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Combination of Organic and Inorganic Fertilizers to Counteract Climate Change Effects on Cultivation of Oilseed Flax (*Linum usitatissimum* L.) Using the APSIM Model in Arid and Semiarid Environments

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Abstract: The impact of climate change on crop production is a major concern in drought-prone regions, which are experiencing increasingly severe drought conditions. The goal of this study was to use the Agricultural Production System Simulator (APSIM) model to simulate and predict flax yield and water balance, as well as to determine the optimal irrigation and fertilizer for flax production to counteract the effects of climate change under arid and semiarid conditions. The model was calibrated using field experimental data from 2019 to 2020 and evaluated using field experimental data from 2021 to 2022 with a combination of four irrigation treatments (full irrigation, 180 mm, deficit irrigation at vegetative and reproductive stage, no irrigation) and four fertilizer rates (no fertilizer, NPK, NPK + flax oil residue, NPK + farm manure) using a plot design for a total of 16 treatments. To determine the key irrigation and fertility periods and irrigation and fertilization amounts that affect flax yield to address climate change, a combination of four irrigation and six fertilizer rates and six irrigation stages were simulated. The results showed that the model successfully predicted flax yield (R^2 = 0.98) and water-use efficiency (WUE) (R^2 = 0.79). When compared to inorganic fertilization, the grain yield and WUE improved by 16.47% and 13.83%; replacing 50% of inorganic fertilizer with flax oil residue achieved the optimal results. The flax yield and WUE increased by 3.37% and 1.25% under full irrigation (180 mm) compared to irrigation of 120 mm with a not-very-significant difference. The positive effect of irrigation on soil water content (SWC) was highest during the budding stage, followed by the flowering stage, fruiting stage, and stemming stage. Therefore, in arid and semiarid areas with scarce water resources, irrigation at a 55% deficiency during the vegetative growth period of flax combined with the application of flax oil residue and NPK (1550 flax oil residue, 45 N, 50.2 P_2O_5, and 33.9 K_2O kg ha^{-1}) might be an effective adaptation strategy for improved future flax production. Our results can facilitate the development of sustainable agriculture practices that reduce water input and improve WUE to counteract climate change effects.

Keywords: oilseed flax; water balance; APSIM; simulation modeling; water-use efficiency; climate change

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1. Introduction

Global climate change has led to increased abiotic and biotic stresses on agricultural production. Drought is the most frequent and detrimental abiotic stress, impairing crop development, yield, and quality, resulting in average yield losses of more than 50% [1,2].

It is projected that more than half of the cultivated land will experience severe drought damage by 2050 [3,4].

China is the world's largest consumer of oilseed flax (*Linum usitatissimum* L.), accounting for 26.8% of all flax imports in 2020 and being the main importer over the past decade with a value of 31,108 million USD [5]. Flaxseed is considered one of the best functional foods due to its high concentrations of α-linolenic acid (55–57%) [6–8]. It has been found to protect against atherosclerosis, cancer, neurological and hormonal problems, and coronary heart disease [9–11]. Apart from contributing to temperature changes, climate change has also affected the distribution of precipitation in Canada, Russia, China, and India—four important oilseed flax-producing nations [9]. Lack of soil water has a detrimental impact on the yield, as well as on the oil and fatty acid content of flax [12,13]. Drought also impairs normal metabolism by causing oxidative damage, elevated membrane lipid peroxidation, impaired leaf development, leaf senescence, and abscission [14]. The hardiness of flax makes it more drought tolerant than many other oil and food crops; however, fiber flax needs at least 600–650 mm of annual precipitation for optimal yield, with at least 110–150 mm of rainfall being necessary during the vegetative period. The reason for this is that flax has a transpiration coefficient of 787–1093, which is the quantity of water required to produce 1 unit of dry matter [4,13]. Consequently, a significant barrier to flax production is water scarcity. The ability to accurately predict the water requirements of flax at different growth stages in its growing environment is crucial for the effective development of water-saving irrigation measures to overcome water scarcity and highly unpredictable droughts and increase flax production.

Understanding and quantifying the water balance of agricultural systems, including crop evapotranspiration processes and soil moisture dynamics, is crucial for developing efficient water usage strategies [15,16]. Agricultural system models can be used to effectively predict the components of water balance and crop yield, providing valuable information to support decision-making [15,17]. Eitzinger et al. used the CERES-Wheat model modified for four different climate scenarios to simulate the water balance of two wheat cultivars at two locations and investigate the effects of water stress on winter wheat production [18]. They found that compared with equivalent stress at other growth phases, water stress during specific growth stages had a higher influence on grain yield, with certain crop cultivars being more vulnerable to drought. Likewise, Singh et al. found considerable variations in the water potential among wheat genotypes under water stress [19]. Huang et al. developed a process-based water balance model (PWBSA) that can be applied to ecosystem and landscape scale studies in arid and semiarid regions [20]. Hammad et al. used the CSM-CERES-Maize model to predict the water and nitrogen requirements of maize under semiarid conditions [21]. Despite the ambiguity of crop simulation models, the effects of specific water stress conditions on crop yields can be reasonably estimated and quantified if they are well-calibrated and validated in field trials [22]. Accordingly, the APSIM (Agricultural Production System Simulator) model has been reported by numerous studies to be able to simulate crop growth under various environmental influences with a high degree of accuracy.

Heng et al. used the APSIM-HWHEAT model to simulate the effects of initial soil moisture content, variety, sowing date, density, and supplementary irrigation on optimizing wheat production in Morocco [23]. Similarly, Chen et al. simulated the water management of wheat and maize in the North China Plain using an APSIM model [24]. Chimonyo et al. simulated the growth, yield, and water-use efficiency (WUE) of sorghum–cowpea intercropping systems in South Africa using APSIM, and showed that APSIM models, although limited under rainfed conditions, can be used to determine the best management practices for intercropping in water-scarce environments [25]. Chen et al. used APSIM and WHCNS models to simulate crop yield, water balance, and water productivity (WP) in fields with spatially variable soil properties [15], whereas Moghaddam et al. simulated the impact of climate change on wheat growth and yield in Iran using the APSIM-Wheat model [26]. Interestingly, Yang et al. studied crop productivity during the growth period in agropastoral ecological zones (maize, potato, fodder oats, and fodder soybeans) and the quantitative sensitivity of WP to precipitation in agricultural and pastoral ecological zones (maize, potato, fodder oats, and fodder soybeans) in Shanxi Province using APSIM and concluded that supplemental irrigation during critical periods of high crop productivity combined with crop models and field experimental studies can mitigate the risk of drought [27]. Gaydon et al. concluded that the APSIM model exhibits statistical robustness in simulating the performance of cropping systems for various crops, varieties, environments, and management practices in Asia and can thus be a useful tool for future research on planting systems in Asia following improvements in simulations of harsh environments (high temperature, salinity) and conservation agriculture [28]. The successful construction and calibration of the APSIM–Flax model [29–33] would facilitate the evaluation of the water balance in cultivated oilseed flax.

Owing to its wide range of industrial applications as well as regional and specialty preferences, flax holds a significant position in the worldwide economy. Unprecedented climate change, however, might hurt flax productivity. Even though the importance of predicting the water balance of many crops, such as rice, wheat, and maize, under water-scarce conditions for guiding irrigation management decisions to conserve water and increase yields has been widely recognized [21,26,28], information on water balance for oilseed flax crops in dark loessial soils and arid or semiarid climates remains limited. Therefore, the main goal of this study was to explore the water balance of flax crops using the APSIM model to reduce irrigation water waste and improve flax WP. We aimed to (1) accurately simulate the water balance and yield of flax under different irrigation and fertilizer treatment scenarios; (2) identify the key irrigation fertility periods that influence flax yield; and (3) determine the amount of irrigation, nitrogen, and organic fertilizer required to improve the yield and quality of flax to counteract the climate change effects.

2. Materials and Methods

2.1. Site and Field Experiment

Li et al. [29–33] constructed and calibrated the APSIM–Flax model by replicating field experiments from 2014 to 2017. The test site of the present study, Xizhai Oilseed Station of the Dingxi Academy of Agricultural Sciences, Gansu province, China, is situated at 104°37′12′′ E, 35°34′48′′ N in the gully area of the plateau in the Yellow River. It has an elevation of 1793 m, an average daily temperature of 7 °C, yearly sunshine hours of 2500 h, a frost-free period of 146 days, an annual rainfall of 300–400 mm, and an average annual evaporation of 1524.8 mm. All the latter factors contribute to the site's arid and semiarid climate. The soil comprises dark loessial soils, with an organic matter content of 11.06 g kg^{-1}, total nitrogen content of 0.99 g kg^{-1}, alkaline nitrogen content of 72.15 mg kg^{-1}, available phosphorus content of 8.31 mg kg^{-1}, available potassium content of 247.02 mg kg^{-1}, and a pH of 8.3.

Repeated field experiments conducted at the Xizhai Oilseed Station of the Dingxi Academy of Agricultural Science between 2019 and 2022 allowed for further evaluation and calibration of the model. The drought-resistant shed experiment was used to conduct a two-factor split-plot arrangement of treatments based on deficit irrigation and inorganic and organic fertilizers. For the experiment, four replicates (blocks, 16 m × 42 m) were set up, each containing four main plots with different irrigation treatments, with each main plot being divided into four subplots subjected to different fertilizer treatments. Flax seeds were sown on 1 April 2019, 2 April 2020, 5 April 2021, and 6 April 2022, and harvested on 31 August 2019, 2 September 2020, 10 September 2021, and 13 September 2022, respectively. Based on geographical characteristics, Dingxi City, Gansu Province, belongs to the southern temperate semihumid and middle temperate semiarid areas, which is the main representative flax cultivation area. The flax variety Dingya No. 26 is suitable for planting in Gansu Province as it is a drought-resistant and medium- and early-spring cultivar with good generalization ability and was bred by Dingxi Institute of Agricultural Science in Gansu Province, exhibiting an average yield of 1528.5 kg ha^{-1}.

The main plots, which were 5 m × 18 m, represented four irrigation levels: full irrigation (D0, 180 mm) (the water requirement during the growth of flax was calculated by referring to the method by [26]); deficit irrigation (55%) during the vegetative growth of flax, from the third-pair-of-true-leaves-unfolded stage to after flowering (D1); reproductive growth of flax, from after flowering (D2); and survival on rainfall without irrigation (D3). Subplots were 5 m × 3 m and represented four levels of fertilizer application: no fertilizer (F0); inorganic fertilizer (F1); combined flax oil residue and inorganic fertilizer (F2); and combined farm manure and inorganic fertilizer (F3). The amount of fertilizer (kg ha^{-1}) applied in each treatment was in accordance with the ratio of m (N):m (P_2O_5):m (K_2O) = 6:5:3.5. In particular, F1 treatment (90 N, 75 P_2O_5, and 52.5 K_2O) was applied according to the total nitrogen content, whereas F2 (1551.72 flax oil residue, 45 N, 50.17 P_2O_5, and 33.88 K_2O) and F3 (3000 farm manure, 45 N, 42 P_2O_5, and 28.5 K_2O) treatments were applied according to 50% of the nitrogen content of inorganic and organic fertilizer. The fertilizer contained urea (N 46%), superphosphate (18%), and potassium chloride (60%); the flax oil residue was the residue left after flax was pressed into cake-like rotten fertilizer (containing 2.9% N, 1.6% P_2O_5, and 1.2% K_2O); while the farm manure was dried chicken manure (containing 1.5% N, 1.1% P_2O_5, and 0.8% K_2O). All fertilizers were applied into the soil once before sowing, the plots were treated with organic fertilizer, with insufficient phosphorus and potassium were supplemented with superphosphate and potassium chloride. The planting density was 7.5 million seeds ha^{-1}, 15 seeds per hole, sown in strips, 3 cm deep, 20 cm apart in rows, with 2 m interval between main plots and subplots, 2 m interval between replicates, and 2 m protection rows around. All plots were irrigated after planting through drip irrigation using an irrigation strip located next to each row of crops. All other management measures were the same as those generally used in the fields.

2.2. Data Collection

The volumetric water content of the soil was measured by collecting soil samples every 10 days during the oilseed flax growing season [34]. Samples were collected from the top 150 cm of the soil profile (SWC) at 0–15 cm, determined using the oven-dry method, and a soil moisture gauge/humidity sensor (HENGKO HT-706 FDR, Shenzhen Hengko Technology Co., Ltd., Shenzhen, China) was used to measure SWC below 15 cm in increments of 30 cm. Li et al. [33,34] provided comprehensive descriptions of data collection for oilseed flax phenology, aboveground dry matter accumulation, and seed yield. Briefly, phenology was recorded manually. The aboveground dry matter accumulation was surveyed using the improved half-leaf method, and seed yield was determined using the calculation weighing method. Rainfall plus irrigation plus (initial SWC minus final SWC) was used to determine regular crop evapotranspiration (ET). Yield/ET was used to determine WUE [35]. WP was determined based on total water use and seed yield [36].

2.3. Soil and Weather Data

Soil file inputs in the APSIM model include saturated hydraulic conductivity (KS), soil bulk density (BD), an air drying coefficient, a 15-Bar lower limit of soil water content (LL15, Permanent Wilt Coefficient), DUL, saturated water content (SAT), initial soil water content (INSOIL), runoff, lower limit (LL), plant available water capacity (PAWC), a fraction of available soil water that can potentially be taken up on that day from that layer (KL) [37], exploration factor for root growth (XF), soil reflectivity, organic carbon (OC), pH, conductivity (EC), NO_3, NH_4, sand, and clay. In the field tests, six levels of the soil profile were created to collect data on soil water, providing soil input for each layer: 0–15, 15–30, 30–60, 60–90, 90–120, and 120–150 cm. The region's source of imported soil data is China soil [38].

Based on the input data above, the model calculates the formula for simulating soil water content (SWC) as follows:

$$SWC = LL15 + (DUL - LL15) \times insoil, \tag{1}$$

where SWC, $LL15$, and DUL are as above; $insoil$ is the initial water content of the soil.

Soil evaporation is divided into two stages: U represents the cumulative evaporation amount of the steady evaporation stage, and cona represents the cumulative evaporation in the decreasing evaporation rate stage.

The relationship between runoff (R) and precipitation (P) is as following:

$$\begin{cases} R = \frac{(P-0.2S)^2}{P+0.8S} & P > 0.2S \\ R = 0 & P \le 0.2S \end{cases}, \tag{2}$$

where R is the daily runoff (mm), P is the daily precipitation (mm), and S is a retention parameter [39].

The relationship between S and curve number (CN) as follows:

$$S = 254\left(\frac{100}{CN} - 1\right), \tag{3}$$

where constant 254 is a unit conversion factor that converts S from inches to millimeters. The curve number is a function of soil type, land use type, management measures, and precipitation, and its value range is between 0 and 100 (not equal to 0); when CN is equal to 100, S is equal to 0, and R is equal to P. The runoff curve number 80 was used in this study because the soil texture in the study area belongs to the gully area of the Loess Plateau. The model uses the following formula to determine water balance [35,40,41]:

$$\Delta\mathrm{S} = \mathrm{P} + \mathrm{I} - \mathrm{E} - \mathrm{T} - \mathrm{R} - \mathrm{D}, \tag{4}$$

where ΔS is the change in SWC, P is precipitation, I is irrigation, E is evaporation, T is transpiration, R is surface runoff, and D is soil profile drainage [35]. The weather data required to simulate the growth process of flax include daily temperature (maximum temperature, minimum temperature, °C), rainfall, solar radiation (MJ m^{-2} d^{-1}), and sunshine hours, for which the data were obtained from the test station and the Dingxi Meteorological Bureau. The weather data required for model operation can be generated using the APSIM met generator, which produces a .met file.

2.4. Model Development

The APSIM (version 7.10 was used) crop module template was developed for oilseed flax [29–33] using the strategy employed by Carberry et al. [42] and Robertson et al. [43,44] to adapt the model to chickpea (*Cicer arietinum* L.) and canola (*Brassica napus* L.), respectively. The present study constructed a flax model using canola as a template, weather data, soil data, and crop management data in the present study area using daily time steps to simulate flax crop development, growth, yield, and water balance in response to temperature, photoperiod, solar radiation, soil water, and nitrogen supply [45]. The parameters of the APSIM model in the present study were optimized based on the projection pursuit and autoregression based on the error backpropagation method (BPPPAR) provided by Fu et al. [30,46] on the model.

2.5. Model Calibration and Evaluation

The water balance for oilseed flax was simulated using the SOILWAT2 module in APSIM, v7.10. The data collected from 2019 to 2020 were used for further calibration based on coefficients from previous studies [29–33]. To improve the parameter accuracy of nitrogen fertilizer treatment, the model was calibrated using the data of full irrigation + NPK fertilizer (D0 + F1). The BPPPAR (Projection Pursuit Auto-Regression based on error Back Propagation) method was used to determine the genetic parameters and progressively observe the phenological and grain development parameters to optimize model performance. The properties of the model were evaluated based on data collected in 2021 and 2022. The root mean square error (RMSE), normalized root mean square error (nRMSE), and index of agreement (d) were utilized to assess the results of the flax model [34,47]. A d-index close to 1 and *RMSE*s close to 0 indicate a model that fits the data well. A lower difference between the predicted and observed values indicates greater simulation accuracy [34,48]. The assessment of *nRMSE* was determined as follows [49]: *nRMSE* < 25%, 25–75%, and >75% were categorized as good, moderate, and poor agreement, respectively [15]. These are displayed in the following equations:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}, \tag{5}$$

$$nRMSE = \frac{\sqrt{\sum_{i=1}^{n}(P_i - O_i)^2/n}}{\overline{O}} \times 100, \tag{6}$$

$$d = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}\left(\left|P_i - \overline{O}\right| + \left|O_i - \overline{O}\right|\right)^2}, \tag{7}$$

where P_i is the predicted value, O_i is the observed value of the *i*th measurement, and *n* is the number of observations. $\overline{O}$ is the average of all observed values [34].

2.6. Model Application

A combination of simulation model and field experiment was utilized. The calibrated model was employed to conduct simulation experiments, which included six irrigation periods (P1: before sowing; P2: stemming stage; P3: budding stage; P4: flowering stage; P5: fruiting stage; P6: maturity stage), four irrigation amounts (I1: 90 mm; I2: 120 mm; I3: 150 mm; I4: 180 mm), and six fertilizer treatments (Table 1). A total of 144 combinations of irrigation and organic–inorganic fertilizers were simulated and evaluated to predict flax yield and WUE. The aim of this approach was to determine the key irrigation and fertility periods that affect flax yield, as well as to determine the optimal amount of irrigation and organic and inorganic fertilizer required to improve WUE and counteract the effects of climate change.

Table 1. Simulation experiment treatments using the APSIM model for oilseed flax with organic–inorganic fertilizer.

Treatments	N (kg ha^{-1})	P_2O_5 (kg ha^{-1})	K_2O (kg ha^{-1})	Flax Oil Residue (kg ha^{-1})
T1	0	0	0	0
T2	90	75	52.5	0
T3	0	0	0	3100
T4	67.5	62.6	43.2	775
T5	45	50.2	33.9	1550
T6	22.5	37.8	24.9	2325

3. Results

3.1. Model Calibration

We manually calibrated the model parameters using field experimental data collected from 2019 to 2020 (Table 2). The parameterized model was then utilized to simulate SWC, flax yield and biomass, ET, and WUE.

The SWC at depths of down to 1.5 m was accurately predicted with a step size of 0.3 m. However, there was a deviation in the measurement at 0.3 m, resulting in a poor d-index of 0.37 and nRMSE of 8.65% (Table 3). The average observed and simulated SWCs at 0.15 m soil depth were 0.17 and 0.16 cm^3 cm^{-3}, respectively, with an RMSE of 0.01 cm^3 cm^{-3} and d-index of 0.81 in 2019 and 0.17 and 0.16 cm^3 cm^{-3} (RMSE of 0.02 cm^3 cm^{-3} and d-index of 0.53) in 2020. A slight underestimation of SWC in 2020 was attributed to rapid soil evaporation in the arid northwestern region.

Table 2. Calibrated parameters for oilseed flax in the APSIM model.

Parameter Types	Parameters	Description	Unit	Calibrated Value
Cultivar parameters	Grains_per_grain_stem	Grains of each grain stem	g	1.26
	Potential_grain_filling_rate	Potential grain filling rate	g grain^{-1} day^{-1}	0.21
	Potential_grain_growth_rate	The potential grain growth rate from flowering to the start of grain fill	g grain^{-1} day^{-1}	0.0012
	Max_grain_size	Max grain size	g	0.0083
	tt_endjuv_to_init	TT from the end of juvenile to floral initiation	°C d	430
	tt_init_to_flower	TT from initiation to flowering	°C d	645
	tt_flower_to_start_grain	TT from flowering to start grain fill	°C d	180
	tt_start_to_end_grain	TT from start grain fill to end grain fill	°C d	821
	vern_sens	Vernalization sensitivity	–	1.5
	Photop_sens	Photoperiod sensitivity	–	3
Soil parameters	DULi	Drainage upper limit	cm^3 cm^{-3}	0.256 (15 cm depth)
	SATi	Saturated water content	cm^3 cm^{-3}	0.43 (15 cm depth)
	LLi	Lower limit	cm^3 cm^{-3}	0.171 (15 cm depth)
Other parameters	RUE	Radiation utilization efficiency	g MJ^{-1}	1.16
	Summer U Winter U	Amount of cumulative evaporation, since soil wetting, before soil supply becomes limiting [50]	mm mm	6 5
	Summer Cona Winter Cona	Soil evaporation is a fraction of the square root of time since the end of the first stage of evaporation [50]	mm mm	3.5 3.5

Table 3. Observed (Obs.) and simulated (Sim.) SWC for oilseed flax averaged over 2 years at four drought stress levels and four fertilizer rates.

Year	Depth (m)	Obs. (cm^3 cm^{-3})	Sim. (cm^3 cm^{-3})	RMSE (cm^3 cm^{-3})	d−Index	nRMSE (%)
2019	0.15	0.17	0.16	0.01	0.81	4.77
	0.30	0.18	0.18	0.01	0.37	8.65
	0.60	0.21	0.21	0.01	0.75	4.74
	0.90	0.19	0.20	0.02	0.70	11.87
	1.20	0.17	0.18	0.02	0.72	9.24
	1.50	0.18	0.19	0.02	0.65	9.79
2020	0.15	0.17	0.16	0.02	0.53	11.10
	0.30	0.18	0.18	0.01	0.69	8.03
	0.60	0.21	0.22	0.02	0.55	9.81
	0.90	0.19	0.20	0.02	0.63	8.61
	1.20	0.18	0.18	0.01	0.82	5.46
	1.50	0.20	0.20	0.01	0.79	7.10

The predicted results for biomass and yield of oilseed flax are shown in Table 4, which demonstrates a good agreement between the observed and simulated values. The average observed and simulated biomass over 2 years and twelve treatments were 5233 and 5249 kg ha^{-1}, respectively, showing a satisfactory prediction with an average RMSE of 52 kg ha^{-1} and a d-index of 0.61. The simulated yield of oilseed flax was 1977 kg ha^{-1}, which slightly overpredicted the observed yield of 1987 kg ha^{-1} averaged across 2 years and four irrigation and three fertilization levels. The improved calibration of the model parameters was attributed to the accumulation of experimental data.

Table 4. Observed (Obs.) and simulated (Sim.) biomass and yield for oilseed flax averaged over 2 years at four drought stress levels and four fertilizer rates.

Irrigation	Yield (kg ha^{-1})				Biomass (kg ha^{-1})			
	Obs.	Sim.	RMSE	d-Index	Obs.	Sim.	RMSE	d-Index
D0F1	2203	2215	29	0.51	5865	5829	39	0.54
D1F1	2179	2178	8	0.75	5687	5670	17	0.70
D2F1	1845	1871	26	0.64	4972	4976	16	0.56
D3F1	1467	1490	24	0.54	4440	4496	75	0.67
D0F2	2289	2284	16	0.47	5894	5927	41	0.64
D1F2	2274	2289	16	0.74	5766	5861	97	0.49
D2F2	1948	1907	41	0.53	4835	4829	28	0.71
D3F2	1586	1553	33	0.53	4436	4440	85	0.49
D0F3	2279	2260	19	0.77	5843	5823	56	0.62
D1F3	2257	2212	46	0.52	5698	5685	98	0.71
D2F3	1956	1967	23	0.67	4991	4980	37	0.57
D3F3	1556	1495	62	0.62	4368	4474	29	0.65
Average	1987	1977	29	0.61	5233	5249	52	0.61

Note: D0, full irrigation (180 mm); D1, deficit irrigation (55%) during the vegetative growth of flax, from the third pair of true leaves unfolded stage; D2, deficit irrigation (55%) during the reproductive growth of flax, from after flowering; D3, only rainfall without irrigation. F1, inorganic fertilizer (90 N, 75 P_2O_5, and 52.5 K_2O kg ha^{-1}); F2, flax oil residue and inorganic fertilizer (1551.72 flax oil residue, 45 N, 50.17 P_2O_5, and 33.88 K_2O kg ha^{-1}); F3, farm manure and inorganic fertilizer (3000 farm manure, 45 N, 42 P_2O_5, and 28.5 K_2O kg ha^{-1}).

The water balance of oilseed flax was accurately simulated by the model, as evidenced by comparison of observed and simulated values in 2019–2020 (Table 5). The average observed and simulated values for ET were 411 and 413 mm, respectively, with an RMSE of 5 mm and a d-index of 0.64. Similarly, the average observed and simulated WUE values were identical at 4.8 kg ha^{-1} mm^{-1}, with an average RMSE of 0.1 kg ha^{-1} mm^{-1} and a d-index of 0.61. The model also demonstrated fairly accurate predictions for WP, which was estimated to be 8.8 kg ha^{-1} mm^{-1} with an average simulated value of 8.9 kg ha^{-1} mm^{-1}, an RMSE of 0.4 kg ha^{-1} mm^{-1}, and a d-index of 0.64.

Table 5. Observed (Obs.) and simulated (Sim.) ET, WUE, and WP for oilseed flax averaged over 2 years at four drought stress levels and four fertilizer rates.

Irrigation	ET (mm)				WUE (kg ha^{-1} mm^{-1})				WP (kg ha^{-1} mm^{-1})			
	Obs.	Sim.	RMSE	d-Index	Obs.	Sim.	RMSE	d-Index	Obs.	Sim.	RMSE	d-Index
D0F1	475	475	7	0.41	4.6	4.7	0.0	0.55	9.8	9.6	0.4	0.53
D1F1	442	437	5	0.80	4.9	5.0	0.1	0.88	10.3	10.4	0.2	0.71
D2F1	383	394	12	0.55	4.8	4.7	0.1	0.44	8.3	9.1	0.9	0.56
D3F1	314	322	9	0.45	4.7	4.6	0.1	0.50	7.2	7.5	0.3	0.69
D0F2	489	490	1	0.60	4.8	4.7	0.1	0.59	9.4	9.7	0.4	0.53
D1F2	431	436	6	0.67	5.0	5.1	0.1	0.78	10.7	10.7	0.2	0.80
D2F2	394	397	3	0.62	4.8	4.7	0.1	0.61	8.0	7.3	0.7	0.52
D3F2	322	322	2	0.75	4.7	4.6	0.1	0.70	7.2	6.9	0.4	0.62
D0F3	481	484	4	0.52	4.7	4.6	0.0	0.67	9.2	9.7	0.5	0.53
D1F3	454	454	2	0.83	5.2	5.1	0.2	0.66	10.5	10.4	0.1	0.80
D2F3	407	408	3	0.74	5.0	5.0	0.0	0.51	8.2	8.3	0.2	0.71
D3F3	337	339	5	0.77	4.8	4.6	0.2	0.44	7.0	6.7	0.3	0.62
Average	411	413	5	0.64	4.8	4.8	0.1	0.61	8.8	8.9	0.4	0.64

3.2. Model Evaluation

The model was evaluated using experimental data collected in 2021 and 2022, which demonstrated good forecasting at various soil depths, except at a depth of 0.3 m when model simulations revealed under-prediction of the SWC with a d-index value less than 0.40. At most soil depths, the index values were greater than 0.60 for the evaluation cultivars. The model performed well even at deeper depths, as seen by the greater d-index (0.60) and lower RMSE (0.01–0.02 cm^3 cm^{-3}) values from 0.9 m and beyond. To avoid overlapping curves, only the average simulated and observed SWC for D0 + F1 and D0 + F2 treatments are shown in Figure 1.

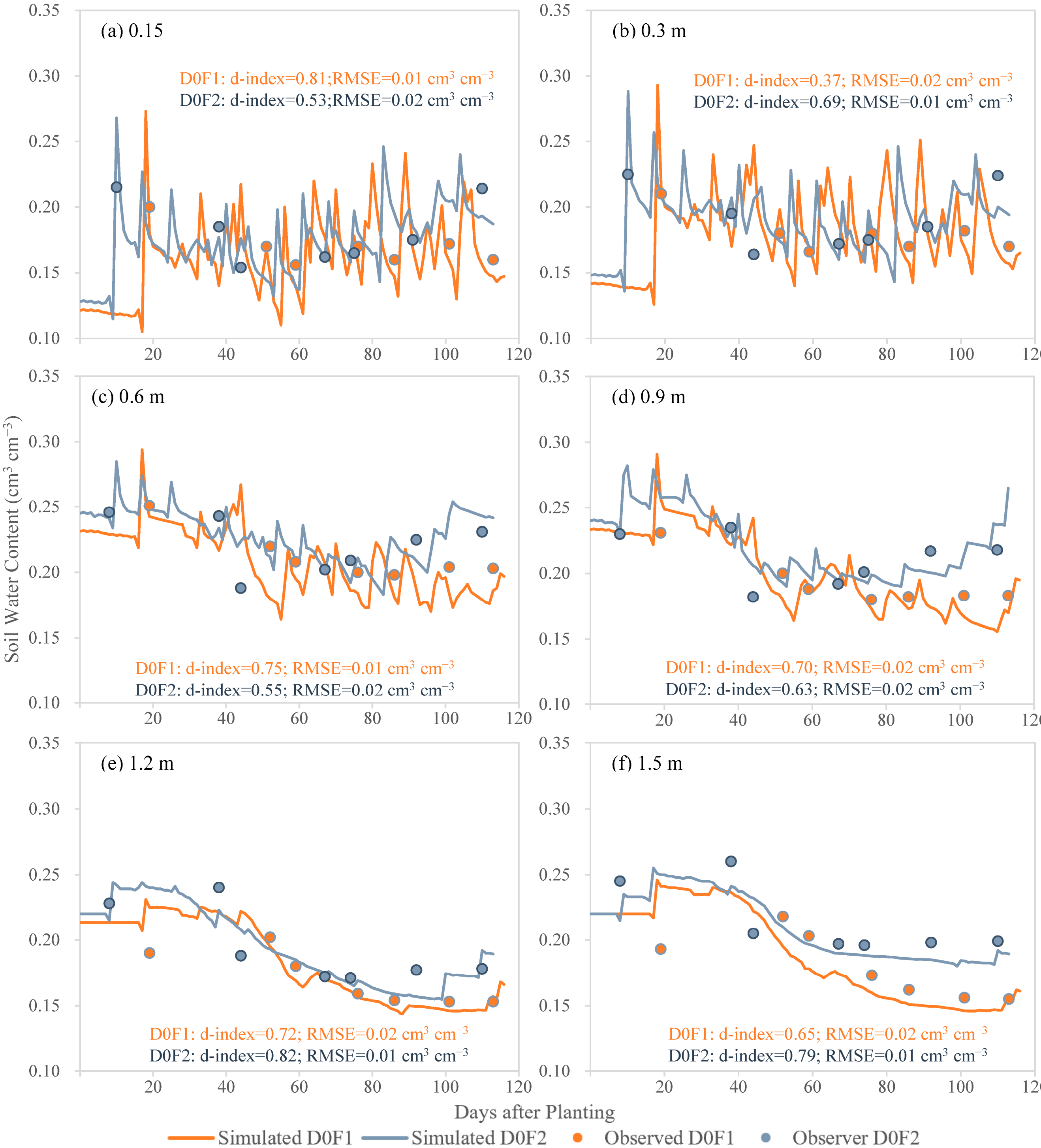

Figure 1. Comparison of simulated and observed SWC for full irrigation (D0) with inorganic fertilizer (F1) and organic–inorganic rates (F2) at depth of 0.15 (**a**), 0.3 (**b**), 0.6 (**c**), 0.9 (**d**), 1.2 (**e**), and 1.5 m (**f**).

The simulated values for grain yield, ET, and WUE of the two years are displayed in Figures 2–4. In 2021, average grain yields of 2024 and 2008 kg ha^{-1} were measured and predicted, respectively. For 2022, the corresponding figures were 2012 and 1984 kg ha^{-1}. The RMSE was 26 kg ha^{-1} and 37 kg ha^{-1} for 2021 and 2022, respectively. A strong linear relationship was found between the predicted and measured oilseed flax yield values (R^2 = 0.79) [31]. The model's ET simulations were similar to the actual measurements, with an average predicted ET of 416 mm compared to the measured ET of 414 mm for every year (Figure 3). The average RMSE of 2021 (3 mm) and 2022 (3 mm) were similar. When comparing the observed and simulated ET from the flax cultivar, a strong linear relationship was observed (R^2 = 0.96) (Figure 3). Although the WUE for 2022 was slightly over-predicted, the WUE for 2021 was simulated by the model within an acceptable range (Figure 4). Overall, we observed that the parameter-calibrated APSIM-Flax model performed well in the simulation evaluation over these 2 years. As shown in Figure 5, there is a direct proportional relationship between flax yield and WUE. However, the correlation between WUE and irrigation amount is not positive, which means that increasing irrigation amount does not necessarily lead to higher WUE.

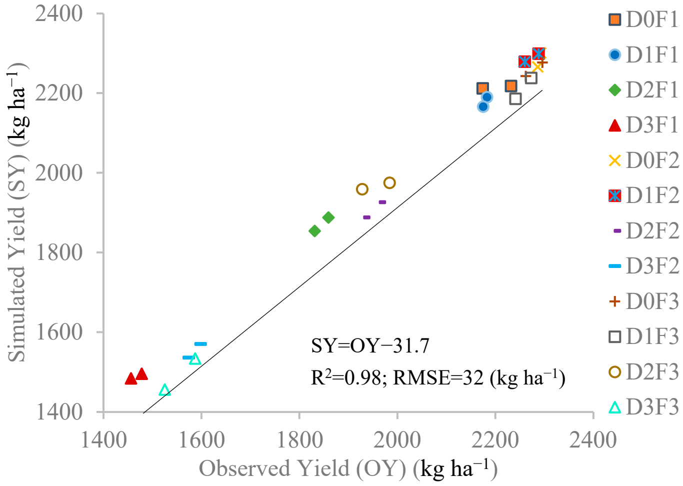

Figure 2. Simulated and observed grain yield for oilseed flax at full irrigation (D0), drought stress during the vegetative stage (D1), drought stress during the reproductive stage (D2), and no irrigation (D3) for three organic–inorganic fertilizer application rates (F1–F3).

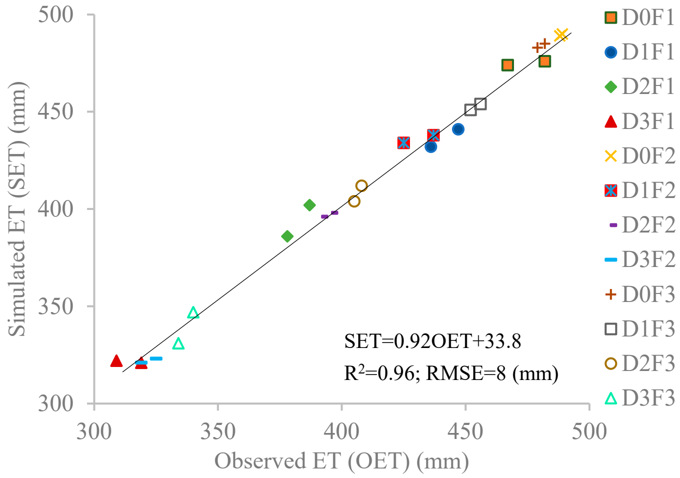

Figure 3. Simulated and observed evapotranspiration (ET) for oilseed flax at full irrigation (D0), drought stress during the vegetative stage (D1), drought stress during the reproductive stage (D2), and no irrigation (D3) for three organic–inorganic fertilizer application rates (F1–F3).

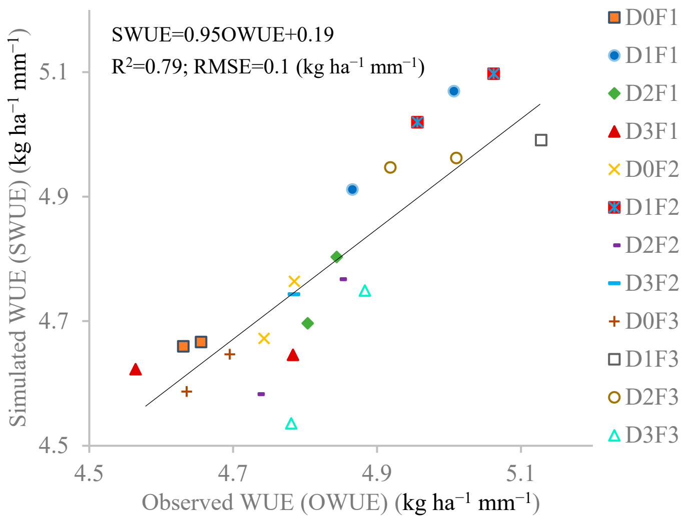

Figure 4. Simulated and observed WUE for oilseed flax at full irrigation (D0), drought stress during the vegetative stage (D1), drought stress during the reproductive stage (D2), and no irrigation (D3) for three organic–inorganic fertilizer application rates (F1–F3).

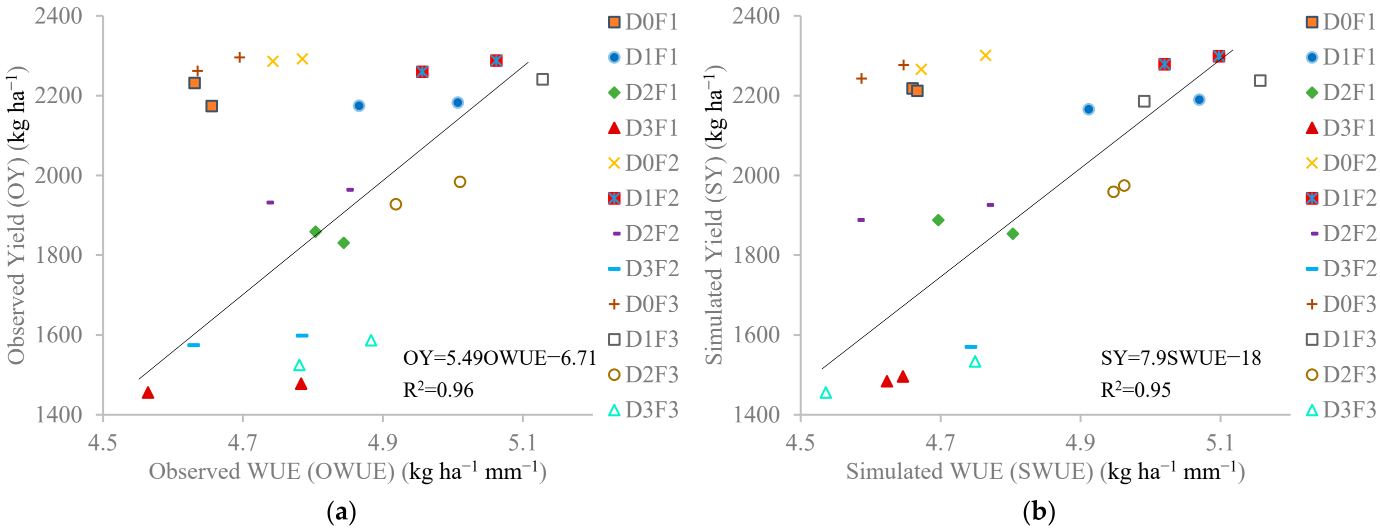

Figure 5. Observed yield and WUE (**a**) as well as simulated yield and WUE (**b**) for oilseed flax at full irrigation (D0), drought stress during the vegetative stage (D1), drought stress during the reproductive stage (D2), and no irrigation (D3) for three organic–inorganic fertilizer application rates (F1–F3).

3.3. Utilizing Model to Address Climate Change

To facilitate the presentation of data and eliminate curve overlap, the simulation results for only four growth periods (P1, P3, P5, P6), two irrigation amount (I2, I4), and six fertilizer (T1, T2, T3, T4, T5, T6) treatments are shown.

3.3.1. Enhance of SWC to Counteract Climate Change Effects

The results of the simulation study indicate that irrigation at different growth stages has a positive effect on SWC. The highest SWC was observed during the budding stage (P3), followed by the flowering stage (P4), fruiting stage (P5), stemming stage (P2), maturity stage (P6), and before sowing (P1). The use of flax oil residue as a partial substitute for inorganic fertilizers did not significantly impact SWC before sowing, but it had a significant influence on SWC throughout the flax growth period. At the budding stage, for soil depths of 0–0.9 m, the SWC was lowest in the treatment with only inorganic fertilizer

(T2) and highest in the treatment with only organic fertilizer of flax oil residue (T3). For soil depths of 0.9–1.5 m, the SWC was higher in treatments with only flax oil residue and with 50% substitution of inorganic fertilizers with flax oil residue (T5). During the fruiting stage, except for certain depths, the SWC was generally lowest in the treatment with only inorganic fertilizer (T2) and higher in the treatments with only flax oil residue (T3) and with 50% substitution of inorganic fertilizers with flax oil residue (T5). At the maturity stage, the SWC was highest in the treatment with only flax oil residue (T3). These findings indicate that solely organic fertilization with flax oil residue and 50% substitution of inorganic fertilizers with flax oil residue can effectively enhance SWC throughout the flax growth period. Our observations revealed a significant increase in SWC for organic fertilizer treatments at the mature stage, with organic treatments exhibiting a substantial increase in SWC by 4.9–7.8% and 5.8–10.5% compared to their respective inorganic counterparts. Overall, during the vegetative growth stage, irrigation in both the budding and flowering stages, as well as the combined application of organic and inorganic fertilizers, were found to increase SWC (Figure 6).

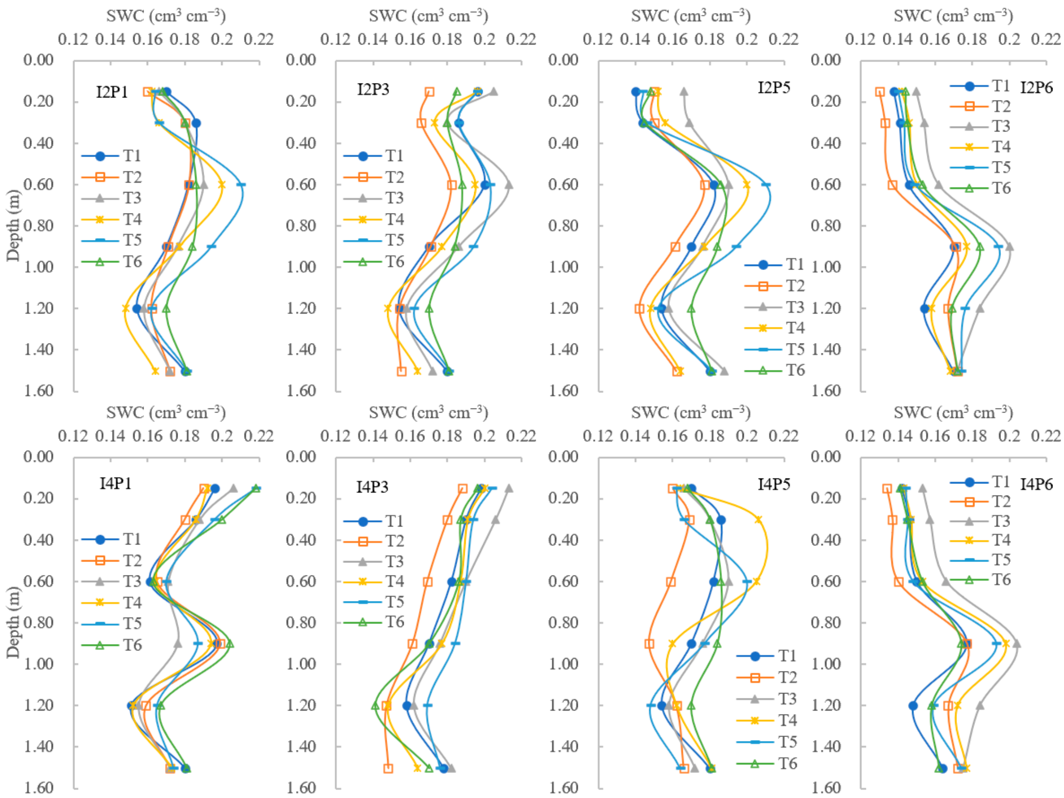

Figure 6. Simulated SWC for oilseed flax at four different irrigation levels (I2: 120 mm; I4: 180 mm) across six distinct fertilizer treatments (T1: no fertilizer; T2: 90 N, 75 P_2O_5, and 52.5 K_2O kg ha^{-1}; T3: 3000 kg ha^{-1} flax oil residue; T4: 775 flax oil residue, 67.5 N, 62.6 P_2O_5, and 43.2 K_2O kg ha^{-1}; T5: 1550 flax oil residue, 45 N, 50.2 P_2O_5, and 33.9 K_2O kg ha^{-1}; T6: 2325 flax oil residue, 22.5 N, 37.8 P_2O_5, and 24.9 K_2O kg ha^{-1}) throughout the six flax growth stages (P1: before sowing; P3: budding stage; P5: fruiting stage; P6: maturity stage).

Based on the findings, it can be concluded that the proposed model has the potential to serve as an effective water management tool under water-deficit conditions, which were employed to determine the optimal period and amount of irrigation and fertilizer required to enhance SWC. The primary objective is to effectively tackle drought issues arising from climate change.

3.3.2. Enhance of Flax Yield and WUE to Counteract Climate Change Effects

As depicted in Figures 7 and 8, the application of flax oil residue as an organic fertilizer has a positive impact on enhancing flax yield and WUE. When compared to no fertilizer and inorganic fertilization, the grain yield of flax increased by 45.52–50.15% and 3.86−4.13%, respectively, while the WUE increased by 55.43−61.77% and 24.33−28.81% under flax oil residue application. The yields and WUE followed the order of T5 > T4 > T3 > T6 > T2 > T1. In comparison to inorganic fertilization, the average grain yield of flax increased by 9.94% and the WUE improved by 25.76% when utilizing flax oil residue organic fertilizer to partially replace inorganic fertilizer. Among them, replacing 50% of inorganic fertilizer with flax oil residue achieved the optimal results, with a grain yield and WUE improvement of 16.47% and 13.83%, respectively, compared to single inorganic fertilization, and a grain yield and WUE improvement of 35.38% and 4.26%, respectively, compared to single organic fertilization.

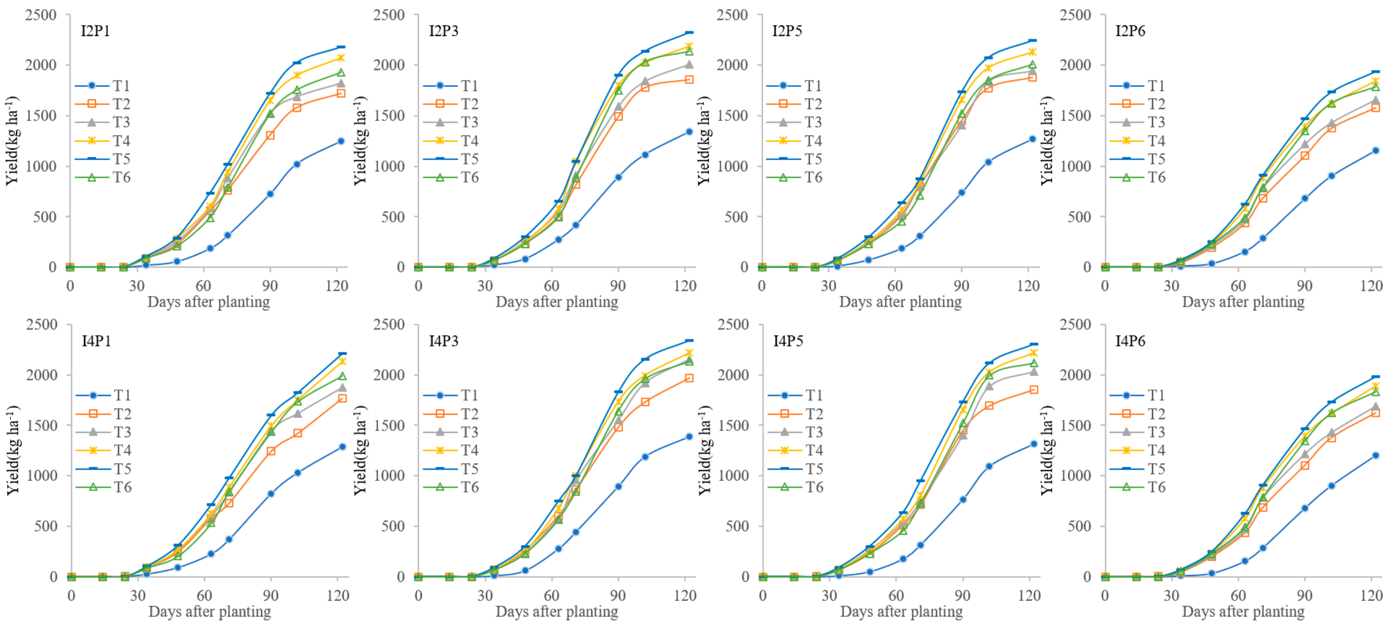

Figure 7. Simulated grain yield for oilseed flax at four different irrigation levels (I2: 120 mm; I4: 180 mm) across six distinct fertilizer treatments (T1: no fertilizer; T2: 90 N, 75 P_2O_5, and 52.5 K_2O kg ha^{-1}; T3: 3000 kg ha^{-1} flax oil residue; T4: 775 flax oil residue, 67.5 N, 62.6 P_2O_5, and 43.2 K_2O kg ha^{-1}; T5: 1550 flax oil residue, 45 N, 50.2 P_2O_5, and 33.9 K_2O kg ha^{-1}; T6: 2325 flax oil residue, 22.5 N, 37.8 P_2O_5, and 24.9 K_2O kg ha^{-1}) throughout the six flax growth stages (P1: before sowing; P3: budding stage; P5: fruiting stage; P6: maturity stage).

The impact of irrigation amount on flax yield and WUE was significantly higher for treatments I2 and I4 compared to I1 and I3. The flax yield and WUE under treatment I4, which involved full irrigation, increased by 3.37% and 1.25%, respectively, compared to treatment I2 with a lower irrigation amount. However, the difference was not very significant. Therefore, it is recommended that treatments I2, which involved a moderate level of irrigation, be used as the optimal irrigation amount to improve flax yield and WUE in water-scarce arid and semiarid conditions. This recommendation is consistent with the results of field experiments.

Irrigation at the flowering and budding stages had a significantly higher impact on flax yield and WUE compared to other stages. The flax yield and WUE under various irrigation stages followed the order: budding stage > flowering stage > fruiting stage > stemming stage > before sowing > maturity stage. Overall, we determined that the key growth stages greatly impacting flax yield were the stemming, budding, and flowering stages, which are the most susceptible to water stress. The application of flax oil residue and inorganic fertilizer correlated with the highest WUE, potentially attributed to the flax oil residue-mediated improved soil water storage and fertilizer retention capacity, as well as improved nutrient status, which was conducive to the growth of flax.

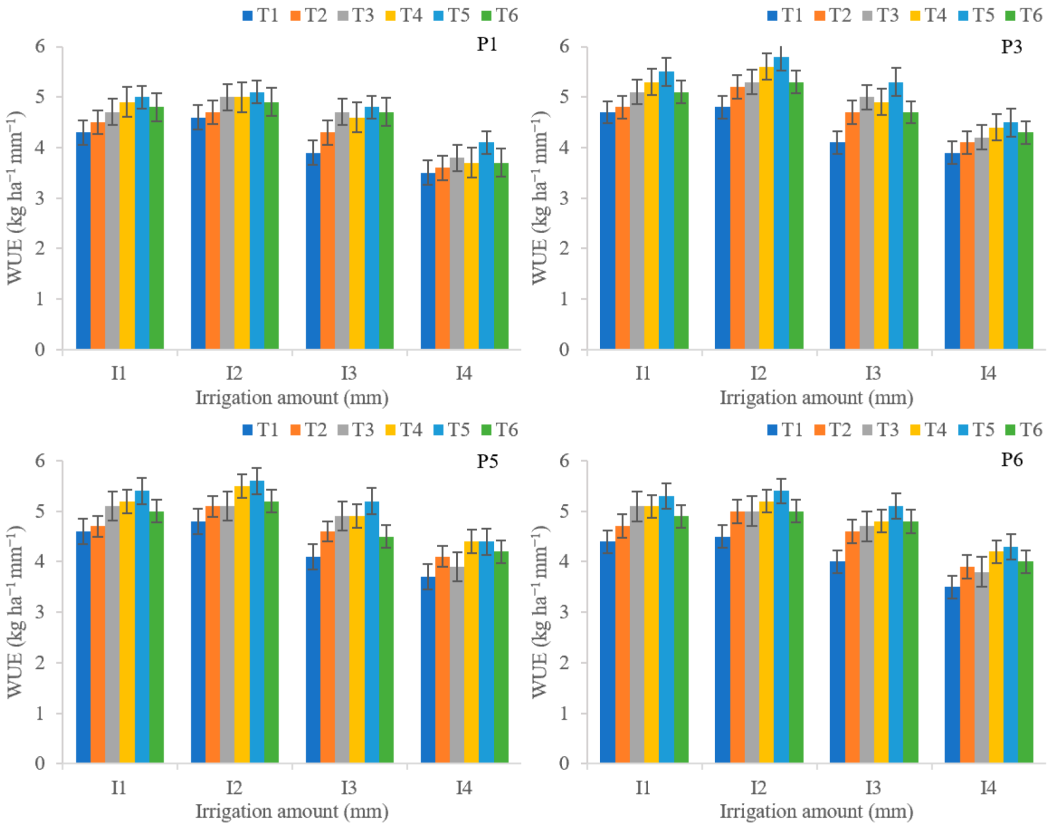

Figure 8. Simulated WUE for oilseed flax at four different irrigation levels (I1: 90 mm; I2: 120 mm; I3: 150 mm; I4: 180 mm) across six distinct fertilizer treatments (T1: no fertilizer; T2: 90 N, 75 P_2O_5, and 52.5 K_2O kg ha^{-1}; T3: 3000 kg ha^{-1} flax oil residue; T4: 775 flax oil residue, 67.5 N, 62.6 P_2O_5, and 43.2 K_2O kg ha^{-1}; T5: 1550 flax oil residue, 45 N, 50.2 P_2O_5, and 33.9 K_2O kg ha^{-1}; T6: 2325 flax oil residue, 22.5 N, 37.8 P_2O_5, and 24.9 K_2O kg ha^{-1}) throughout the six flax growth stages (P1: before sowing; P3: budding stage; P5: fruiting stage; P6: maturity stage).

Based on the findings, the recommended scheme for ensuring flax yield and quality while conserving resources is the coupling mode of 55% deficit irrigation during flax vegetative growth and the combined application of flax oil residue and inorganic fertilizer (1550 flax oil residue, 45 N, 50.2 P_2O_5, and 33.9 K_2O kg ha^{-1}). This approach effectively balances WUE and nutrient management, leading to optimal crop performance with minimal environmental impact.

4. Discussion

We provided and validated predictions of yield and water balance for the cultivation of the flax cultivar Dingya No. 26 in Dingxi, Gansu Province, from 2019 to 2020 under various drought scenarios. We also conducted model evaluation in the same region from 2021 to 2022. Finally, we identified the key irrigation fertility period affecting flax yield and determined the irrigation fertilizer management system that is more suitable for arid and semiarid areas.

4.1. APSIM Model Simulations

The model showed high accuracy in the prediction of SWC (d-index between 0.53 and 0.82) and was satisfactorily validated (d-index between 0.55 and 0.77). Heng et al. found that the APSIM model can efficiently simulate SWC and suggested that it can also accurately simulate the SWC in areas with different irrigation systems under arid and semiarid conditions [23]. Similarly, Chen et al. reported that the SOILWAT module of the APSIM model can be a useful tool for modeling SWC [15]. In addition, Moghaddam et al. successfully demonstrated that the parameterized APSIM-Wheat model could efficiently evaluate the effects of nitrogen fertilizer and water shortage on wheat performance in Iran [26]. Based on these studies and our findings, the model can be used as a water resource management tool for areas under water-scarce conditions.

Our study showed that the ET (d-index value between 0.41–0.8), WUE (d-index value between 0.44–0.88), and WP (d-index value between 0.53–0.71) of flax under various water and fertilizer treatments were effectively simulated. Further analysis and comparison simulation showed that the vegetative growth stage was the most sensitive stage during flax growth and development, with WUE and WP in the combined application of flax oil residue and inorganic fertilizer being the highest among all water and fertilizer treatments. These results provide methods for adapting the management of cultivated lands in arid and semiarid regions to climate change. Wang et al. compared two simulation methods, APSIM RUE/TE and CERES-Wheat, to predict differences in water vapor pressure and crop water demand and provided a method for the simulation of yield and the calculation of maximum yield in water-stressed areas [51]. Keating et al. used the APSIM model to study the impact of climate change on the horizontal balance of the dryland agricultural system in the Murray–Darling Basin of Australia through two methods: dynamic simulation and statistical modelling [52]. Yang et al. performed simulations that quantified the potential impacts of climate change on wheat WUE and field water balance of various soil types, emphasizing the importance of plant available water holding capacity (PAWC) in determining the responses of crop interactions to major components of water balance [53]. Based on these, simulating the water balance of crops through crop models was shown to help formulate production management strategies for adaption to climate change.

The model used in this study predicted flax yield (RMSE between 8–161 kg ha^{-1}, d-index between 0.51–0.96) and biomass (RMSE between 16–192 kg ha^{-1} and d-index between 0.54–0.95) under various irrigation and fertilization conditions. Our calibration improved the predicted biomass and yield by decreasing the RMSE outputs, in contrast to the results reported by Li et al. [31,33]. The model parameters were more accurately calibrated owing to the accumulation of experimental data. Yang et al. also reported that the calibrated and validated APSIM model can efficiently predict crop yield and soil moisture dynamics and can thus be used as a useful tool for assessing crop productivity through scenario analysis [27].

4.2. Effects of Combined Application of Organic and Inorganic Fertilizers and Deficit Irrigation on Water Balance and Yield of Flax

Our study showed that the application of organic fertilizer had the greatest effect on SWC, which was significantly higher than that in plots treated with inorganic fertilizer after the budding period of flax, whereas the SWC was the lowest under any treatment during the green fruit stage. In particular, the combined application of flax oil residue and inorganic fertilizer resulted in an increase in SWC, with the SWC being the highest during the green fruit and ripening stages and significantly higher compared with that in plots after the application of inorganic fertilizer. The combined application of flax oil residue and inorganic fertilizer led to the improved retention and storage of water and therefore provides an effective management measure for coping with climate change-induced droughts and achieving adaptive flax cultivation. This was consistent with the study by Cui et al. who concluded that the combined application of organic and inorganic fertilizers could improve soil water utilization, especially by promoting the use of deep soil reservoirs to meet the water demand of flax crops after the budding period [54].

Accurate determination of ET is essential for improving crop WUE and developing water-saving management practices [55]. In our model simulation of ET, we observed a strong linear relationship between ET and flax yield. Our results showed that among the four fertilization treatments, the combined application of flax oil residue and inorganic fertilizer exhibited the highest WUE. We then used the calibrated model to quantify the growth stages of oilseed flax that could be irrigated for deficit regulation, the duration of allowable deficit, and degree of water deficit to ensure the lack of adverse effects on crop yield and achieve significant improvements in crop WUE. However, following water stress, the WUE at each growth stage was instead higher, with the water requirement during the period also being higher. The critical water demanding periods for the cultivation of oilseed flax are stemming, budding, and flowering, and if the water supply does not meet the needs of flax growth during this period, both biomass and yield are reduced. During the budding to flowering period, the plant stems and leaves grow rapidly, followed by a very rigorous reproductive growth, all of which result in increased water consumption.

WP is a comprehensive index for measuring the level of agricultural production and scientific rationality of agricultural water use [56]. Different studies have also found that the irrigation required to obtain maximum WP is far less than that required to obtain maximum crop yield [15,24]. Our study showed that flax crops consume less water during their early growth period; thus, their irrigation during this period enables them to withstand drought in advance, promotes root rooting, and regulates their vegetative growth, laying the foundation for higher economic yield, whereas we found that the mild water deficit between the final flowering and seed fruit stages did not affect the yield. This was consistent with the studies by [23,26], which showed that conventional and overirrigation were not a good option due to water shortages in arid areas, and that small amounts of irrigation during sowing can have a large impact on yield. Hammad et al. also concluded that crops should be irrigated during the growth period under water-restricted conditions, and farmers should conduct adequate irrigation accompanied with optimal nitrogen fertilization rates to obtain higher food yields [21].

The suitable deficit irrigation of 55%, which can limit water to drought-sensitive growth phases of flax, maximize WP, and stabilize flax yield, is mainly based on the experience of field trials. According to statistics, the area of insufficient irrigation in the United States accounts for approximately 25.62% of the total area of water-saving irrigation [57]. Other groups also found that deficit irrigation can improve WP by reducing soil water evaporation losses and avoiding the negative impact of drought stress at specific phenological stages on biomass distribution between reproduction and nutrients [58,59]. Payero et al. also suggested that the combination of deficit irrigation and reduced fertilization was optimal as the resulting increased yield from the simultaneously applied deficit irrigation and optimized fertilization (higher WP) was higher than the combined yield increase after these two factors were separately applied [60].

4.3. Optimized Irrigation and Fertilizer Management Recommendations in Arid and Semiarid Areas

4.3.1. Deficit Irrigation

Our results showed no significant differences in yield between full and deficit irrigation during the vegetative growth period of flax. Moreover, we found that deficit irrigation also stimulated the drought resistance and tolerance characteristics of flax to a certain extent. This was consistent with the study by [61], which showed that the impact of water deficit on crop yield and quality depends largely on the period, duration, and extent of water deficit. Considering the water shortage caused by climate change and the inability of plants to absorb additional nitrogen, deficit irrigation (55%) and organic fertilizer application could significantly increase the number of capsules per plant and grain yield of flax. Therefore, the irrigation strategy should be as follows: when the seedlings are 6–10 cm high and at the third pair of true leaves unfolded stage, little amounts of water should be poured (10 mm) to avoid washing out the flax seedlings, followed by 30 mm of irrigation at the stemming stage. In the case of before budding and flowering, 60 mm irrigation should be performed to meet the water needs of rapid plant growth, flowering, and fruiting. Seedling irrigation can promote their strong and early emergence, while budding and flowering irrigation can promote the increase in the numbers of flowers and grain, improve the thousand-grain weight, and increase yield. If the flax is dry after flowering and the soil is short of water (cracking), proper irrigation (20 mm) could facilitate good flowering and fruiting while preventing lodging so as not to reduce yield. This was consistent with the study by [54]. Yang et al. also found that systematic analysis combining crop models and field experimental studies with supplemental irrigation during critical periods for achieving high crop productivity could mitigate the risk of drought [27].

4.3.2. Combined Application of Organic and Inorganic Fertilizers

Organic fertilizers are being strongly advocated by several regional and national initiatives as core management strategies for improving soil health and counteracting climate change. These initiatives call for the precise application of organic fertilizer and technology, revealing the important role of application precision in the synergistic achievement of crop yield increase, soil carbon sequestration, and environmental emission reduction. In addition, organic fertilizer application can improve soil water and fertilizer retention capacity and increase soil organic carbon (SOC) content, which might have a significant impact in arid areas, partially mitigating the impact of rainfall changes caused by climate change [62]. Gram et al. also reported that the combined application of mineral and organic fertilizers can improve maize yield and nitrogen efficiency because the increased content of soil organic matter can improve soil biological processes and soil moisture status, in turn increasing resilience to drought [63]. Through our simulation study, we determined that the recommended fertilization scheme suitable for increasing flax yield in arid and semiarid areas is the combination of organic fertilizer flax oil residue and inorganic fertilizer at a dosage of 1550 flax oil residue, 45 N, 50.2 P_2O_5, and 33.9 K_2O kg ha^{-1}. This scheme might be an effective management measure for reducing environmental pollution, enhancing fertility, improving WUE, and facilitating the adaptation of crops to climate change.

The study provides confidence in utilizing the model as a decision-making tool for oilseed flax irrigation management in arid and semiarid regions. However, there are some limitations to this study. First, the model simulations can be improved with additional research data. As the real world is far more complex than models, many models are only suitable for specific regions and specific varieties after parameter tuning, and they often show uncertainty when applied to a wider area for simulation prediction. Second, qualitative research was employed instead of quantitative research in addressing climate change. The study is based on the widely accepted notion that climate change leads to drought. By using models, management strategies were identified that can enhance WUE and flax yield in arid and semiarid regions with limited water resources. However, this approach lacks the application of models for the accurate prediction of future climate scenarios. Therefore, further research exploring management strategies based on predicted outcomes through quantitative methods is necessary. Lastly, the impact of climate change on agriculture is also evident through high temperatures and carbon emissions, which were not addressed in the study and warrant further investigation in the future.

In summary, as experimentation becomes more challenging due to increased labor and input costs, agricultural system models provide a good complement for evaluating variable weather conditions in different environments. Global warming, climate changes, and degraded soil conditions in Gansu Province threaten food security in the region. Therefore, accurate prediction of water balance and the yield of flax crops based on the APSIM model can help guide irrigation and fertilizer management decisions under conditions of water scarcity to save water and increase yield.

5. Conclusions

Our simulation study showed that by using field data, the APSIM model faithfully reproduced the water balance and yield of oilseed flax crops and determined the major water-sensitive growth stages of flax. Additionally, we simulated the dynamic changes in flax yield and water balance under various irrigation and fertilization conditions and found that organic fertilizers improved the efficient use of both water and fertilizer. Although adequate irrigation can lessen the effects of climate change, it is not preferred in a region as severely arid as Gansu Province in China. Our study highlights that deficit irrigation, in combination with the application of organic and inorganic fertilizers, should be implemented in arid and semiarid regions where adequate irrigation is not available to mitigate the effects of drought on crop yields induced by climate change.

Author Contributions: Project administration, conceptualization, methodology, writing—original draft, writing—review and editing, Y.L., B.W. and Y.G.; methodology, writing—review and editing L.W. (Ling Wu) and X.Z.; data curation, formal analysis, investigation, L.W. (Lili Wu), H.Z. and J.T. All authors have read and agreed to the published version of the manuscript.

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