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Modeling Crop Water Productivity Using a Coupled SWAT–MODSIM Model

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Abstract: This study examines the water productivity of irrigated wheat and maize yields in Karkheh River Basin (KRB) in the semi-arid region of Iran using a coupled modeling approach consisting of the hydrological model (SWAT) and the river basin water allocation model (MODSIM). Dynamic irrigation requirements instead of constant time series of demand were considered. As the cereal production of KRB plays a major role in supplying the food market of Iran, it is necessary to understand the crop yield-water relations for irrigated wheat and maize in the lower part of KRB (LKRB) where most of the irrigated agricultural plains are located. Irrigated wheat and maize yields (Y) and consumptive water use (AET) were modeled with uncertainty analysis at a subbasin level for 1990–2010. Simulated Y and AET were used to calculate crop water productivity (CWP). The coupled SWAT–MODSIM approach improved the accuracy of SWAT outputs by considering the water allocation derived from MODSIM. The results indicated that the highest CWP across this region was 1.31 kg·m^{-3} and 1.13 kg·m^{-3} for wheat and maize, respectively; and the lowest was less than 0.62 kg·m^{-3} and 0.58 kg·m^{-3}. A close linear relationship was found for CWP and yield. The results showed a continuing increase for AET over the years while CWP peaks and then declines. This is evidence of the existence of a plateau in CWP as AET continues to increase and evidence of the fact that higher AET does not necessarily result in a higher yield.

Keywords: Karkheh River Basin; dynamic irrigation scheduling; irrigated wheat; irrigated maize; uncertainty analysis; coupled SWAT-MODSIM

1. Introduction

Global human population growth requires increased food production, yet less water resources are available for agriculture. This critical situation can only be resolved if water is managed more efficiently, and crop yield per unit of water consumption increases [1]. Water shortage affects every continent in the twenty-first century. Around 1.2 billion people, or almost one-fifth of the world's population, live in areas of physical scarcity, and 500 million people are approaching this situation. Another 1.6 billion people, or almost one-quarter of the world's population, probably face economic water shortage (where countries lack the necessary infrastructure to take water from rivers and aquifers) [2]. Spatial and temporal distribution of precipitation, which rarely coincides with demand, is a critical problem in this context [3].

Crop water productivity (CWP) is defined as the ratio of crop yield (Y) to the amount of water required to produce that yield [4]. Increasing CWP is necessary to meet a decreasing water availability and is a key element in improving agricultural water productivity, which is central to both economic and social development [5].

Therefore, there is a high intresrt in increasing the productivity of water in the agricultural sector to meet the future food demand [6]. In arid and semi-arid regions where the agricultural sector is the main consumer of water resources and less opportunities exist for the development of new water resources, the accurate estimation of CWP and increasing the productivity of existing water resources is vital. Various researchers studied CWP at specific locations, with specific agricultural and water management practices. Zwart and Bastiaanssen [4] reviewed 84 literature sources. They found that globally measured average CWP values per unit water use are 1.09, 1.09, 0.65, 0.23 and 1.80 $kg \cdot m^{-3}$ for wheat, rice, cotton seed, cotton lint, and maize, respectively. They found that the range of CWP is 0.6–1.7 $kg \cdot m^{-3}$ for wheat, 0.6–1.6 $kg \cdot m^{-3}$ for rice, 0.41–0.95 $kg \cdot m^{-3}$ for cotton seed, 0.14–0.33 $kg \cdot m^{-3}$ for cotton lint, and 1.1–2.7 $kg \cdot m^{-3}$ for maize. Nhamo, et al. [7] evaluated crop evapotranspiration, crop production and agricultural gross domestic product contribution to assess the crop water productivity of Malawi from 2000 to 2013. They found an overall increase of 33% crop water productivity. Giménez, et al. [8] used different full and deficit irrigation practices to calibrate and validate soil water balance in western Uruguay using the soil water balance simulation model SIMDualKc. They found water productivity values, ranging from 1.39 to 2.17 $kg \cdot m^{-3}$ and 1.75 to 2.55 $kg \cdot m^{-3}$ when considering total water use and crop AET, respectively. Borrego-Marín, et al. [9] analyzed the impact of drought (2005, 2012) and drought management plans (2006–2008) on agricultural water productivity in Guadalquivir River Basin in Spain for the period of 2004 to 2012. They found significantly higher water productivity in irrigated than rain-fed agriculture. There is also much interest in the different methods to improve the CWP. Kima, et al. [10] analyzed the effective depth of irrigation water that can keep the soil moisture close to saturation for irrigation intervals to increase water productivity.

In general, the models on crop-water relations can be divided into two categories: empirical and process-based models [11]. Most of the empirical models are regression-based models, where a correlation is established between the statistical crop yield and local weather-related, geostatistical-related, and management-related (e.g., irrigation) factors. Therefore, they can only estimate yield, without predicting crop water uptake and soil evaporation. The process-based models simulate the physiological development, growth and yield of a crop based on the interaction of environmental variables and plant physiological processes (e.g., photosynthesis and respiration) [11,12]. They often have a weakness either in crop growth simulation or hydrology. Examples of process-based models include Soil Water Atmosphere Plant (SWAP) [13], Soil Vegetation Atmosphere Transfer (SVAT) [12], GIS-based Environmental Policy Integrated Climate model GEPIC [14], generic crop model (InfoCrop) [15,16], FAO's crop water productivity and yield response model (AquaCrop) [17–19], and the global water assessment model (WaterGAP) [20]. There are two fundamental limitations in many of the studies which have used these models: (i) The crop yield and consumptive water use estimated for a given area are not linked with the water resources availability of that region. Therefore, one cannot assess the aggregate impact of regional water resources availability, land use, and climate changes on crop production directly. (ii) Uncertainties associated with crop models are not taken into account and remained largely unquantified. There are some studies [21–24] that account for model-related uncertainties in crop yield prediction. To the best of our knowledge, the aforementioned issues have not been considered together in one package. Soil and Water Assessment Tool (SWAT) [25] has been used widely to assess the impact of management practice, and climate and land use changes on water quality and quantity and crop yield [26,27]. Using SWAT calibration, and uncertainty tool "SWAT-CUP", [28] many studies have considered the uncertainties of SWAT output variables such as discharge, and crop yield [29–31]. Although SWAT has significant capabilities in the simulation of hydrologic components and crop yield interactively, the lack of an optimal water allocation module inhibits the dynamic pattern of irrigation scheduling and increases uncertainty in Y and AET predictions.

Water allocation models can be used to optimize water allocation among different users. Some examples of water allocation models are integrated water allocation model (IWAM) [32], REsource ALlocation Model (REALM) [33], Water Evaluation and Planning (WEAP) [34], and river basin network flow model for conjunctive stream-aquifer management (MODSIM) [35]. MODSIM has been used in several studies to address the problem of water allocation between non-consumptive and consumptive water demands at the basin scale [36–38].

This paper aims to study the water productivity of irrigated wheat and maize in agricultural lands of the Lower KRB (LKRB) by using a coupled SWAT–MODSIM model considering dynamic irrigation requirements. To the best of our knowledge, previous studies have not considered dynamic time series of irrigation demands in the estimation of CWP through the aforementioned modeling approach. SWAT is used to estimate spatial and temporal distributions of water availability and irrigation water requirements, while MODSIM [35,39] simulates the processes of reservoir operations for water allocations. The use of the coupled hydrological-water allocation model substantially improves accuracy of Y and AET simulations and results in the implementation of more rational and sustainable water management practices.

Karkheh River Basin (KRB) has traditionally been the central point of agricultural activities in Iran. The basin, located in the arid southwest of Iran, is one of the most productive agricultural areas of the country. It is known as the food basket of Iran [40] and produces about 10% of the country's wheat. Available water resources and desirable climatic conditions make it a suitable basin for growing a broad range of crops. In the KRB, water availability is of great importance in supporting economic and social development [41]. Due to limited potential for developing new water resources and a significant decrease in downstream runoff due to both climate change and human interventions, improving the productivity of the existing water resources in the basin is one of the most important management challenges to sustainable food production [42]. Rafiee and Shourian [43] used a simulation-optimization approach to find the optimal irrigation plan and crop pattern in the Azadegan plain in the KRB. In the basin, excessive irrigation is a key management practice that leads to remarkable water losses [44]. Therefore, several studies have concentrated on the issue of food production in KRB [40,45]. It is also projected that the problem of water will further increase due to climate change in southern parts of the basin [42].

The coupled SWAT–MODSIM approach in this study has some novel features: (i) it considers dynamic irrigation requirements instead of constant time series of demands; (ii) it is a fully coupled model and both models have feedback on each other; (iii) it is supported by a full tutorial which facilitates the application of the coupled model in other similar research studies.

This paper is organized to (i) calibrate (1997–2010) and validate (1990–1996) crop yield at five important agricultural regions in LKRB; (ii) model the spatial and temporal variability of crop yield as well as crop consumptive water use with uncertainty analysis for wheat and maize at a subbasin level, and calculate CWP; and (iii) analyze the relation between yields and consumptive water use by quantifying the applied irrigation water and crop yield in each of the five regions by using the coupled model.

2. Methodology

2.1. Study Area

Karkheh River Basin, with a total area of about 51,000 km^2, is located in the south-western part of Iran between 30° N to 35° N and 46° E to 49° E. KRB is the third largest agricultural river basin in Iran [41] with a significant hydropower generation capacity. The southern part of the basin receives an average annual precipitation of about 250 mm·year^{-1}, whereas the northern part receives up to 700 mm·year^{-1} [46]. During the period 2006–2010, the average annual precipitation of the southern part decreased to 150 mm·year^{-1} [47]. Precipitation in many regions is insufficient to meet crop water requirements, therefore irrigation is very important in LKRB [42,48–50]. The LKRB has been selected for water productivity analysis in our study. The Karkheh Reservoir, in the most downstream part of the basin, is the largest reservoir in the basin, and is operated for irrigation and hydropower. Table 1 presents the characteristics of Karkheh Dam operation, which are considered in our model. LKRB has two major agricultural production systems. The rainfed system, which is dominant in Dashte Abbas and Dolsagh, and the fully irrigated areas, which are scattered in all five regions [44]. The average annual rainfall (2005–2010) in LKRB has recently been as low as 150 mm·year^{-1} [51]. Over the past three decades, large rainfed areas have turned into irrigated areas mainly because of increasing access to water (mainly groundwater). However, irrigation efficiencies in KRB are still low as 35%–50% [48,51]. The productivity of water is very low, i.e., 0.5 kg·m^{-3} for most of the field crops [41,46]. The total irrigated area in LKRB is 360,000 ha with a planned expansion to 500,000 ha [44]. Major crops such as wheat and maize are grown over 55% of the area [44,48].

Table 1. Characteristics of Karkheh dam in Karkheh River Basin.

Dam Name	Status	Normal Level (Meter above Sea Level) m.a.s.l	Storage (Miliion Cubic Meter) MCM	Purpose
Karkheh	Operational	220	4616	Irrigation and hydropower

The LKRB comprises of five major agricultural regions, i.e., Dashte Abbas, Dolsagh, Arayez, Hamidiyeh, and Azadegan (Figure 1). The distribution of wheat and maize in these five regions is given in Table 2. The spatial distribution of the main gauge stations for calibration and validation in the basin is also presented in Figure 1.

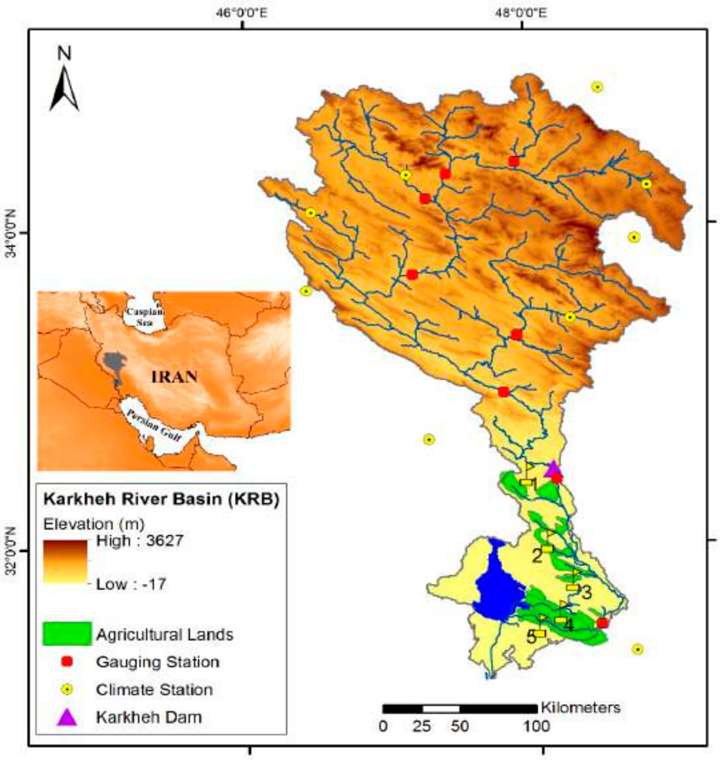


Figure 1. The five important agricultural regions in lower Karkheh River Basin: 1—Dashte Abbas, 2—Dolsagh, 3—Arayez, 4—Hamidiyeh, 5—Azadegan.

Table 2. Distribution of wheat and maize in five major agricultural lands in Lower Karkheh reported by Iran Water and Power Resources Development Co. (2010).

Agricultural Land	Total Area (ha)	Irrigated Wheat Area (ha)	Rainfed Wheat Area (ha)
Dashte Abbas	19,025	9720	2100
Dolsagh	16,133	6320	4200
Arayez	28,900	11,200	4300
Hamidiyeh	17,050	12,840	1100
Azadegan	71,093	50,050	7100

2.2. Description of SWAT Model

Soil and Water Assessment Tool (SWAT) is a continuous time, process-based, semi-distributed, hydrologic model running on daily or sub-daily time steps. The model has been developed to quantify the impact of land management practices and climate on water, sediment, and agricultural chemical yields in large complex watersheds with varying soils, land uses, and management conditions over long periods of time. The program, therefore, lends itself easily to climate and land use change analyses. In SWAT, the spatial heterogeneity of the watershed is preserved by topographically dividing the basin into multiple subbasins, and further into hydrologic response units (HRU) based on soil, land use, and slope characteristics. These subdivisions enable the model to reflect differences in evapotranspiration for various crops and soils. In each HRU and on each time step, the hydrologic and vegetation-growth processes are simulated based on the curve number or Green-Ampt rainfall-runoff partitioning and the heat unit phenological development method.

2.3. SWAT Model Calibration, Validation, and Uncertainty Analysis

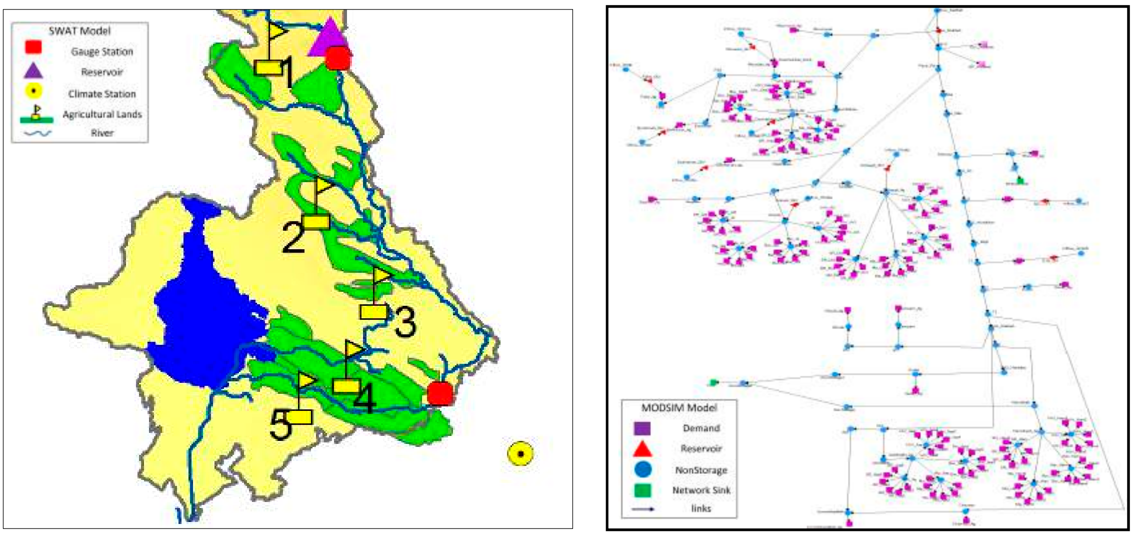
Sensitivity analysis, calibration, validation and uncertainty analysis of SWAT is performed using river discharge as well as wheat and maize historical yield data by utilizing the SUFI-2 algorithm [28,52] in the SWAT-CUP software package [53]. This algorithm maps all uncertainties (parameter, conceptual model, input, etc.) on the parameters, expressed as uniform distributions or ranges, and attempts to capture most of the measured data within the model's 95% prediction uncertainty (95PPU) in an iterative process. The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling. For the goodness of fit, as we are comparing two bands (the 95PPU for model simulation and the band representing measured data plus its error), two indices referred to as P-factor and R-factor are used [52]. The P-factor is the fraction of measured data (plus its error) bracketed by the 95PPU band and varies from 0 to 1, where 1 indicates 100% bracketing of the measured data within model prediction uncertainty, i.e., a perfect model simulation). The quantity (1-P-factor) could hence be referred to as the model error. For discharge, a value of >0.7 or >0.75 has been reported to be adequate [28,52]. This depends on the scale of the project and adequacy and precision of historical data. The R-factor, on the other hand, is the ratio of the average width of the 95PPU band and the standard deviation of the measured variable. A value of <1.5, again depending on the situation, would be desirable for this index [28,52]. These two indices are used to judge the strength of the calibration/validation and predictive uncertainty. A larger P-factor can be achieved at the expense of a larger R-factor. Hence, often, a balance must be reached between the two. In the final iteration, where acceptable values of R-factor and P-factor are reached, the parameter ranges are taken as the calibrated parameters. SUFI-2 allows usage of eleven different objective functions such as R^2, Nash–Sutcliff efficiency (NSE), and mean square error (MSE). In this study, we used NSE and percent bias (PBIAS) for discharge [54] and root mean square error for crop yield [31].

2.4. Description of the MODSIM Model

MODSIM is a generic river basin management decision support system, originally conceived in 1978 at Colorado State University, making it the longest continuously maintained river basin management software package currently available [55]. MODSIM represents a river basin as a network of links and nodes. Unregulated inflows, evaporation and channel losses, reservoir storage rights and exchanges, stream–aquifer modeling components, reservoir operating targets, and consumptive and instream flow demands are considered in MODSIM [56]. More details can be found in Labadie [55].

2.5. Model Setup and Data Collection

The soil data was obtained from Food and Agriculture Organization [57]; land use, crop and agricultural management data were from Mahab [51]; the digital elevation model was provided by hole-filled NASA Shuttle Radar Topographic Mission (SRTM) [58]; major local rivers and climate data at nine climate stations in the basin were from Iran Water and Power Resources Development Co [44]. The Karkheh reservoir was included in the model with historical reservoir operation time series data starting from 2000. The data were provided by the Ministry of Energy [59]. Monthly discharge data for eight hydrological stations were provided by the local water authorities. Observed monthly discharge and winter wheat, barley, and maize yields were used for model calibration (1997–2010) and validation (1990–1996). The selection of calibration parameters was based on a sensitivity analysis and past modelling experiences at the same location [28,60]. As a result, 26 parameters were selected for calibrating both discharge (20 parameters) and crop yield (six parameters). The watershed system, river network, and water allocation system in MODSIM are illustrated in Figure 2.



(**a**) (**b**)

Figure 2. (**a**) LKRB system in the SWAT River network and (**b**) water allocation system in MODSIM.

2.6. Coupling Hydrologic and Water Allocation Models

Optimal water allocation among competing users including hydropower generation is missing in SWAT. The main feature of MODSIM DSS is in allocating available water resources to different users optimally, irrespective of what sources they come from. That is why the idea of coupling SWAT and MODSIM as two powerful tools for modeling both water availability and water allocation (management) is a very attractive idea.

Although there are some studies, which have used both SWAT and MODSIM models [61–63] in watershed modelling, they are not fully linked with feedback and most are not available for use by other researches. In this work, water allocations from the reservoir to different demand sites and the associated spatial units in SWAT (HRUs) are done based on the schedule derived from MODSIM's water allocation solutions obtained by iterative minimum cost network flow programs. Subsequently, net irrigation requirement and inflow to the reservoir from SWAT outputs files (output.rch and output.hru) at the corresponding HRUs and rivers will be extracted and converted as inputs to

MODSIM. Once the amount of water allocated to each demand node (equivalent to HRUs in SWAT) is determined by MODSIM, SWAT is run using new updated-by-MODSIM irrigation scheduling. The quantities of water transferred to different HRUs are estimated for every time step. Figure 3 illustrates the structure of both models considering the unit of data exchanging between them.

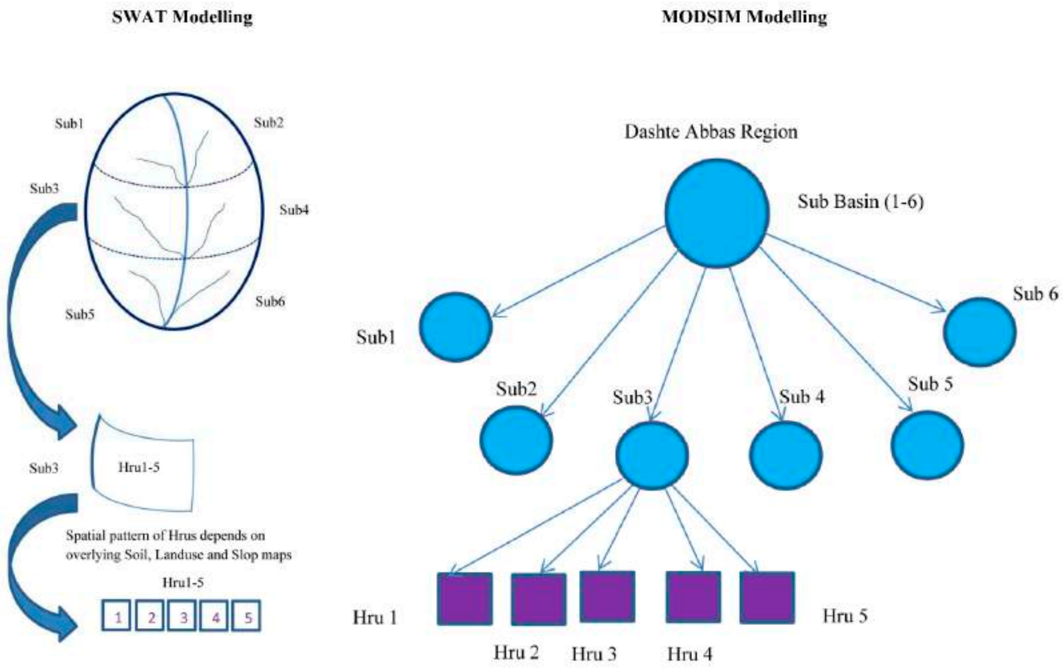


Figure 3. Overview of the input–output and information exchange in the SWAT–MODSIM (SM) model.

The conceptual framework of SWAT–MODSIM execution is illustrated in Figure 4. Here are the eight steps to a successful implementation of the coupled SWAT–MODSIM model:

1 Build the SWAT and MODSIM models for the specific watershed, ensuring that each HRU that receives water should have a related demand node in MODSIM.
2 Calibrate and validate the SWAT model using SWAT-CUP
3 Extract the M95PPU of inflow to the reservoirs (from 95ppu.txt SWAT-CUP or 95ppu_No_Obs.txt files) and net irrigation requirements (water deficit in each time step) by subtracting potential evapotranspiration (PET) from actual evapotranspiration (AET) in the SWAT-CUP output file 95ppu_No_Obs.txt.
4 Import the net irrigation requirement and inflow to the reservoir to MODSIM from SWAT-CUP outputs.
5 Execute the MODSIM model.
6 Extract the allocated water to each demand node for each time step from MODSIM outputs.
7 Import the monthly irrigation from MODSIM into SWAT management files for related HRUs.
8 Re-execute the SWAT-CUP with new management files.

More details can be found in the Supplementary material.

2.7. Estimation of Crop Water Productivity (CWP)

CWP combines physical accounting of water with yield or economic output to indicate the value of a unit of water and can be calculated as:

$$\mathrm{CWP} = \frac{\mathrm{Y}}{\mathrm{AET}} \tag{1}$$

where CWP is the crop water productivity in kg·m^{-3}, Y is the crop yield in kg·ha^{-1}, and AET is the seasonal actual evapotranspiration in m^3·ha^{-1}, assumed here to be the crop's consumptive water use, so the above definition of CWP does not account for the waste of water due to irrigation inefficiencies. Note that Y is the annual yield while AET is calculated on a monthly basis. The spatial resolution of Y, AET, and CWP is at a subbasin level, but for comparison with other studies and the available statistics, the results are aggregated to the level of agricultural lands.

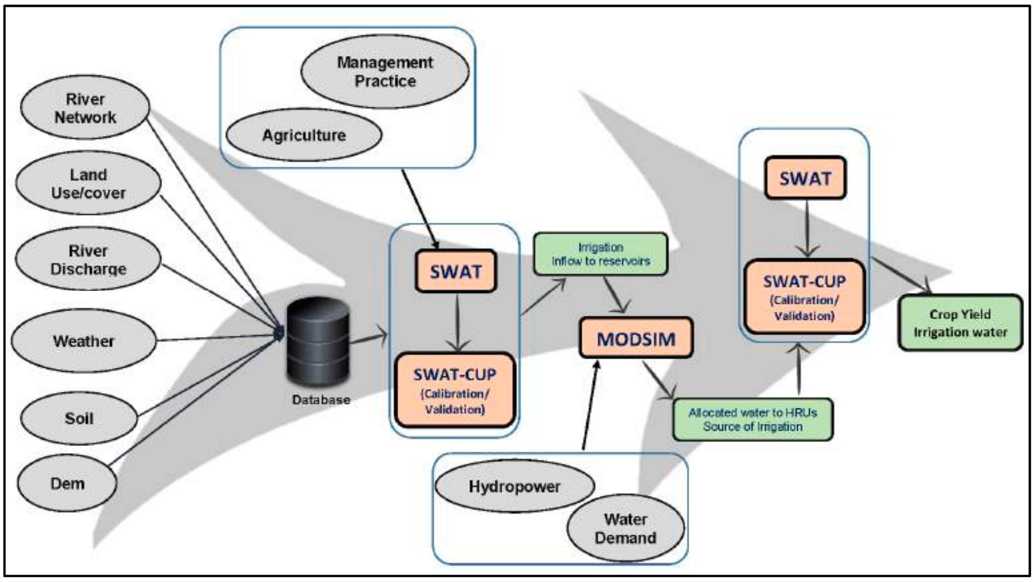


Figure 4. Overview of the input–output and information exchange in the SWAT–MODSIM (SM) model.

3. Results and Discussion

3.1. Calibration and Validation of the Coupled Model for Wheat and Maize

As described in Section 2.3, 26 parameters were selected for calibration and validation based on our previous study and literature sources. In the final iteration, eight parameters were found to be sensitive parameters in our study. In this paper, for the sake of brevity, we only report the results of our analyses for the calibration and validation of crop yields. More details on the calibration and validation of discharge and sensitivity analysis of parameter can be found in Vaghefi, et al. [42]. Calibration and validation tasks were done based on the execution of steps described in Section 2.6. At first, auto-irrigation with an unlimited source of water was used as a source of irrigation for the agricultural region in LKRB to find the maximum amount of irrigation, which is needed at the HRU level for each time step. After estimation of the net irrigation requirements and inflow to Karkheh Reservoir, MODSIM was run. Finally, the management files of agricultural regions in LKRB were updated considering MODSIM results for irrigation scheduling and the actual crop yields were obtained by re-running of SWAT calibration by SWAT-CUP. Using this sequential procedure, the calibration and validation results of the SWAT model improved considerably (Table 3, Figures 5 and 6). The results show that observed yields are generally inside or quite close to predicted yield bands for both wheat and maize. For irrigated wheat, the yield varies from 1850 to 3900 kg·ha^{-1}, with the highest yield found in the Hamidiyeh (2007 kg·ha^{-1}) region and the lowest in the Dashte Abbas (1990 kg·ha^{-1}). For the irrigated maize, the lowest yield belongs to the Dolsagh region (2900 kg·ha^{-1}) and the highest to the Hamidiyeh region (7200 kg·ha^{-1}). For the irrigated wheat, the P-factors are generally larger than 0.77 for calibration and vary from 0.73 to 0.86 for the validation period (Table 3).

The R-factor values are also in acceptable ranges. For the irrigated maize production, the uncertainties are larger than the irrigated wheat as indicated by generally larger R-factor values. This is because of the higher sensitivity of maize production to the water stress than wheat.

Table 3. Calibration (1997–2010) and validation (1990–1996) results of the coupled SWAT-MODSIM model for irrigated wheat and maize using the SMS model in LKRB.

Agricultural Region	Calibration				Validation			
	P-Factor	R-Factor	P-Factor	R-Factor	P-Factor	R-Factor	P-Factor	R-Factor
	Wheat	Wheat	Maize	Maize	Wheat	Wheat	Maize	Maize
Dashte Abbas	0.77	0.21	0.79	0.65	0.76	0.34	0.65	0.59
Dolsagh	0.85	0.39	0.86	0.65	0.75	0.25	0.61	0.71
Arayez	0.83	0.43	0.79	0.69	0.74	0.27	0.61	0.73
Hamidiyeh	0.78	0.29	0.73	0.42	0.73	0.36	0.68	0.87
Azadegan	0.84	0.23	0.76	0.43	0.73	0.29	0.69	0.89

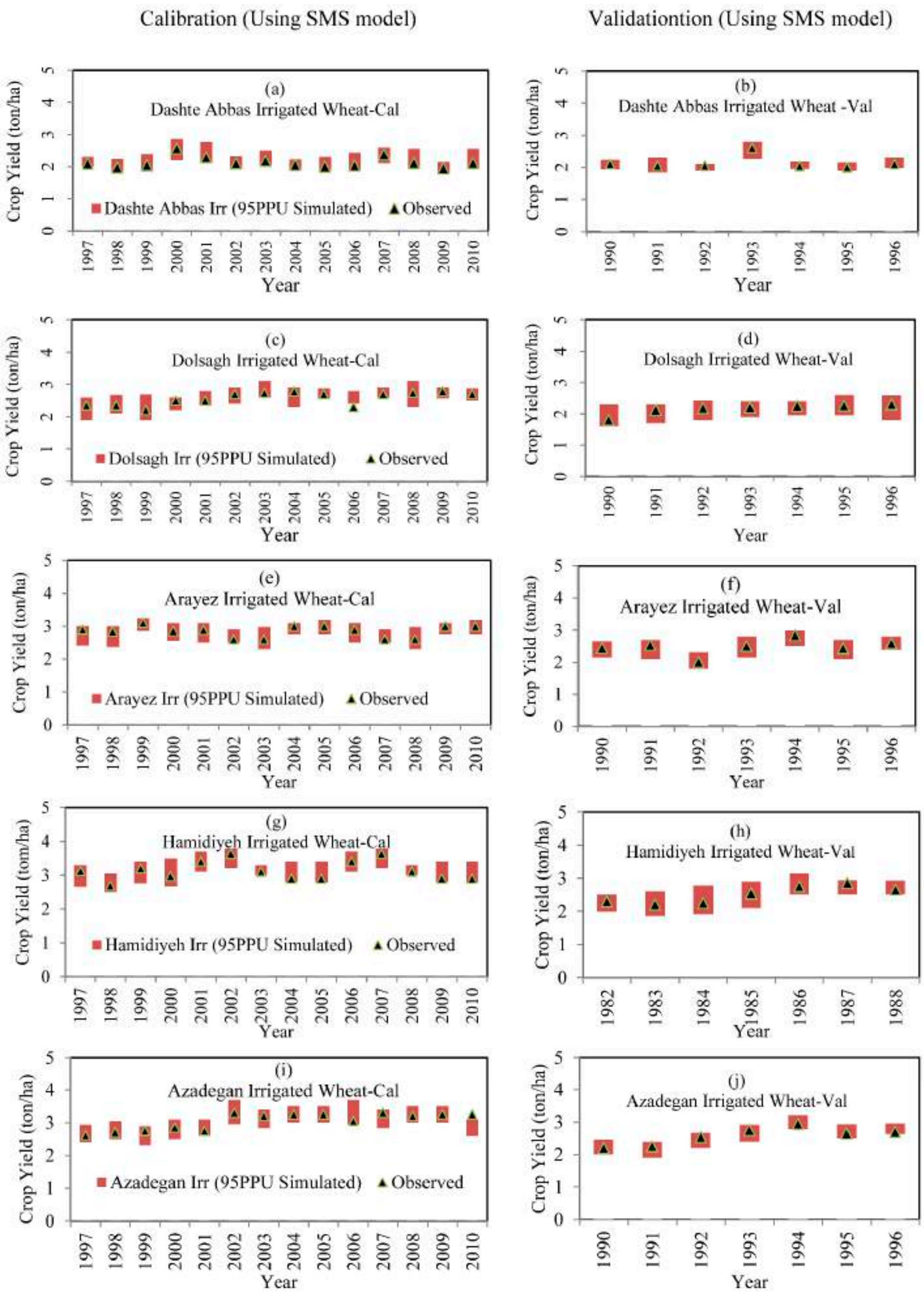


Figure 5. Results of the SWAT calibration and validation for wheat yield in Dashte Abbas (**a**,**b**), Dolsagh (**c**,**d**), Arayez (**e**,**f**), Hamidiyeh (**g**,**h**), Azadegan (**i**,**j**) plains.

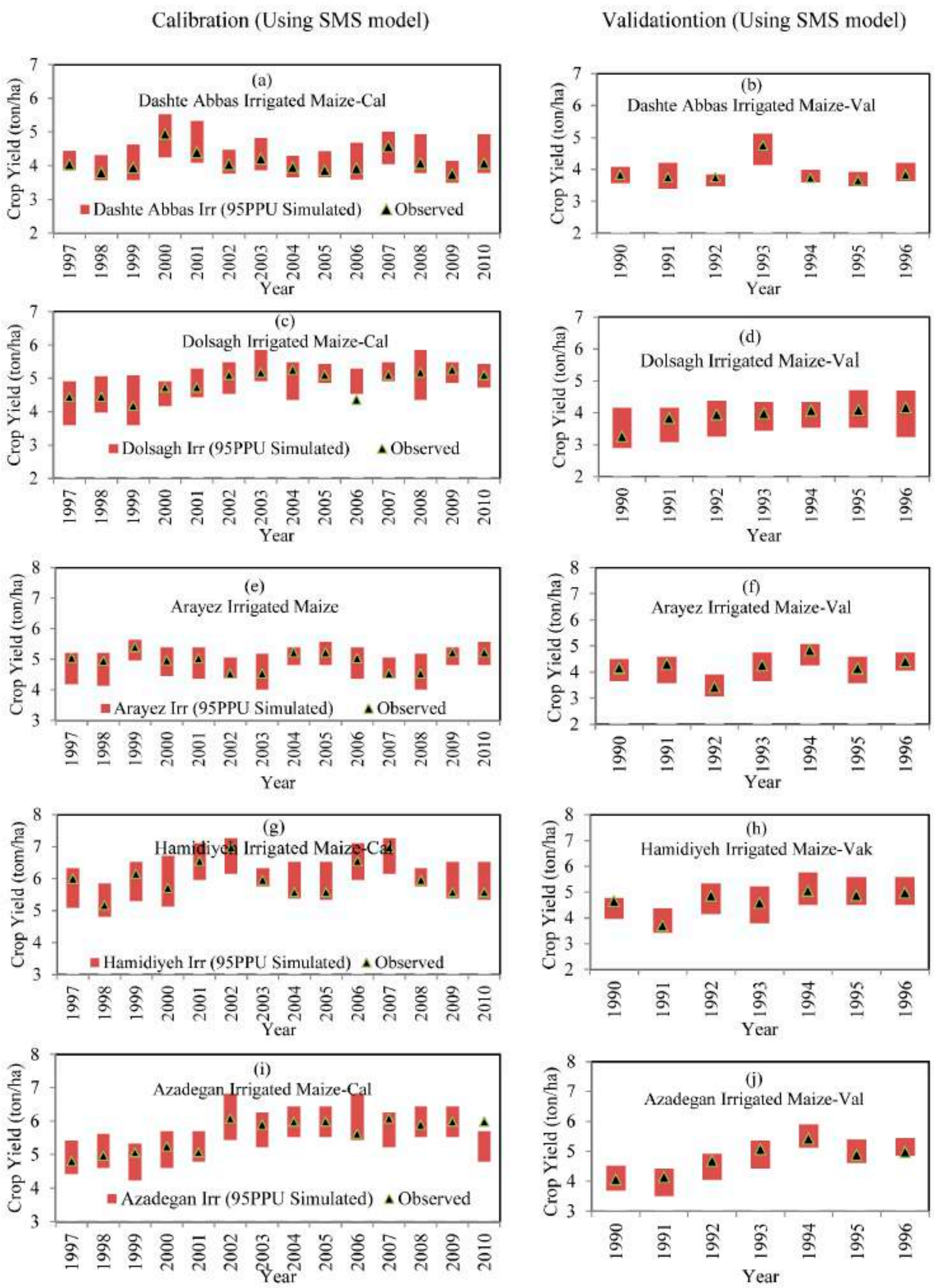


Figure 6. Results of the SMS calibration and validation for maize yield in Dashte Abbas (**a**,**b**), Dolsagh (**c**,**d**), Arayez (**e**,**f**), Hamidiyeh (**g**,**h**), Azadegan (**i**,**j**) plains.

3.2. Water Productivity of Wheat and Maize

The results of the coupled model for both calibration and validation periods and for the entire region indicates that the basin-wide wheat water productivity (WWP) is equal to 0.94 kg·m^{-3}, ranging from 0.55 kg·m^{-3} to 1.21 kg·m^{-3}. The highest WWP can be ascribed to higher yields under limited water supply conditions. Lower WWP is mainly due to higher water application and relatively lower wheat yields (Figure 7a). The basin-wide maize water productivity (MWP) is equal to 0.8 kg·m^{-3}, ranging from 0.55 kg·m^{-3} to 1.15 kg·m^{-3} (Figure 7b).

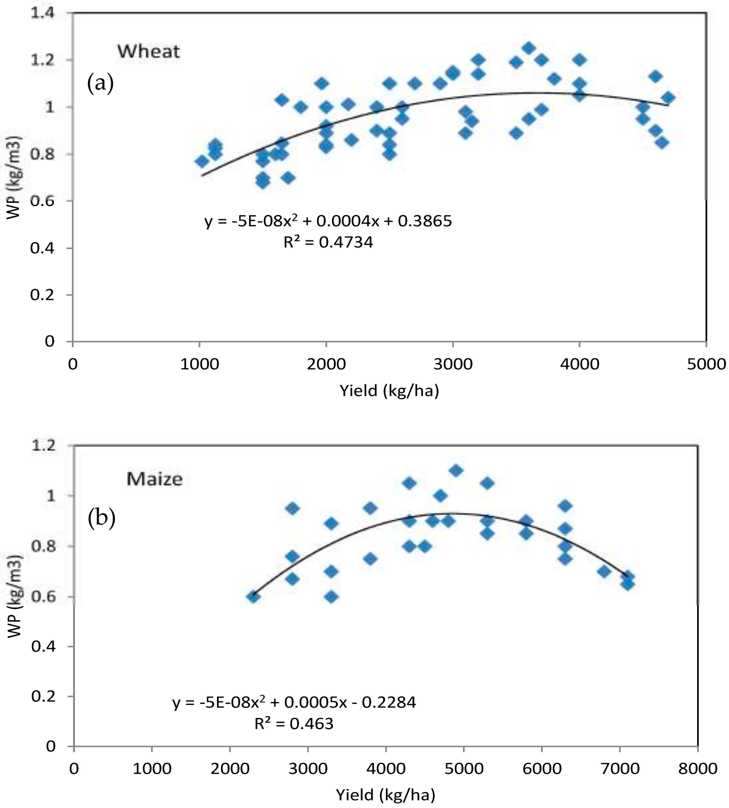


Figure 7. Relationship between yield and irrigation water applied for wheat (**a**) and maize (**b**).

3.3. Yield-Irrigation Water Relations

The relation between wheat and maize yield and irrigation water applied for both calibration and validation periods is presented in Figure 8. Data points of all regions from 1990 to 2010 for irrigated wheat and maize are used in this illustration. One can observe from the figure that wheat yields vary from 1.3 ton·ha^{-1} to 3.5 ton·ha^{-1} with an average of 2.5 ton·ha^{-1} for irrigated wheat, and from 2.1 to 7.2 ton·ha^{-1} with an average of 5 ton·ha^{-1} for maize. The irrigation water applied to the agricultural regions is summarized in Table 4. Irrigation water varies from 2300 m^3·ha^{-1} to 6662 m^3·ha^{-1} and 4320 m^3·ha^{-1} to 10,200 m^3·ha^{-1} for irrigated wheat and maize respectively. The variation of irrigation water applied is from 200 mm to 600 mm for irrigated wheat and from 400 to 1450 mm for maize (Figure 8a,b).

Table 4. Results of the SM model for irrigation water applied to wheat and maize (m^3·ha^{-1}) in LKRB.

Agricultural Region	Wheat			Maize		
	I_{max}	I_{min}	Iavg	I_{max}	I_{min}	Iavg
Dashte Abbas	5980	2300	3120	8500	4320	6280
Dolsagh	6662	2563	3476	9469	4812	6996
Arayez	5560	3210	4150	9300	6340	9020
Hamidiyeh	5184	3500	4230	10,200	6800	9100
Azadegan	5890	4127	4690	9320	5890	8910

There is a positive relation between Y and CWP for both maize and wheat. There is a sharper increase in WWP in response to increasing yield compared with maize. This suggests that a unit increase in water results in a larger additional yield in wheat than irrigated maize, leading to a greater improvement in CWP. It means that wheat yield is more responsive to additional water. This result is in agreement with what is reported by [64]; they have found that for the smaller yield range, less incremental water is required to increase a unit of crop yield.

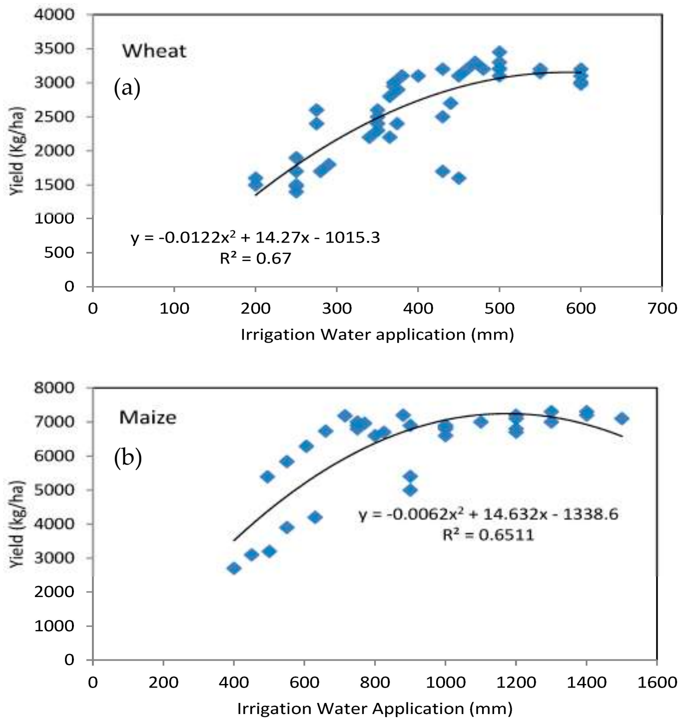


Figure 8. Relationship between crop water productivity and crop yield for wheat (**a**) and maize (**b**).

4. Summary and Conclusions

In this study, crop water productivity of LKRB was assessed using the coupled SWAT–MODSIM model. The time series of actual irrigation demands of agricultural regions was dynamically simulated by the SWAT model and fed into the MODSIM water allocation model. Through an iterative procedure, the irrigation operation of SWAT was updated based on allocated water by MODSIM. Implementation of the coupled model improved the calibration and validation of Y and simulation of AET and CWP. The P-factors in the coupled models are generally larger than 0.77 for calibration and vary from 0.73 to 0.86 for the validation period.

The analysis showed that there are considerable differences in crop yields and productivity of water in irrigated areas of the five agricultural regions of LKRB. The variation of irrigation water applied was from 200 mm to 600 mm for irrigated wheat, and from 400 to 1450 mm for maize. The results showed that basin-wide WWP is equal to 0.94 $kg \cdot m^{-3}$ and MWP is equal to 0.8 $kg \cdot m^{-3}$. The results suggested that higher water consumption does not necessarily result in a higher yield.

Supplementary Materials: The following are available online at www.mdpi.com/2073-4441/9/3/157/s1, a comprehensive user manual of coupled SWAT-MODSIM model. The Software is freely available for download from our web page: www.2w2e.com.

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