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PREDICTING THE WATER REQUIREMENT, SOIL MOISTURE DISTRIBUTION, YIELD, WATER PRODUCTIVITY OF PEAS AND IMPACT OF CLIMATE CHANGE USING SALTMED MODEL

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Abstract

It's important to study the effect of climate change on crops and water supplies, during this critical period of water scarcity and increasing food demand. These changes include evapotranspiration, which will affect crop growth and water requirement. This research work explores the impacts of climate change on water requirements, soil moisture distribution, yield and water productivity of peas. Two consecutive field trials were conducted during the 2017 and 2018 growth seasons of peas in El Nubaria zone, Egypt, on sandy soil conditions. Two irrigation schedules were studied, the first is irrigation at 30% depletion of field capacity, FC, the second schedule irrigation used actual weather station data under drip irrigation system. Under both irrigation schedules, measured and observed data were used for calibration and validation of the SALTMED model. The model was tested to study the impact of the future scenarios (RCPs, 4.5 and 8.5) for 2040, on water requirements, soil moisture content, yield and water productivity of peas, for the same study conditions. The field data indicated there was a high uniformity of soil moisture distribution under the 30% depletion of FC irrigation schedule, compared with the irrigation schedule using weather station data, for both seasons. The highest yield was (2.7 and 3.3 t ha^{-1}) for 2017 and 2018 seasons, respectively, under the 30% depletion of FC irrigation schedule. The highest water productivity was (0.95 and 1.07 kg m^{-3}) with total applied of water (2840 and 3070 m^3 ha^{-1}) for 2017 and 2018 seasons, respectively, with irrigation at 30% depletion of FC. The calibration and validation of SALTMED model indicated there were a slight variations between the observed and simulated results, with high coefficients of determination, RMCE and CRM values for total dry matter, productivity, water productivity and soil moisture under both irrigation schedules and for both seasons. The predicted data using SALTMED model showed the crop water requirements will increase for RCPs, 4.5 and 8.5 scenarios of 2040. The predicted yield and water productivity tend to decrease in 2040 under both scenarios. In general, SALTMED model is a good tool for predicting total dry matter and yield and can run with different scenarios and under different conditions.

Key words: Irrigation scheduling, weather station data, water productivity, peas, SALTMED simulation model, climate change

Introduction

The agricultural sector is one of the sectors that will be negatively affected by climate change, particularly in developing countries. These changes include temperature, and precipitation rate. The IPCC (2014) reported that climate change will affect evapotranspiration rates, thereby impacting soil moisture and consequentially crop water use. The predicted climate change in Egypt, based on different Representative Concentration Pathways (RCPs) scenarios, indicated that there is an increase in evapotranspiration (ETo) due to increasing minimum and maximum air temperatures. Abdrabbo *et al.*, 2015 reported that ETo would increase by 4.7% to 19.6% for the Middle Egypt region. Water resources are a limiting factor for agricultural production, and water saving becomes a clear necessity. Also, in the near future, water scarcity will be a real big problem for the global economy. Therefore, water consumption, in all life activities, should be improved as a rare and important commodity (Marwa *et al.*, 2017). Therefore, it is very important, when facing

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future change in water availability, to develop a sustainable water management plan. However, using modern means of irrigation control can help in scheduling both irrigation and fertigation processes very accurately, providing different cultivated crops with their exact requirements of water and fertilizers at the correct time for the plant. Moreover, it will consume the minimum amount of water, fertilizers, energy and labor and it will avoid plant stress due to water deficiency (Marwa *et al.,* 2017).

The advantages of using models are that simulations are cheaper and faster than field trials and that you can get more and higher level of detail from the simulation runs (El-Shafie *et. al.,* 2018; Dewedar *et al.,* 2019).

A number of last SALTMED studies proved that the model can a accurately simulate crop dry matter, yield and soil water content (Ragab, 2002; Ragab *et al.*, 2005a Ragab *et al.*, 2005b; Hirich *et al.,* Pulvento *et al.*, 2013; 2012; Kaya *et al.*, 2015; Ragab, 2015; Afzal *et al.*, 2016; Æosiæ *et al.*, 2017). For this reason, SALTMED simulation model (Ragab, 2019) is a useful tool for predicting total dry matter, crop productivity, and soil water content in this study. On the other hand a simulation model will be a good tool to maximize the efficiency of water distribution under irrigation systems, which will affect the total efficiency of irrigation. This will help in saving time and reduce the economic cost of field experiments.

Peas (*Pisum sativum*) is one of the most widely consumed legumes in the world and is grown in different regions and environments in many countries. Peas are high in digestible protein, carbohydrates, fats, minerals and vitamins (Tao *et. al.,* 2017).

The main objective of this research paper was to test the SALTMED simulation model using observed trials data, under a two irrigation schedules with soil moisture sensors, irrigation at 30% depletion of field capacity (FC), as well as irrigation scheduling using actual climate data (for 2017 and 2018 seasons). The second objective was to predict how the climate change will affect water requirements, soil moisture distribution, yield and water productivity of peas, using two scenarios of the future climate data (RCP4.5 and RCP8.5) for 2040.

Materials and Methods

The trial site and crop

Two successive winter seasons of 2017 and 2018 for peas crop, were carried out on the National Research Centre Research Station (30.8667N°, 30.1667E° and 21 m above sea level), El Nubaria zone, Egypt, on sandy soil. The field trials data were done to test and evaluate the SALTMED model, under a two irrigation schedules with soil moisture sensors: irrigation at 30% depletion of field capacity FC and an irrigation schedule using actual climate data, under drip irrigation system. Also, to predict (using SALTMED model) how climate change affects water requirements, soil moisture distribution, yield and water productivity of peas, under the same experimental conditions using two scenarios of future climate data (2040).

The soil of the experimental site is sandy soil, representative soil samples from the different parts of the experimental area were taken from the depths layers of (0 to15, 15 to 30, 30 to 45 and 45 to 60 cm. Soil samples of similar depths were mixed thoroughly, and a composite sample was taken for each depth for different analyses. The soil physical analysis was identified on site and in the laboratory (Table 1).

The chemical properties of irrigation water were implemented using methods according to Gee and Bauder (1986) and Klute and Dirksen (1986) and the results are presented in table 2.

Experimental and irrigation system description

An automatic drip irrigation system was set up according to the treatments, and hydraulically tested prior to use in the pilot site. The system consisted of a pump, pressure gauges, a filter, an injection unit, control panel, solenoid valves, meteorological station, soil moisture sensors and a measurement unit. The emitters were built-in with 4.0 l h^{-1} discharge at 1.0 bar pressure and a 0.3 meter emitter spacing, and 0.7 m laterals spacing.

Table 1: Some physical properties of the soil.

Depth, Cm	Particle Size distribution, %				Texture Class	θS% on volume basis			HC (cm h^{-1})	BD (g cm^{-3})	P (cm^3 voids cm^{-3} soil)
	Course Sand	Fine Sand	Silt	Clay		FC	PWP	AW			
0-15	8.4	77.6	8.5	5.5	Sandy	16	8	8	6.68	1.69	0.36
15-30	8.6	77.7	8.3	5.4	Sandy	16	8	8	6.84	1.69	0.36
30-45	8.5	77.5	8.8	5.2	Sandy	16	8	8	6.91	1.69	0.36
45-60	8.8	76.7	8.6	5.9	Sandy	16	8	8	6.17	1.67	0.37

*FC: Field Capacity, PWP: Permanent Wilting Point, AW: Available Water, HC: Hydraulic conductivity (cm h^{-1}), BD: Bulk density (g cm^{-3}) and P: Porosity (cm^3 voids cm^{-3} soil).

Table 2: Some chemical properties of irrigation water.

pH	EC dS m^{-1}	Soluble cations, meq l^{-1}				Soluble anions, meq l^{-1}				SAR
		Ca^{++}	Mg^{++}	Na^{+}	K^{+}	$CO3^{-}$	HCO^{3-}	SO^{4-}	Cl^{-}	
7.3	0.5	2.15	0.5	3	0.31	0.01	2.33	1.45	2.17	4.61

*****EC = electric conductivity, SAR = Sodium adsorption ratio

The experimental design was a split plot with three replications. The experiment's total area was 1000 m^2 and was subdivided into two plots of 500 m^2 with 0.7 m spacing between furrows.

Peas seeds were sown on October 1st and harvested on December 29th in both 2017 and 2018. The row and plant spacing was 0.7 and 0.25 m, respectively. Fertilizer requirements of peas were applied in the same amount of all treatments according to the recommendations of Institute of Horticulture Research, Egypt.

The experiment consisted of two irrigation schedules, irrigation water requirements. The first involved using soil moisture sensors connected linked to a solenoid valve and control panel, to automatically irrigation at 30% depletion of field capacity (FC) and stop irrigation at 100% of the field capacity, under drip irrigation system. The sensors were installed at depths from 0 to 15, from 15 to 30 and from 30 to 45 cm.

The second is irrigation scheduling method involved using located meteorological data obtained from El Nubaria station at, that is affiliated to the National Research Centre (NRC), Egypt, under drip irrigation system.

The average meteorological parameters needed for peas' crop water requirement calculation were recorded using a computer model and applying Penman-Monteith equation. the following Eq. (1) was used to calculate the crop evapotranspiration (ETc), Allen *et al.* (1998).

$$ETc = Kc \times ETo \quad (1)$$

ETc is crop evapotranspiration (mm day^{-1}), Kc is crop coefficient and ETo is the reference evapotranspiration (mm day^{-1}).

The average monthly of the meteorological station data are shown in Table 3.

The water conveyed to the plot goes through a flow meter to measure the total quantities given to the each plot. The crop measurements and yield were taken in the same way and time as that of the experimental plots, 90 days after the sowing seeds peas were harvested to measure and calculate the total dry matter, crop productivity and water productivity.

Model description

In the current study the new version of the SALTMED model (version 3.04.25) was used.

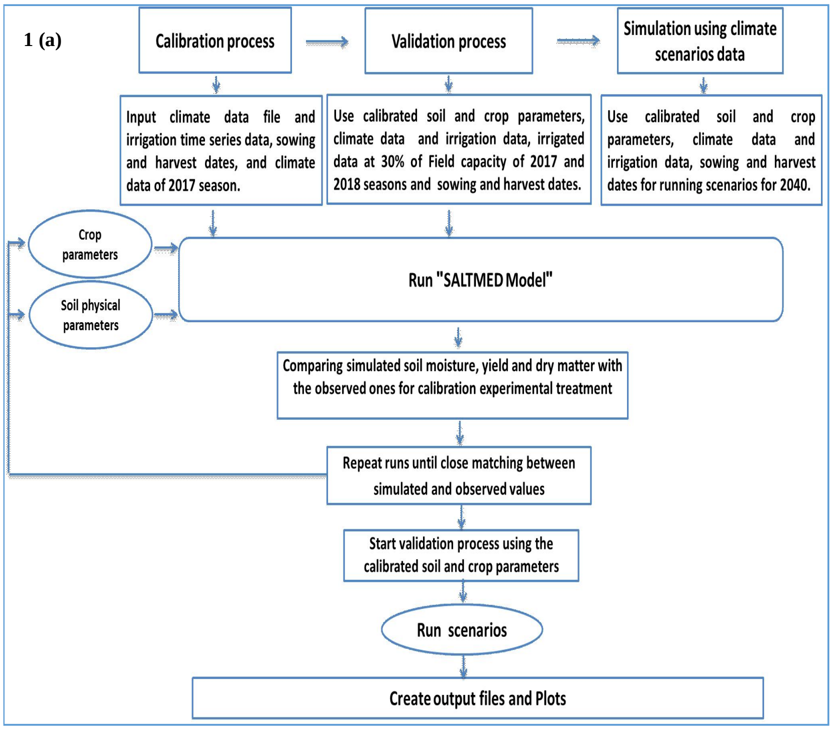
Ragab (2002, 2015) and Ragab *et al.* (2005a, 2005b) provided the model detailed information and the equations of evapotranspiration, water and and crop growth. The model can run and test using all the irrigation systems, here drip irrigation was used. Two irrigation schedules were selected, the first using soil moisture sensors, the second using the actual data to calculate the reference evapotranspiration (ETo) using the data obtained from the field meteorological station (minimum and maximum temperature, humidity, net radiation, wind speed and precipitation).

The pea crop-requirements input values were the Leaf Area Index (LAI), height of plants, maximum and minimum root depth, and stages and growth days. The irrigation input data were those applied in the experiment site for the both irrigation schedules. The first is scheduling irrigation with soil moisture sensors (irrigation at 30% depletion of field capacity FC); the second is irrigation scheduling using actual climate data during two growing seasons 2017 and 2018 under drip irrigation system. Also, to predict (using SALTMED model) the effect of the climate change on applied irrigation requirements, soil moisture distribution, yield and water productivity of pea crops, under the same experimental conditions using two scenarios of future climate data (2040) Fig. 1 (a and b), shows flow charts of how scenarios data (RCP4.5 and RCP8.5) for 2040 were used in SALMED model?. For the future scenarios, Representative Concentration Pathways (RCPs) 4.5 and 8.5 were selected for 2040 impact assessment. The RCPs are greenhouse gas concentration trajectories for future climate adopted by the Intergovernmental Panel on Climate Change (IPCC, 2013). Global Climate Models for climate scenario

Table 3: Average of two seasons (from sowing to harvesting) meteorological data at the experimental station of El Nubaria.

Month	Min Temp °C	Max Temp °C	Precipit-ation mm day^{-1}	Relative Humidity %	Wind m sec^{-1}	Sun Hours	Radiation MJ m^{-2} day^{-1}	ETo mm day^{-1}
Season of 2017								
October	18.5	27.7	0.7	61.4	3.3	9.5	18.9	4.67
November	14.7	23.0	0.7	66.2	2.7	7.9	14.1	2.93
December	12.8	20.4	0.3	70	3	6.1	10.7	2.4
Season of 2018								
October	19.8	29	0.1	61.4	3.2	10	19	4.7
November	16.1	24.5	0.7	63.1	2.6	8.5	14.4	3.1
December	12.5	19.3	0.9	66	3.4	6.6	11.2	2.5

simulations provided daily data on maximum and minimum temperature, precipitation, and net radiation (MIROC5 Atmosphere and Ocean Research Institute "The University of Tokyo", National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan, Model for Interdisciplinary Research on Climate). The averages of the future climate change scenarios and predicted change in temperature and ETo for 2040 at the experimental station of El-Nubaria are shown in tables 4 and 5.



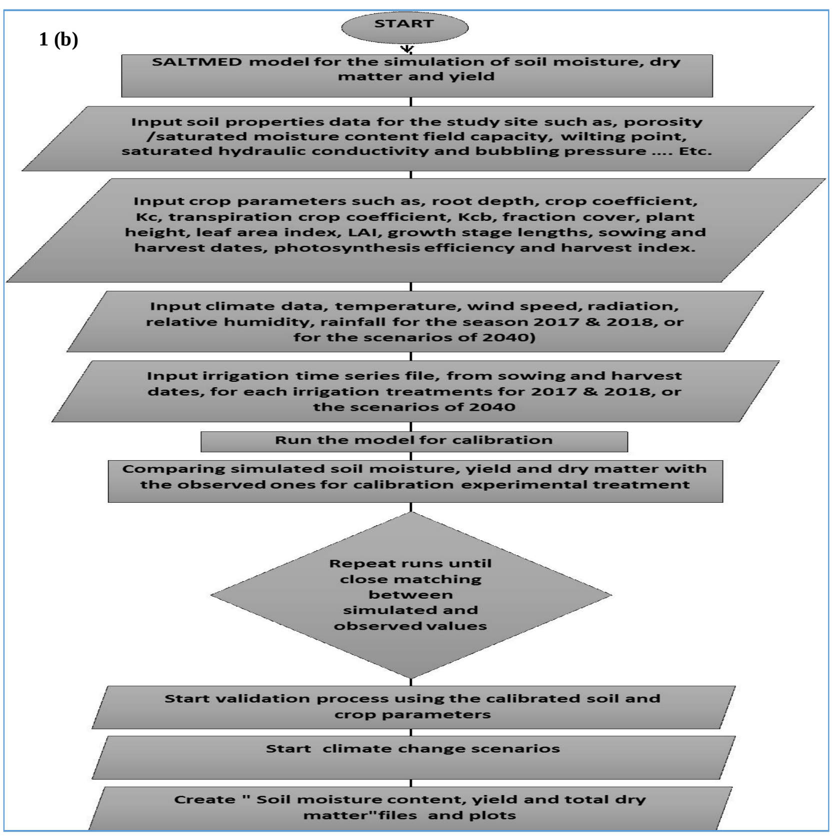


Fig. 1 (a and b): Flow chart of how scenarios data (RCP4.5 and RCP8.5) for 2040 were used in SALMED model?.

Model calibration

Soil water content, dry matter and crop productivity for scheduling irrigation using actual climate data obtained from the meteorological station were compared with the measured values during 2017 season to fine-tuning of the relevant SALTMED model parameters.

For the soil water content calibration, soil properties including bubbling pressure, saturated hydraulic conductivity, saturated soil water content and pore distribution index, "lambda" were fine-tuned until close matching between the model output and observed data was achieved.

The crop coefficients (Kc), basal crop coefficient (Kcb), fraction cover (Fc) and plant height were adjusted.

Model validation

For validation process the simulated and observed soil moisture, dry matter and yield data were compared, for each field experiment (2017 and 2018 seasons) under irrigation schedules.

Statistical and graphical methods were used to test the model; the observed and simulated of soil water contents data and the applied irrigation were conceived as a graph. So the model's response, particularly the trend over time, can be visually quantified.

Loague and Green (1991) proposed a statistical approach to comparing observed and simulated data.

For the model performance the following equations were used:

The coefficient of determination, R^2, statistics demonstrate the ratio between the scatter of predicted values to the average observed values:

$$R^2 = \left(\frac{1}{N}\frac{\Sigma(y_o - \bar{y_o})(y_s - \bar{y_s})}{\sigma_{y_o} - \sigma_{y_s}}\right) \quad (2)$$

Where

$\bar{y_o}$ = averaged observed data

$\bar{y_s}$ = averaged simulated data

σ_{y_o} = observed data standard deviation

σ_{y_s} = simulated data standard deviation.

The Root Mean Square Error RMSE data show how much the predicted values under or overestimate the observed data.

$$RMSE = \sqrt{\frac{\Sigma(y_o - y_s)^2}{N}} \quad (3)$$

Where y_o = observed data

y_s = simulated data

N = all the number of observed data

The coefficient of residual mass (CRM), as the following

$$\mathbf{CRM} = \frac{(\Sigma y_o - \Sigma y_s)}{\Sigma y_o} \quad (4)$$

The CRM is a calculate of the tendency of the model's predictive values under or overestimate the observed data. If the CRM values are negative, this indicates that the model underestimates the measurements and if the values are positive, this indicates a tendency to overestimate. The previous analyses were calculated using Excel (Microsoft Inc.)

Results

Calibration of SALTMED Model

Soil moisture distribution calibration

The process of soil moisture distribution calibration was achieved for layers 0–15, 15–30 and 30–45 cm, under scheduling irrigation with the actual climate data of the 2017 season, and was compared the observed data with the predicted data. Fig. 2 shows the relation between the observed and predicted soil moisture distribution values. Coefficients of determination, R^2 were 0.95, 0.94 and 0.90, successively for depths of 0-15, 15-30 and 30-45 cm. The values of RMSE were 0.005, 0.005 and 0.005, the values of CRM were -0.043, 0.033 and -0.004 successively for depths of 0- 15, 15- 30 and 30-45, under irrigation scheduling using the actual the climate data of 2017 season.

Calibration of dry matter and yield

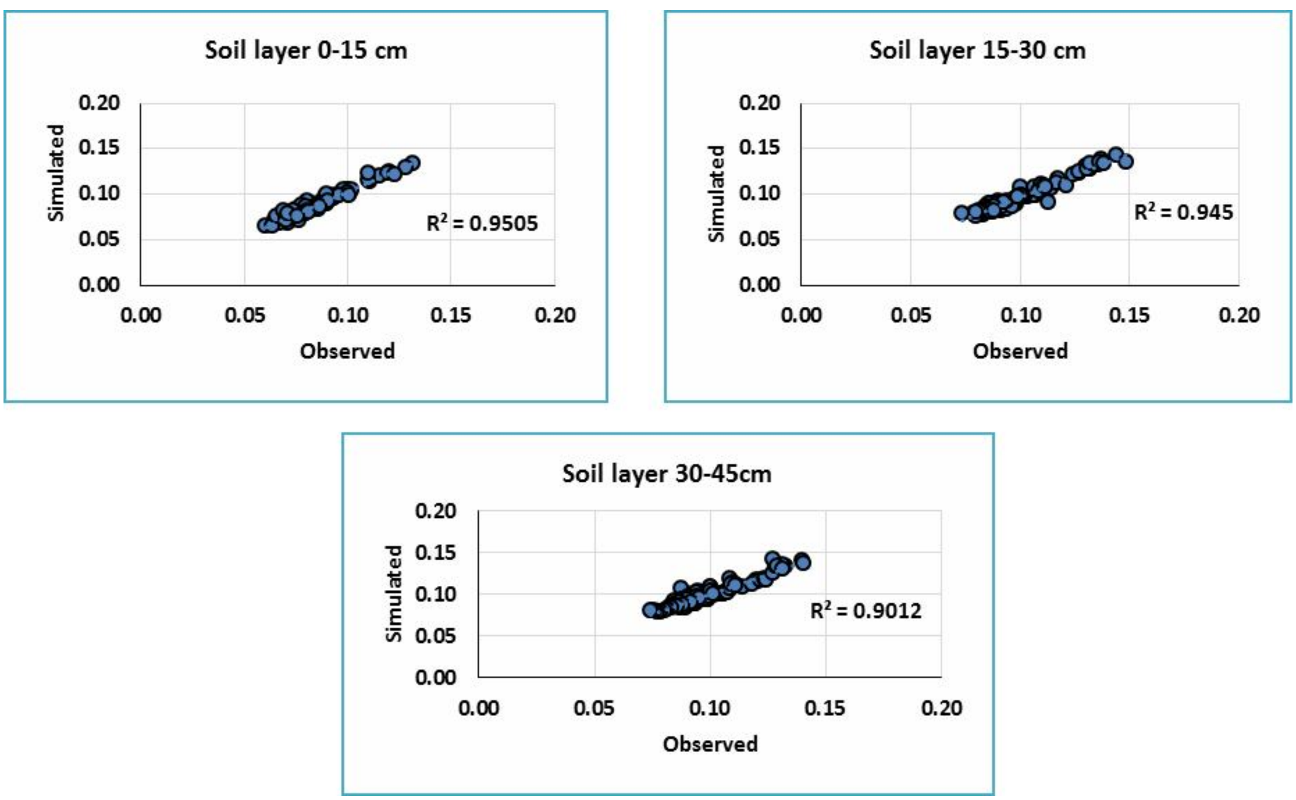


Fig. 2: The observed and simulated soil moisture correlation under irrigation using the climate data of the 2017 growth season, during calibration of SALTMED model.

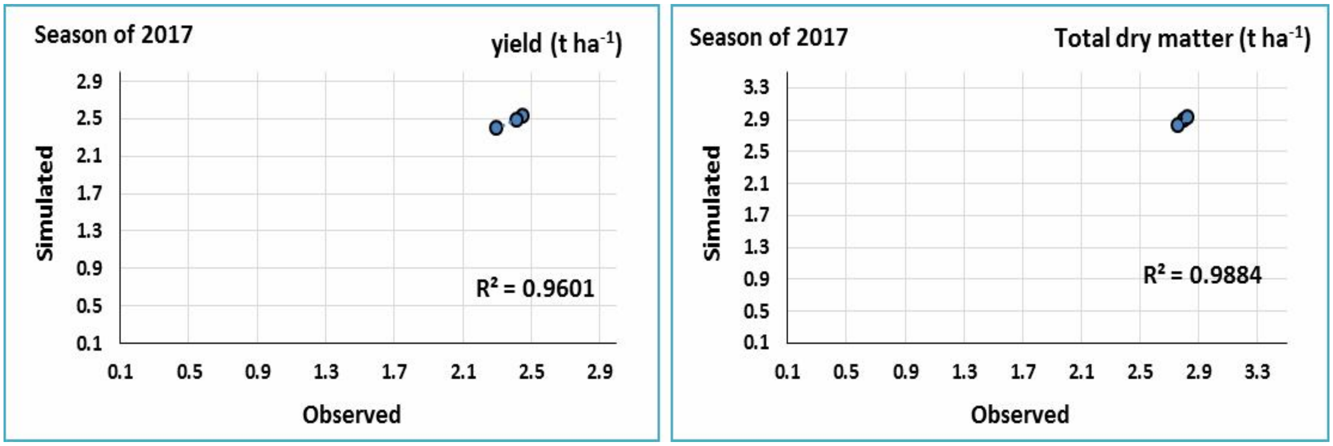


Fig. 3: The observed and simulated total dry matter and yield correlations values using the climate data of the 2017 growth season, simulated with SALTMED as calibration.

As shown in Fig. 3 the coefficient of determination (R^2) of observed and simulated total dry matter and yield were 0.99 and 0.99, respectively. The RMSE was 0.07 and CRM was 0.02, the data indicate a high agreement correlation for observed and predicted total dry matter and yield data during the model calibration.

The pea crop yield was calibrated with high correlation with an observed crop productivity of 2.4 t ha^{-1} and a simulated crop productivity of 2.3 t ha^{-1}.

Depletion % and deficit of irrigation

Figs. 4 and 5 show that the depletion % and deficit of irrigation under scheduling irrigation using weather station data and scheduling irrigation using sensors (30% depletion of FC), for 2017 and 2018 seasons. The results indicated the irrigation intervals under scheduling irrigation using sensors (30% depletion of FC), are very close compared with the scheduling irrigation using weather station data for 2017 and 2018 seasons. On the other

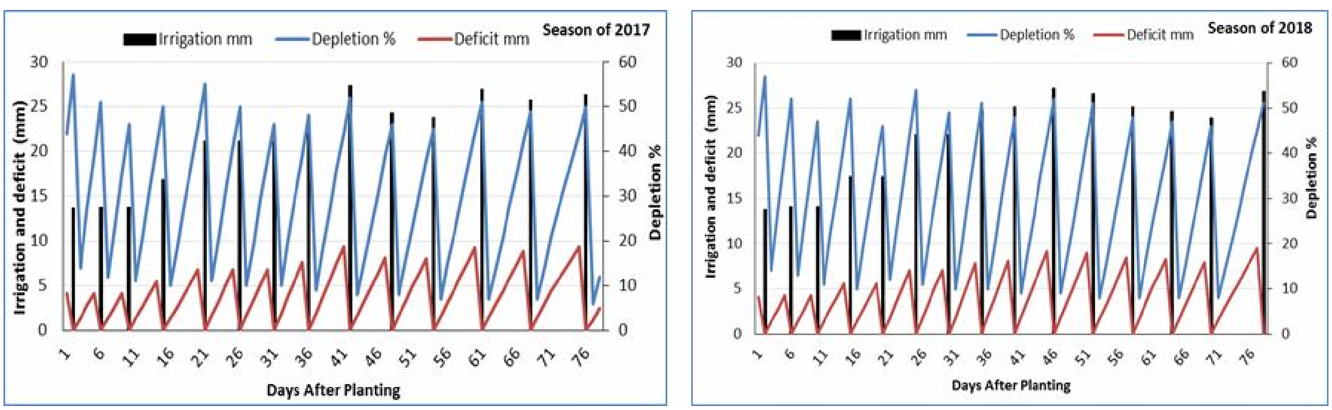


Fig. 4: The depletion (%) and deficit irrigation (mm) under scheduling irrigation using weather station data for 2017 and 2018 seasons.

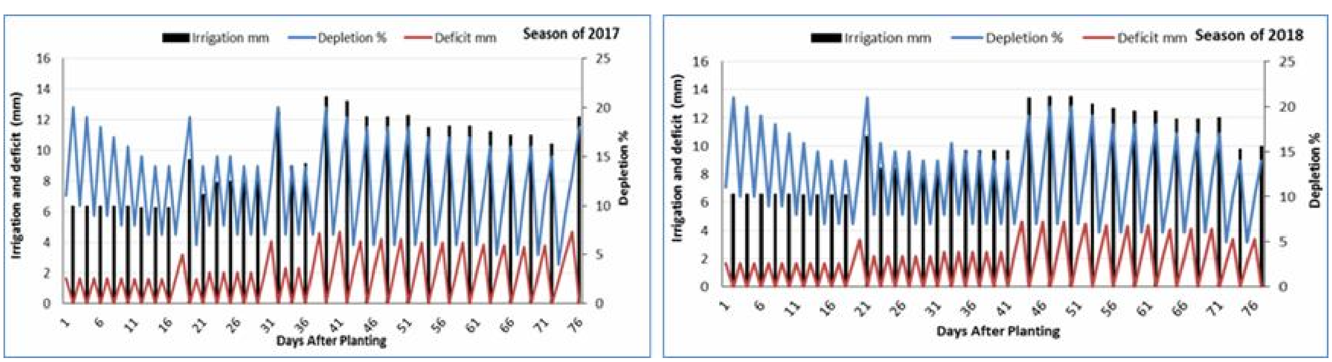


Fig. 5: The depletion (%) and deficit (mm) of irrigation under irrigation using sensors (30% depletion of F.C) for the 2017 and 2018 growth seasons

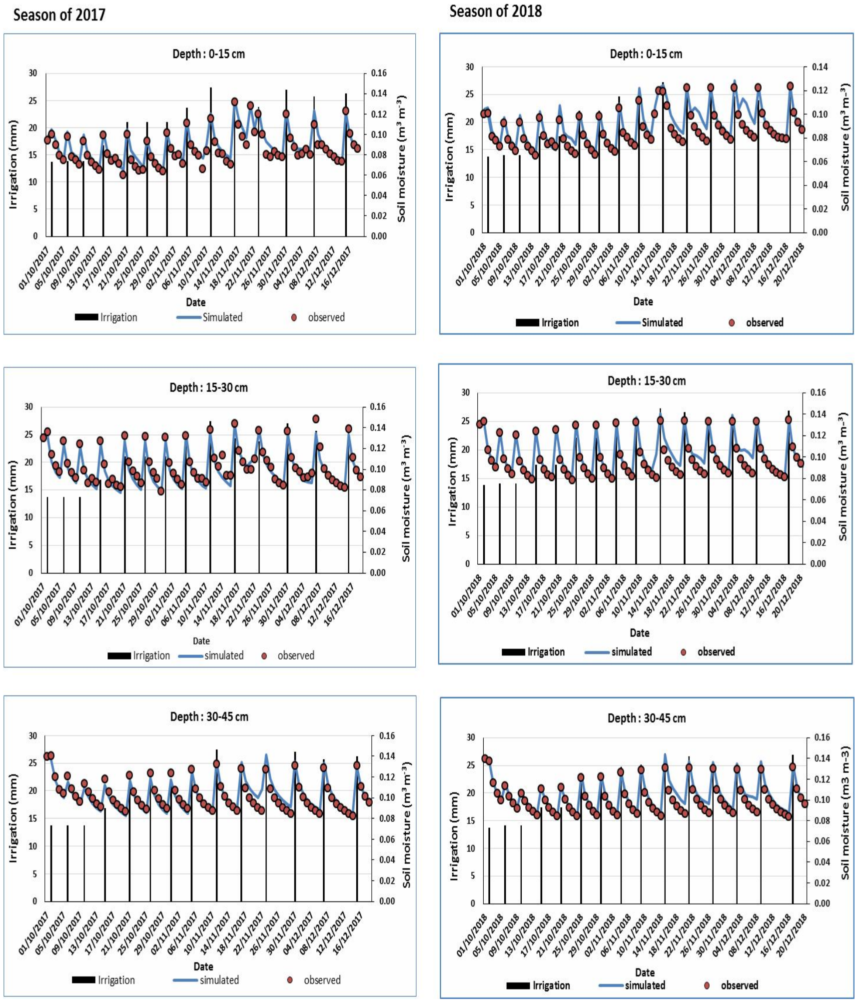


Fig. 6: Observed and simulated soil moisture in all soil layers using the weather station climate data of 2017 and 2018 growth seasons, simulated with SALTMED during validation. Irrigation intervals are plotted as a histogram.

hand, the crop water requirements under scheduling irrigation using sensors, 30% depletion of FC, (2837 and 3069 m^3 ha^{-1}) are lower than the crop water requirements under scheduling irrigation using weather station data (2996 and 3251 m^3 ha^{-1}) for 2017 and 2018 seasons, respectively.

Table 4: Average of two future climate scenarios of 2040 (from sowing to harvesting of peas) for the experimental station of El Nubaria.

Month	Min Temp °C	Max Temp °C	Relative Humidity %	Wind m sec^{-1}	Sun Hours	Radiation MJ m^{-2} day^{-1}	ETo mm day^{-1}
The RCP4.5 scenario of 2040							
October	20	29	60	3.5	10	18.7	5.03
November	16.5	25	60	3.1	8.6	14.4	3.67
December	12.7	21.4	65	3.3	6.3	10.9	2.79
The RCP8.5 scenario of 2040							
October	20	29	59	3.7	10.1	18.9	5.18
November	17	25.5	58	3.3	8.3	14.1	3.89
December	13.9	20.9	60	3.4	6.8	11.4	3.05

Model validation

The validation was processed using the 2017 and 2018 season's data under different scheduling irrigation, with the same information of the model's calibration.

Soil moisture content

As shown in Fig. 6 the soil moisture under scheduling irrigation with weather data for 0–15, 15–30 and 30–45 cm layers were kept around 0.060 to 0.132, 0.078 to 0.148 and 0.082 to 0.148 m^3 m^{-3} and (0.065 to 0.123, 0.078 to 0.134 and 0.083 to 0.139 m^3 m^{-3} over the seasons of 2017 and 2018, respectively. Fig. 7 shows the soil moisture content under scheduling irrigation at 30% depletion of FC. The soil water content for 0–15, 15–30 and 30–45 cm layers were kept around 0.058 to 0.136, 0.07 to 0.132 and 0.072 to 0.141 m^3 m^{-3} and 0.064 to 0.140, 0.07 to 0.132 0.076 to 0.139 m^3 m^{-3} over the seasons of 2017 and 2018, respectively.

Table 6 summarizes statistical evaluation values for the observed and simulated soil moisture during the model performance test, for the two irrigation schedules for the 2017 and 2018 seasons. The determination coefficient R^2, RMSE and CRM were calculated to indicate whether the model is suitable for predicting soil moisture content.

A high agreement relation was achieved for observed and predicted soil moisture data for all layers. The R^2 for the soil moisture under scheduling irrigation using weather station data in the soil layers (0-15, 15-30 and 30-45) were (0.95, 0.94 and 0.90) and (0.90, 0.94 and 0.94) for 2017 and 2018 seasons, respectively. The R^2 for the soil moisture under scheduling irrigation at 30 % depletion of F.C in the soil layers (0-15, 15-30 and 30-45) were (0.96, 0.92 and 0.94) and (0.97, 0.91 and 0.93) for 2017 and 2018 seasons, respectively.

The different indicators of R^2 RMSE, CRM and the simulated results under both irrigation schedules for both seasons referred that, the model is suitable to predict and assessment soil

Table 5: Predicted changes in temperature and ETo for climate change scenarios for the year 2040.

Month	Min Temp°C		Max Temp °C		ETo mm day^{-1}	
	2017	2018	2017	2018	2017	2018
The RCP4.5 scenario of 2040						
October	1.5	0.2	1.3	0	0.36	0.33
November	1.8	0.4	2	0.6	0.74	0.57
December	-0.1	0.2	1	2.1	0.39	0.29
The RCP8.5 scenario of 2040						
October	1.5	0.2	1.3	0	0.51	0.48
November	2.3	0.9	2.5	1	0.96	0.88
December	1.1	1.4	0.5	1.6	0.65	0.55

water content.

Total dry matter and crop productivity

Figs. 8 and 9 show the observed and predicted peas total dry matter and crop productivity under both irrigation schedules for the two seasons. The higher dry matter and crop productivity were obtained under scheduling irrigation at 30% depletion of FC, the total dry matter was 3.3 and 3.97 t ha^{-1} and the yield was 2.7 and 3.3 t ha^{-1} for 2017 and 2018 seasons, respectively. The total dry matter was 2.83 and 3.5 t ha^{-1} and the yield was 2.4 and 2.93 t ha^{-1} under scheduling irrigation using weather data pipe for 2017 and 2018 seasons, respectively.

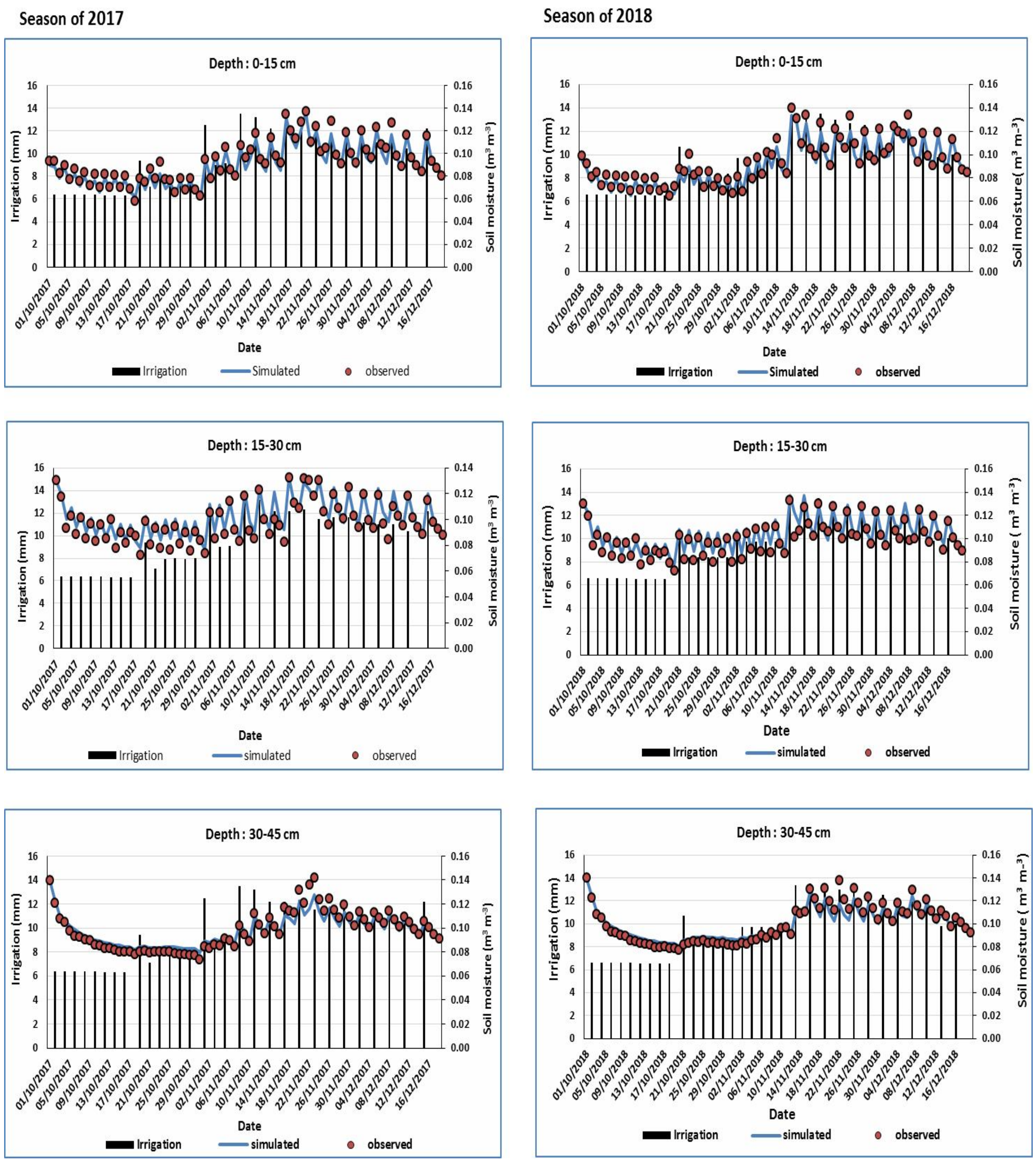


Fig. 7: Observed and simulated soil moisture in all soil layers under scheduling irrigation using sensors (30% depletion of FC) of 2017 and 2018 seasons, simulated with SALTMED during validation. Irrigation intervals are plotted as a histogram.

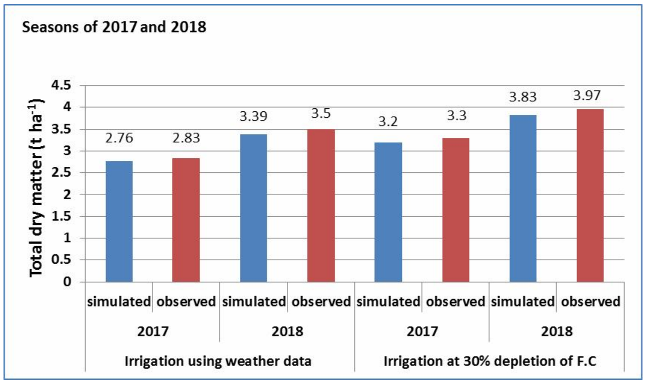


Fig. 8: Total dry matter of peas under two irrigation schedules for the 2017 and 2018 growth seasons.

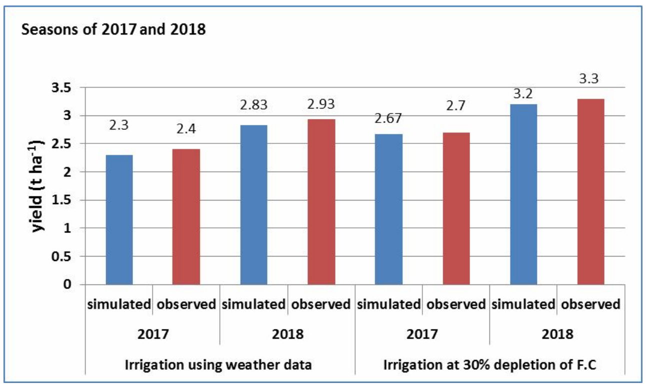


Fig. 9: Peas yield under two irrigation schedules for the 2017 and 2018 growth seasons.

The coefficient of determination, R^2 indicated that there was a high relation for observed and predicted peas total dry matter and yield for both scheduling irrigation during the two seasons as shown in Figs. 10 and 11. The relation between observed and predicted data R^2 for the total dry matter was 0.98 and 0.98;, R^2 for peas productivity was 0.96 and 0.95 under scheduling irrigation using the weather data for 2017 and 2018 seasons, respectively. The R^2 under scheduling irrigation at 30% depletion of FC was 0.98 and 0.99 for the total dry matter and was 0.99 and 0.97 for peas yield for 2017 and 2018 seasons, respectively. The uniformity of irrigation intervals provides higher and uniform soil moisture distribution under irrigation system, it helped to achieve a good growth and increased dry matter and productivity.

Water productivity (kg m^{-3}) is an indicator of the relationship between total peas productivity (kg ha^{-1}) and the total applied irrigation (m^3 ha^{-1}) during the crop growth season.

Fig. 12 shows the water productivity under the two irrigation schedules and two growing seasons. The highest water productivity was an indication that crop yield was high with less of the total applied of water during the growing season. The highest water productivity was

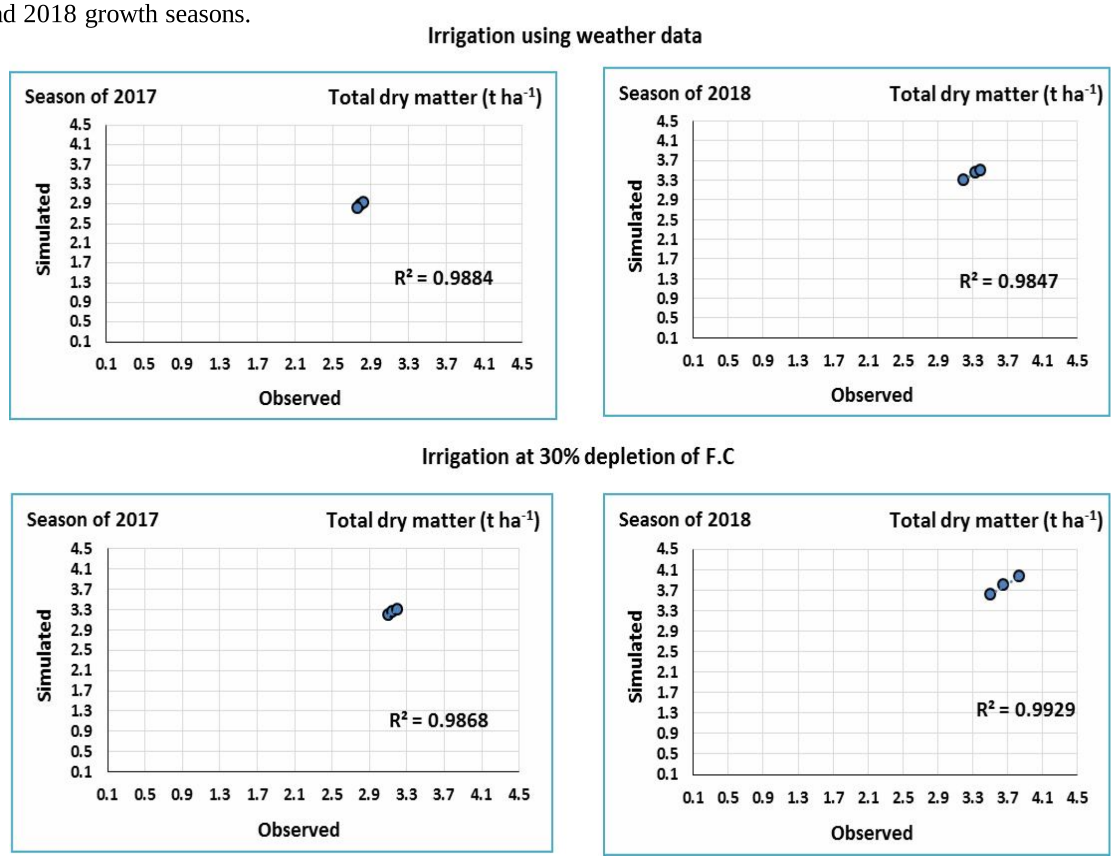


Fig. 10: The observed and simulated dry matter correlation values for peas under two scheduling irrigation schedules for the 2017 and 2018 seasons, during validation of SALTMED model

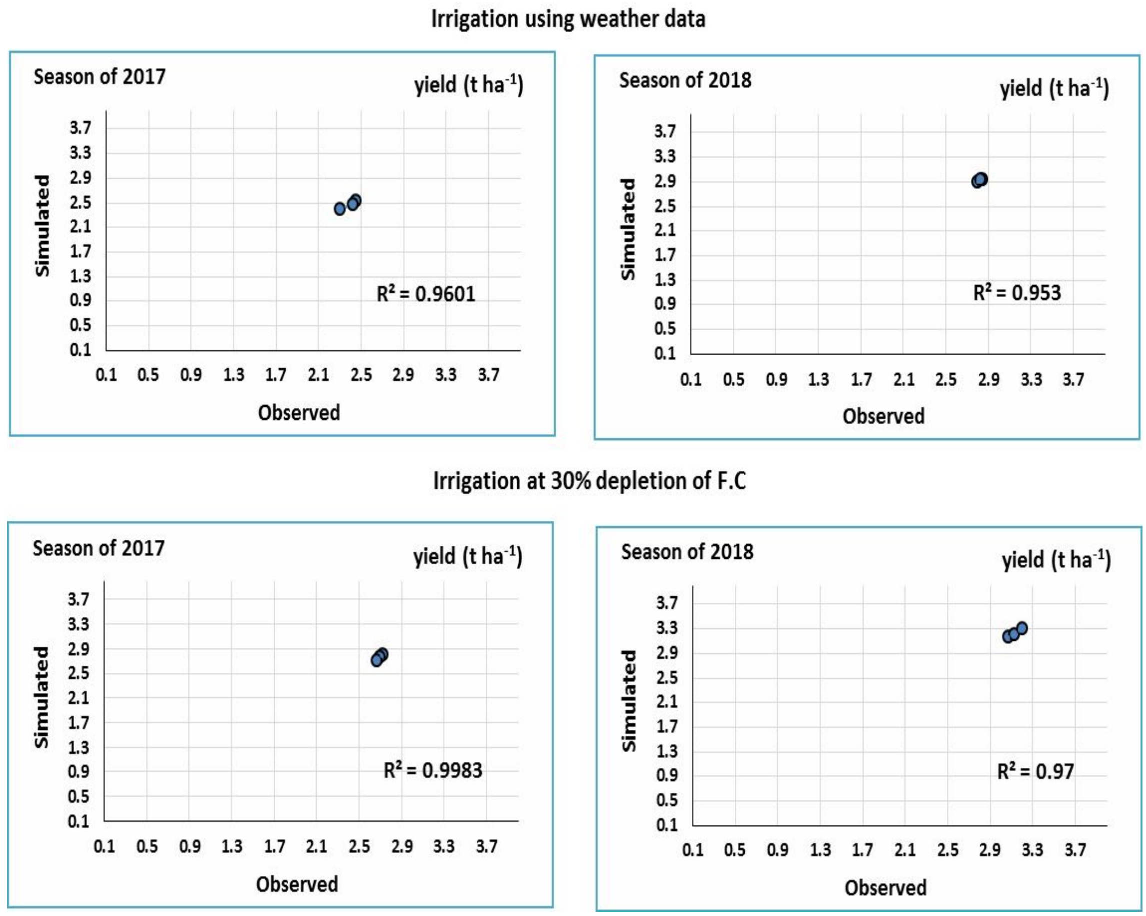


Fig. 11: The observed and simulated yield correlation values for peas under two irrigation schedules for the 2017 and 2018 growth seasons, during validation of SALTMED model.Water productivity

under scheduling irrigation at 30% depletion of FC, the water productivity was 0.95 and 1.07 kg m^{-3} with total applied of water 2840 and 3070 m^3 ha^{-1} for 2017 and 2018 seasons, respectively.

The water productivity was 0.8 and 0.9 kg m^{-3} and with total applied of water 3000 and 3250 m^3 ha^{-1} under scheduling irrigation using weather data for 2017 and 2018 seasons, respectively.

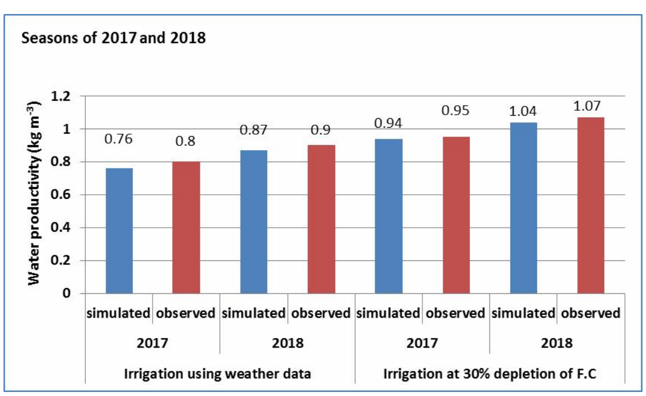


Fig. 12: Peas crop water productivity under two scheduling irrigation for 2017 and 2018 seasons.

As shown in Fig. 13 there was a high relation in observed and predicted water productivity (kg m^{-3}) for two irrigation schedules during two growing seasons. For the scheduling irrigation using the weather station data, the R^2 was 0.96 and 0.95 for 2017 and 2018 seasons, respectively. For the scheduling irrigation (irrigation at 30% of FC), the R^2 was 0.99 and 0.97 for 2017 and 2018 seasons, respectively.

Table 7 shows the difference correlations and statistical measurement values R^2, RMCE and CRM of observed and predicted crop productivity, dry matter and water productivity of peas, during model evaluation under two irrigation schedules for the two growing seasons. There were small differences in correlations for crop productivity, dry matter and water productivity, statistical measurement values between observed and predicted data for both irrigation schedules for the two growing seasons. In general, the maximum crop productivity, dry matter and water productivity were obtained under an irrigation schedule at 30% depletion of FC with less water applied for irrigation, 284 and 307 mm per season for the 2017 and 2018 seasons, respectively. The lowest yield,

Table 6: The coefficient of determination (R^2), RMSE and CRM for soil moisture in the different soil layers for the two growing seasons.

Season of 2017									
Scheduling irrigation	Soil layers, cm								
	0-15			15-30			30-45		
	R^2	RMSE	CRM	R^2	RMSE	CRM	R^2	RMSE	CRM
Weather station climate data*	0.95	0.005	-0.043	0.94	0.005	0.033	0.90	0.005	-0.004
At 30% depletion of FC	0.96	0.005	0.039	0.92	0.005	-0.034	0.94	0.005	0.004
Season of 2018									
Weather station climate data	0.90	0.007	-0.053	0.94	0.005	-0.036	0.94	0.005	-0.036
At 30% depletion of FC	0.97	0.005	0.038	0.91	0.005	-0.033	0.93	0.005	0.004

* Use in model calibration

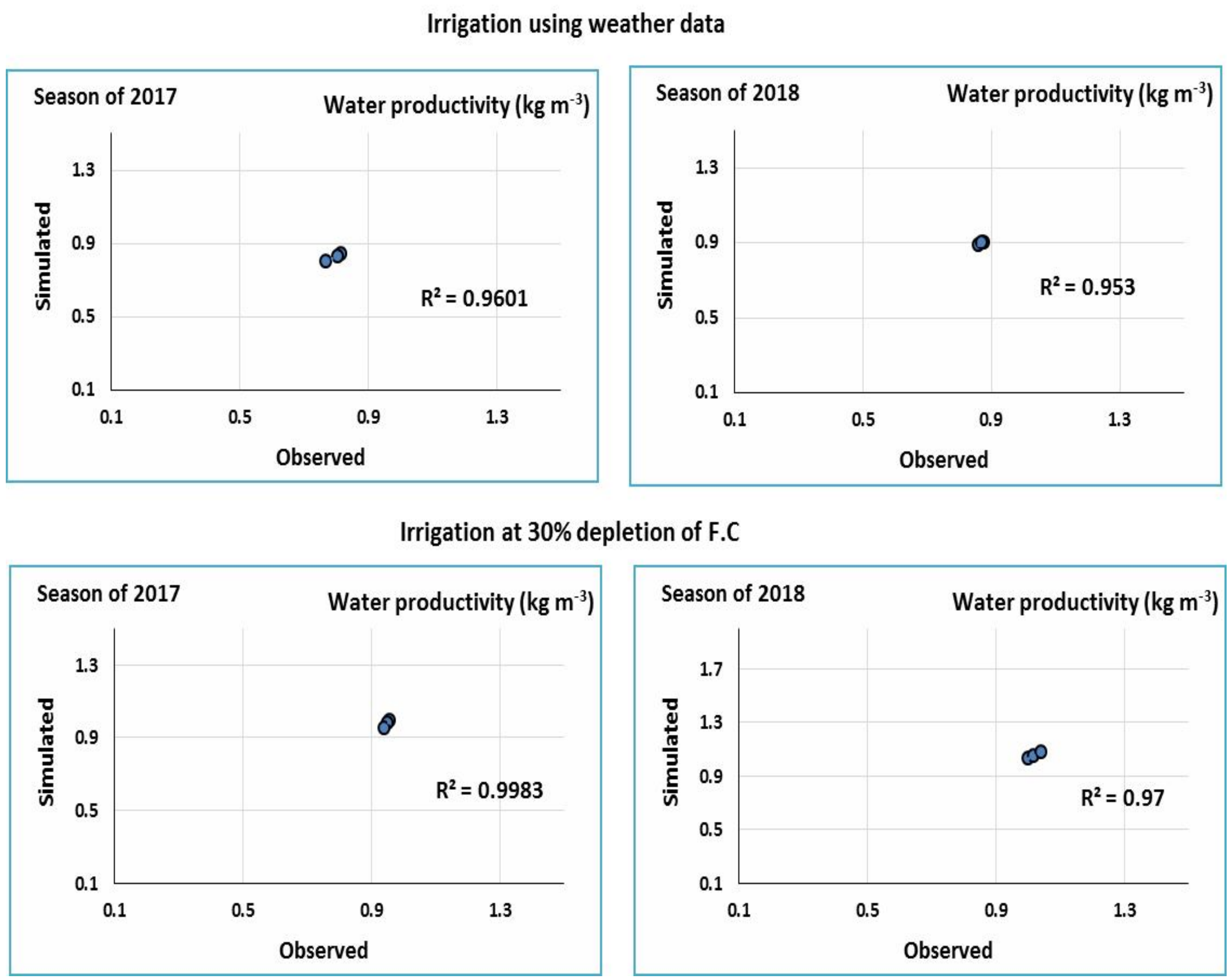


Fig. 13: The observed and simulated water productivity correlation values for peas under two scheduling irrigation for 2017 and 2018 seasons, during validation of SALTMED model.

dry matter and water productivity were obtained under an irrigation schedule using weather station data, although a higher amount of irrigation water was applied, 300 and 325 mm per season for the 2017 and 2018 seasons, respectively.

Predict the impact of the climate change

Impact of climate change on water requirement

Fig 14 shows the water requirements under irrigation scheduled using weather station data, for the 2017 and 2018 growing seasons and predicted irrigation using (RCPs 4.5 and 8.5) scenarios for 2040 climate data. There is an increase in water requirement for both scenarios. The highest water requirement was obtained from the RCP8.5 scenario (3855 $m^3 ha^{-1}$), and then the RCP4.5

Table 7: Observed and simulated yield and water productivity of peas.

Scheduling irrigation		Observed	Simulated	*Relative difference	R^2	RMCE	CRM	Irrigation mm
Season of 2017								
Irrigation using weather data	Yield (t ha^{-1})	2.4	2.3	0.04	0.96	0.08	0.03	300
	Total dry matter (t ha^{-1})	2.83	2.76	0.02	0.98	0.08	0.02	
	Water productivity (kg m^{-3})	0.8	0.76	0.05	0.96	0.02	0.03	
Irrigation at 30% depletion of FC	Yield (t ha^{-1})	2.7	2.67	0.01	0.99	0.06	0.02	284
	Total dry matter (t ha^{-1})	3.3	3.2	0.03	0.98	0.1	0.03	
	Water productivity (kg m^{-3})	0.95	0.94	0.01	0.99	0.02	0.02	
Season of 2018								
Irrigation using weather data	Yield (t ha^{-1})	2.93	2.83	0.03	0.95	0.09	0.03	325
	Total dry matter (t ha^{-1})	3.5	3.39	0.03	0.98	0.1	0.03	
	Water productivity (kg m^{-3})	0.9	0.87	0.03	0.95	0.02	0.03	
Irrigation at 30% depletion of FC	Yield (t ha^{-1})	3.3	3.2	0.03	0.97	0.09	0.02	307
	Total dry matter (t ha^{-1})	3.97	3.83	0.03	0.99	0.1	0.03	
	Water productivity (kg m^{-3})	1.07	1.04	0.02	0.97	0.03	0.02	

*Relative difference = [(Observed – Simulated) / Observed]

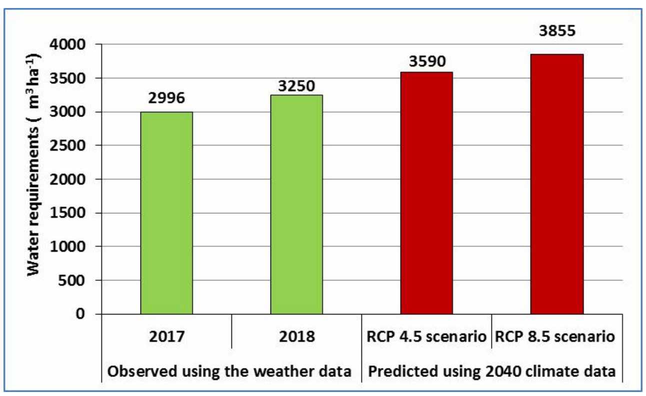


Fig. 14: Water requirements under two irrigation schedules for the 2017 and 2018 growing seasons and predicted irrigation requirements using two climate change scenarios for 2040 climate data.

scenario (3590 m^{3}ha^{-1}), compared to the 2017/18 seasons' data. The obtained climate data of the two future scenarios (RCP4.5 and RCP8.5) indicated there will be a higher minimum and maximum temperature compared to the 2017 and 2018 seasons.

Impact of climate changes on soil moisture distribution

After validated, to predict the soil moisture distribution the model was run using the two RCPs 4.5 and 8.5 scenarios of 2040, with the same information of the calibrated and validated soil and crop parameters.

The histogram of the predicted soil moisture distribution for soil layers from 0 to 45 cm under RCP4.5 and 8.5 scenarios data of 2040 is shown in Fig. 15. The results show that there is an increase in soil moisture distribution and its uniformity for all soil layers, with the RCP4.5 data compared with the RCP8.5 data. The lowest amount of irrigation water was applied under the RCP4.5 scenario (359 mm per season), while under the RCP8.5 scenario 385.5 mm per season would be required. Table 5 shows there is an increase in evapotranspiration for the RCP8.5 scenario compared with the RCP4.5 scenario. Also, there is an increase in evapotranspiration for the both scenarios (2040), compared with the current study data (Table 3).

Fig. 15 shows that the predicted soil moisture with the RCP4.5 scenario was kept around 0.055 to 0.12, 0.072 to 0.17 and 0.061 to 0.128 m^3 m^{-3} and with the RCP8.5 scenario values were 0.05 to 0.1, 0.065 to 0.11 and 0.058 to 0.12 m^3 m^{-3} for the season of 2040, for 0–15, 15–30 and 30–45 cm depths, respectively.

Impact of climate changes on yield and water productivity

The predicted data of yield and water productivity are presented in Figs. 16 and 17. The SALTMED model predicted that there will be a decrease of yield in 2040. Fig.16 shows that the yield will be decreased by around 4.1% and 21.5% for RCP4.5 scenario and by 12.5% and 38.3% ??for RCP8.5 scenario compared to the 2017 and 2018 seasons, respectively. However, the yield will be decreased by around 21.5% and 38.3% successively for RCPs 4.5 and 8.5 of 2040, compared with 2018. There is high decrease in predicted water productivity with a similar trend in yields for both scenarios. The decrease

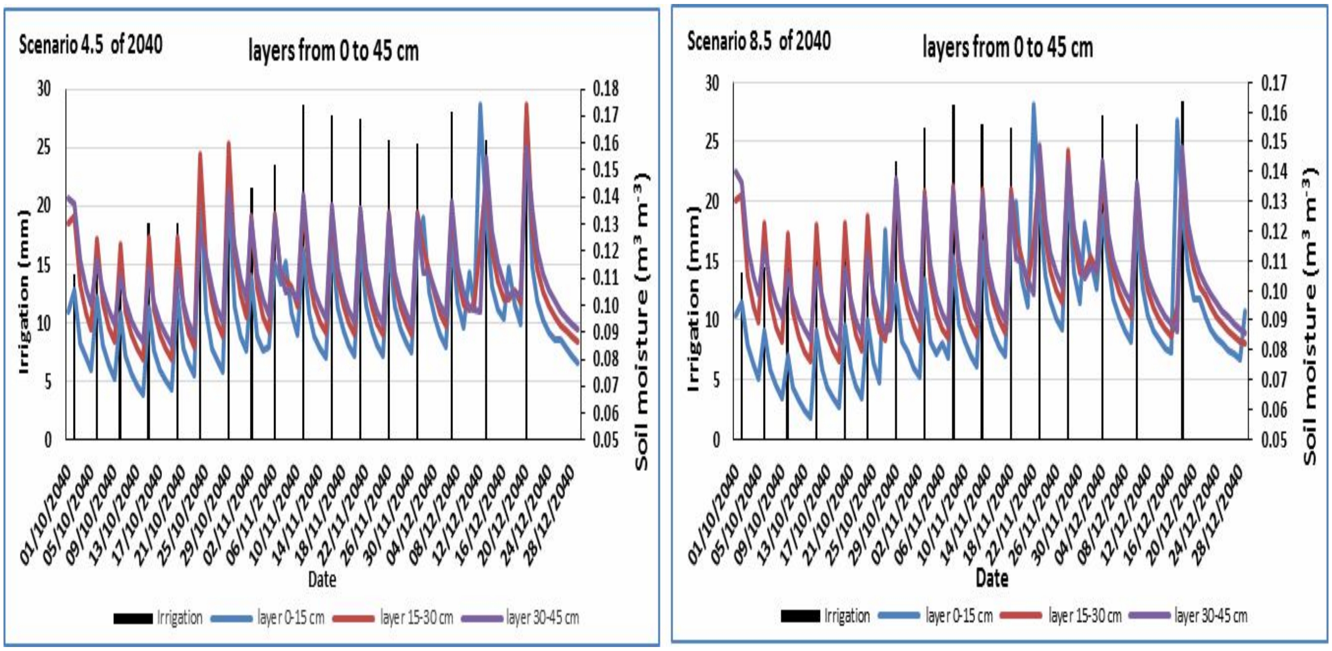


Fig. 15: Simulated soil moisture in all soil layers under two climate change scenarios (RCP 4.5 and RCP 8.5) of 2040, simulated with SALTMED after validation. Irrigation intervals are plotted as a histogram

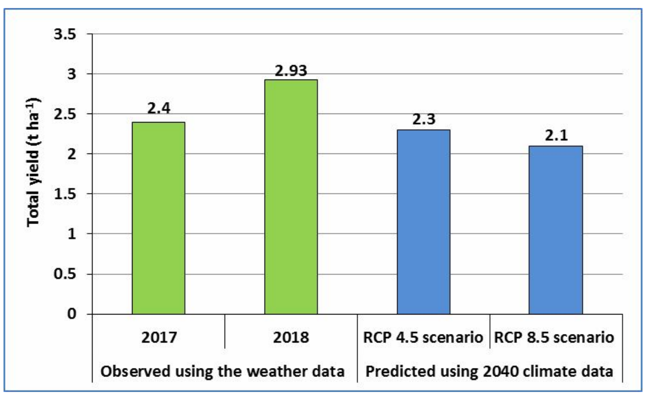


Fig. 16: Observed yield under two irrigation schedules for the 2017 and 2018 growth seasons and predicted yield for two climate change scenarios for 2040 climate data.

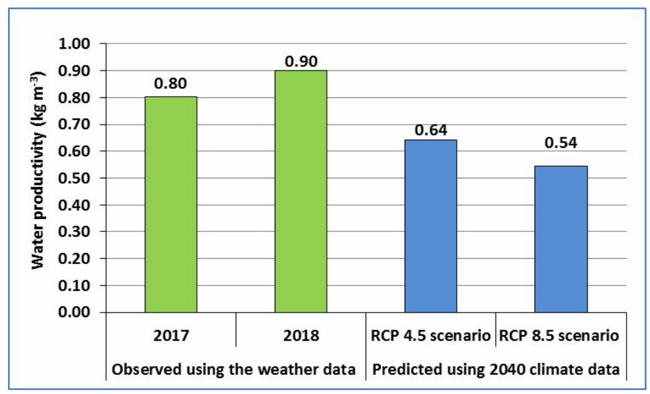


Fig. 17: Observed water productivity under two irrigation schedules for the 2017 and 2018 growth seasons and predicted water productivity for two climate change scenarios for 2040.

in water productivity was 20% and 28.8% for the RCP4.5 scenario and 32.5% and 40% ??for the RCP 8.5 scenario, compared to 2017 and 2018 seasons, respectively (Fig. 17).

Discussion

Through the model calibration the data indicated there was a slight variation of the observed and predicted soil water content data for all the soil layers. The RMSE and CRM values indicated that, the SALTMED model has the able to simulate soil water content at different depths, with slight differences between predicted and observed data.

The peas crop total dry matter and crop productivity calibration were done for the irrigation schedule using the actual climate data of 2017 season to adjust the crop parameters. There are high relations in observed and predicted of peas dry matter and crop productivity values. The data referred that the SALTMED simulation model had a high accuracy in simulating total dry matter and crop productivity under the irrigation schedule using the actual climate data of 2017 season.

Determination of irrigation water requirements and scheduling and management of irrigation are important. Therefore, irrigation management is about controlling the quantity and time to control the rate of irrigation to be effective. The irrigation intervals under scheduling irrigation using sensors (30% depletion of FC), are very close compared with the scheduling irrigation using weather station data for both seasons as shown in Figs. 4 and 5. This is possibly due to the crop can get the available or portion water from the root zone (the sensor area) with uniformity of irrigation intervals without facing the deficit water under scheduling irrigation using sensors (30% depletion of FC), for 2017 and 2018 seasons (Ewaid *et. al.,* 2019)**.**

During the validation the soil the histogram of the simulated and predicted soil water content data for soil depths 0- 15, 15-30 and 30- 45 cm for scheduling irrigation with the actual climate data and using sensors (irrigation at 30% depletion of FC) for the 2017 and 2018 seasons are shown in Figs. 6 and 7. The results indicated that there is little variation in the observed and predicted soil moisture data for asoil layers, under both scheduling irrigation treatments for the two seasons. There is also a high relationship in the observed and predicted soil moisture distribution for irrigation schedules.

The surface soil layer is the layer that was most affected by the weather factors and the plant roots. Also, the surface layer is exposed to further dynamic changes resulting from the plant uptake, soil infiltration rate and soil evaporation (Silva *et al.,* 2013; Hirich *et al.,* 2012; Afzal *et al.,* 2016; El-Shafie *et al.,* 2017).

The data also indicated high uniformity of soil moisture distribution under scheduling irrigation using sensors (irrigated at 30% depletion of FC), compared with the scheduling irrigation using weather station data for 2017 and 2018 seasons. This is due to the fact that the irrigation rate can change the soil moisture distribution and water storage (Cao *et al.,* 2003; El-Noemani *et al.,* 2015a; El-Noemani *et al.,* 2015b; Wahba *et al.,* 2016; Marwa *et al.,* 2017; Youssef *et al.,* 2018). Also, shorter intervals and low irrigation rate under drip irrigation were higher and produced uniform soil water distribution in the surface soil than in deeper soil layers. On the other hand, long irrigation intervals and a high irrigation rate under drip irrigation were favoured for water infiltration and lateral infiltration, but with higher deep percolation and un-uniform surface and sub-surface soil moisture distribution (Liu *et al.,* 2011). However, long times of irrigation may cause water stress, especially in sandy soils (Jordan *et al.,* 2003).

In general, the relationship between simulated and observed results under both irrigation schedules showed a good correlation that is a good indicator that SALTMED is a suitable model for predicting the soil water contents. These results are consistent with Pulvento *et al.* (2013), Pulvento *et al.* (2015a), Fghire *et al.* (2015) Rameshwaran *et al.* (2015), El-Shafie *et al.* (2017), Abdelraouf and Ragab (2018a) and Abdelraouf and Ragab (2018b).

The increase in dry matter, crop productivity and water productivity is due to the fact that the narrow irrigation intervals under scheduling irrigation at 30% depletion of FC gives more uniform water during the plant growing season. Boydak *et al.* (2007) reported that the highest yields of sesame were obtained from narrow irrigation intervals under semi-arid conditions in Turkey, the reduced irrigation intervals will increase yield per hectare it will also increase the number of sesame capsules per plant. Zhang *et al.* (2019) poited out that in the arid and semi-arid region, evapotranspiration is high. However, the currently used irrigation interval is too long and lowers the maize yield. The narrow intervals between irrigation, (6 days between irrigation) gave the highest yield in comparison with the wide intervals between irrigation (9 and 12 days between irrigation) (Zhang *et al.,* 2019).

During the validation of dry matter, crop productivity and water productivity the R^2 values referred that there is a high correlation for simulated and predicted data. Also, the results showed that the SALTMED is a good model for predicting total dry matter and yield of peas crop and can be useful to run with "what is the impact of different scenarios" to assessment the effect of irrigation scheduling under different conditions on the dry matter and yield. This results according to Ragab *et al.* (2015), Afzal *et al.* (2016), El-Shafie *et al.* (2017), Abdelraouf and Ragab (2018a) and Abdelraouf and Ragab (2018b).

In this research work explores the effect of climate change change on soil moisture distribution, there is an increase in evapotranspiration for the both scenarios (2040), compared with the current study data This increase in evapotranspiration affects the amount of irrigation, and also the soil moisture content. This is because the irrigation rate, can change the soil moisture distribution and water storage (Cao *et al.,* 2003). The surface soil layer (0-15 cm) was affected more under the RCP8.5 scenario compared with the RCP 4.5 scenario. The surface layer is the layer that was most affected by the weather factors and the plant roots. (Hirich *et al.,* 2012; Afzal *et al.,* 2016; El-Shafie *et al.,* 2017).

The decrease in water productivity is due to an increase in crop water requirement with a decrease in crop yield for both scenarios (RCPs 4.5 and 8.5) for 2040 data. This is due to the increase in the minimum and maximum temperatures compared to the 2017 and 2018 seasons. The calculation of the water requirements depends on the evapotranspiration (ETo). To calculate the evapotranspiration the Penman-Monteith equation is used Allen *et al.* (1998). The increase in evapotranspiration rate is due to the increase in maximum and minimum temperature, these values will affect on crop water requirements (Abdrabbo *et al.,* 2015).

In general, yield and water productivity, as predicted using the SALTMED model, tend to decrease in 2040 under both scenarios. According to these results, the evapotranspiration will increase in the study area (El Nubaria, Egypt), the growing season for the cultivation of peas will be reduced and there will have to be a change in the dates of cultivation or short-growing varieties will have to be used.

Conclusion

The purpose of the research work was to test the SALTMED model performance with two trials on peas under two irrigation schedules. After validation the model was used to predict the impact of two scenarios of the future climate data (RCP4.5 and RCP8.5) for 2040 on peas parameters under the same experimental conditions. The field trials showed that the irrigation intervals under irrigation scheduled at 30% depletion of field capacity given high uniformity of irrigation and soil moisture distribution with lower water requirements, compared with the irrigation scheduled using weather station data for the 2017 and 2018 growth seasons. The results indicated that scheduling irrigation at 30% depletion of field capacity gave the higher crop productivity and water productivity during both the 2017 and 2018 growth seasons. The increase in crop productivity and water productivity are referring to the fact that the narrow irrigation intervals under irrigation scheduled at 30% depletion of FC gives more uniform water during crop growth periods. The model calibration and validation showed there was a strong correlation for observed and simulated values under both irrigation schedules during the 2017 and 2018 growth seasons. These results indicate that the SALTMED model is a good tool for predicting crop parameters, to assess the future effect with different scenarios on irrigation management. There is an increase in predicted water requirements under both scenarios in 2040 using SALTMED model. The yield and water productivity tend to decrease in 2040 under both scenarios. According to the results, the evapotranspiration will increase in the study area (El Nubaria, Egypt), so the cultivation period of the peas crop needs to reduce, the cultivation dates will need to change or pea varieties with short-growing seasons will have to be used.

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