMED-simulated SWC values for the $I_{80}$ treatment under SI. In DI, the $I_{120}$ treatment presented the lowest RMSE, MAE, and MARE values. In Figure 13, the R value of the $I_{120}$ treatment under SI or DI was the lowest compared with other treatments. The slope and intercept for the fitted line equation for the $I_{80}$ treatment had the highest and the lowest values of 0.68 and 0.06, respectively, under SI, while these values were 0.66 and 0.05 under DI, according to the scatter plots in Figure 13. This indicates that around the 1:1 line, there was less scatter and more clustering. As a result, the SALTMED model can account for both temporal and
spatial variations in SWCs in response to various treatments. According to Aly et al. [56], the SALTMED-simulated SWC values during the growing season of cucumber were very close to the observed values, with R ranging from 0.82 to 0.94 during calibration and 0.76 to 0.91 during validation. Hirich et al. [87] showed that the model could predict SWC into soil layers during the sweet corn growing season, with R values ranging from 0.91 to 0.95 and RMSE values ranging from 0.017 to 0.029 for calibrated data, and R values ranging from 0.91 to 0.96 and RMSE values ranging from 0.027 to 0.062 for validated data. According to Karandish and Simunek [86], the SALTMED model could simulate SWCs with a higher degree of accuracy under water-saving irrigation than under full irrigation.

![Graphs showing measured vs. simulated soil water content (SWC) for different irrigation levels across irrigation systems during the validation period.](image)

Figure 13. The measured and the SALTMED-simulated soil water content (SWC) for different irrigation levels across irrigation systems during the validation period (i.e., the 2019/2020 growing season). \( I_{80} = 80\% \) crop evapotranspiration \( \text{(ET}_c\text{)} \), \( I_{100} = 100\% \text{ET}_c \), \( I_{120} = 120\% \text{ET}_c \). SI = surface irrigation, and DI = drip irrigation.
When using the SALTMED model, it is important to have a reliable description of the crop’s response to applied treatments in addition to simulating soil water. As a result, we tested the SALTMED model’s ability to capture temporal variations in biological and grain yields for various treatments during the growing seasons 2018/2019 (calibration period) and 2019/2020 (validation period). During the calibration and validation periods, the SALMED model performed better in the non-water stress (I$_{100}$ and I$_{120}$) treatments than in the water stress (I$_{80}$) treatment, as shown in Table 4. The SALTMED model overestimated biological yield by 0.65–24.37% (except for the I$_{100}$ treatment under SI, which underestimated biological yield by 0.11%) and grain yield by 0.13–19.18%, respectively, when compared with observed yields in 2018/2019 season. In the validation period, the SALTMED-simulated values also overestimated observed biological and grain yields by 3.8–29.81% and 2.02–25.41%, respectively. The I$_{100}$ treatment under SI or DI had the lowest RE in the calibration and validation periods. The SALTMED model, according to Karandish and Simunek [86], performed well when simulating maize growth parameters, with a |RE| of 3.5–12%. Our RF range corresponds to the RF range reported by Kaya et al. [88] for quinoa yield (|RE| = 1.2–12.6%), the range reported by Hirich et al. [89] for corn yield (|RE| = 0–29.1%), and the range reported by Ragab et al. [34] for tomato and potato yields (|RE| = 0–21.5%). Over the calibration and validation years (Table 4), close matches between simulated and observed biological yield were observed, with RMSE, MAE, and MARE averaging 2.47, 2.01, and 12.68%, respectively. During the seasons, grain yield followed the same pattern as biological yield. The average RMSE, MAE, and MARE were 0.88, 0.741, and 11.58%, respectively, indicating that the model accurately predicted grain yield at various irrigation water levels. These findings are similar to those of Hirich et al. [87], who discovered that the relationship between observed and simulated yield produced RMSE values of 1.11 in sweet corn. In general, the performance criteria for statistical comparison of the observed and simulated data showed that the SALTMED model was well capable of simulating the yield of a wheat crop.

### Table 4. Statistical indices comparing the observed and SALTMED-simulated wheat yields for various irrigation treatments during the calibration (the 2018/2019 growing season) and validation (the 2019/2020 growing season) periods.

<table>
<thead>
<tr>
<th>Growing Season</th>
<th>Treatments</th>
<th>Biological Yield</th>
<th>Grain Yield</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Irrigation Systems</td>
<td>Irrigation Levels</td>
<td>Observed</td>
<td>Simulated</td>
</tr>
<tr>
<td>2018/2019</td>
<td>SI</td>
<td>I$_{80}$</td>
<td>15.75</td>
<td>18.20</td>
</tr>
<tr>
<td></td>
<td>I$_{100}$</td>
<td>18.00</td>
<td>17.98</td>
<td>-0.11</td>
</tr>
<tr>
<td></td>
<td>I$_{120}$</td>
<td>15.50</td>
<td>18.37</td>
<td>18.54</td>
</tr>
<tr>
<td></td>
<td>DI</td>
<td>I$_{80}$</td>
<td>14.45</td>
<td>18.22</td>
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<tr>
<td></td>
<td>I$_{100}$</td>
<td>16.88</td>
<td>17.98</td>
<td>6.52</td>
</tr>
<tr>
<td></td>
<td>I$_{120}$</td>
<td>16.93</td>
<td>18.37</td>
<td>8.53</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td></td>
<td>2.27</td>
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<tr>
<td></td>
<td>MAE</td>
<td></td>
<td>1.74</td>
<td></td>
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<tr>
<td></td>
<td>MARE, %</td>
<td></td>
<td>10.80</td>
<td></td>
</tr>
<tr>
<td>2019/2020</td>
<td>SI</td>
<td>I$_{80}$</td>
<td>15.11</td>
<td>19.61</td>
</tr>
<tr>
<td></td>
<td>I$_{100}$</td>
<td>17.49</td>
<td>18.16</td>
<td>3.80</td>
</tr>
<tr>
<td></td>
<td>I$_{120}$</td>
<td>16.84</td>
<td>18.95</td>
<td>12.55</td>
</tr>
<tr>
<td></td>
<td>DI</td>
<td>I$_{80}$</td>
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<td>19.61</td>
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<td>I$_{120}$</td>
<td>16.84</td>
<td>18.95</td>
<td>12.55</td>
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<tr>
<td></td>
<td>RMSE</td>
<td></td>
<td>2.67</td>
<td></td>
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<tr>
<td></td>
<td>MAE</td>
<td></td>
<td>2.27</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MARE, %</td>
<td></td>
<td>14.55</td>
<td></td>
</tr>
</tbody>
</table>
4. Conclusions

It is important to identify appropriate water irrigation management strategies to reduce the waste of water resources and improve water productivity in irrigation practices. Management strategies are commonly tested through field experiments that are expensive and time-consuming to produce consistent and reliable results. An alternative option for these experiments is to use validated mathematical models. This study discussed the use of irrigation water levels across surface and drip irrigation systems and the application of mathematical models (e.g., CROPWAT and SALTMED) in wheat fields. The study showed that there is a great potential for water savings when using a drip irrigation system, which gives much higher water productivity than a surface irrigation system at the same irrigation water level. Evaluation of the irrigation schedules using the CROPWAT model showed that different irrigation levels need to integrate irrigation application methods. The graphical and statistical comparisons confirmed the ability of the SALTMED model to predict soil water content and simulate the effects of different irrigation water levels on the biological and grain yields of wheat within acceptable limits. The SALTMED model can be an effective tool for identifying the correct irrigation strategy to maximize crop production as well as benefiting from the application of the CROPWAT model to develop accurate irrigation schedules under different management conditions and water supply schemes.

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