As simple as possible but not simpler?: the case of irrigation modeling at catchment scale in southwestern France

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ORIGINAL PAPER

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Abstract

The estimation of irrigation water requirements (IWR) amount and timing is crucial for designing water management strategies at the regional scale. Irrigation requirements can be estimated with different types of models: very complex and detailed crop models, agent-based models, or simplified modeling approaches. Because simplified approaches are often preferred, in this study, we evaluate the consequences of using simplified approaches for IWR assessment at a catchment scale and the consequences of various modeling choices, providing information on the uncertainties. To this end, different simple modeling approaches based on the CropWat model are compared with an agent-based approach (MAELIA), which serves as a benchmark. To assess simulations in detail, partial variance is calculated for several indicators characterizing daily simulated irrigation. Our sensitivity analysis, applied over a sub-catchment of the Aveyron River (southwestern France), shows a high variability in simulations produced by CropWat between the modeling assumptions tested, principally explained by the rules for irrigation triggering and the quantification of daily irrigation. The analysis also shows that several simplified approaches are able to reproduce the irrigation simulated by the high-accuracy MAELIA model, but not necessarily corresponding to an optimal irrigation scheme. Hence, this study confirms the possibility of assessing daily irrigation with simplified approaches, but warns about high modeling uncertainties, reflecting uncertainty in effective irrigation practices. This uncertainty can be taken into account by water managers and modelers through the combination of a set of irrigation models.

Introduction

Water withdrawals for irrigation water requirements (IWR) have a huge impact on low flows in water-stressed agricultural catchments (Martin et al. 2016). Their impact may increase with climate change as a consequence of the decrease in water resources in summer and the increase in crop water requirements (Wanders and Wada 2015), as is expected in France (Collet et al. 2015). Hence, IWR assessment is essential for managing water resources in water-stressed agricultural catchments. It might become essential to take into account irrigation withdrawals processes and their evolution while performing hydrological modeling

and considering future climate change. Moreover, IWR assessment may help to evaluate the relevance of adaptation strategies to climate change scenarios in association with hydrological projections. The IPCC (2014) recommended planning water management at the catchment scale. In France, a new planning and dialog tool was created, coined "PTGE" (*Projets de Territoire pour la Gestion de l'Eau,* i.e., Territory Project for Water Management; MTES and MAA 2019), to build water management strategies at the local scale. To support the design of such planning or strategies, many hydrological simulations have been coupled with estimations of irrigation withdrawals based on IWR assessment (Collet et al. 2013; Dehghanipour et al. 2020; Gorguner and Kavvas 2020; Kolokytha and Malamataris 2020; Wanders and Wada 2015). Likewise, several studies estimated crop water stress induced by limited water resources for irrigation (Collet et al. 2013; Elliott et al. 2014).

IWR in a catchment can be estimated from observation data. However, observation data are often lacking, leading to a preferential use of automatic irrigation algorithms for irrigation assessment (Uniyal and Dietrich 2019; Wriedt et al. 2009), i.e., algorithms based on soil–crop water balance

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models. Specifically, irrigation algorithms simulate automatic triggering and nominal irrigation depths to quantify irrigations. This enables, for example, long-term IWR projections in the context of climate change. Most often, irrigation is triggered according to decision rules based on soil moisture deficit or crop water stress thresholds. Irrigation amounts can be fixed (Bouras et al. 2019; Rouhi Rad et al. 2020), or can be calculated to fill the soil reservoir totally (Collet et al. 2013; Hori et al. 2008) or partially (Funes et al. 2021; Smith et al. 2012). To estimate soil moisture or crop water stress, a soil–crop water balance model is often used. The development and the use of sophisticated crop models have been largely investigated (Di Paola et al. 2016). The spatio-temporal distribution of farmers' practices strongly determines irrigation dynamics and amounts (Bergez et al. 2012; Zaccaria et al. 2013). McInerney et al. (2018) explored the impacts of different spatio-temporal distribution methods of observed irrigation among hydrological response units (HRUs) of a catchment and showed that the choice of distribution method might have an important impact on flows. An approach was developed to estimate IWRs at the regional scale based on a high-accuracy reproduction of farmers' practices, taking into account spatio-temporal variability. This approach is agent-based and is called the "MAELIA" (Modelling of socio-Agro-Ecological system for Landscape Integrated Assessment) platform (Allain et al. 2018; Martin et al. 2016; Therond et al. 2014). In this last example, farmers' practices are represented on an individual basis, using decision algorithms and taking into account field size and spatial allocation, irrigation equipment, and working time constraints. Nevertheless, the complexity of the spatio-temporal distribution of farmers' practices is often overlooked in efforts aiming to develop operational methods of irrigation quantification and to deal with the lack of data. However, the spatio-temporal variability of irrigation practices might be high and might have strong impacts on hydrology, and simplifying assumptions might lead to biases that should be evaluated.

Few previous studies performed a sensitivity analysis of IWR assessment methods. Multsch et al. (2015) quantified wheat IWR with different potential evapotranspiration formulas and crop coefficients sets and analyzed the variability obtained. Wada et al. (2013) and Wan et al. (2018) developed a hydrological multi-model approach to estimate global IWR. However, to our knowledge, the sensitivity of IWR assessment to different automatic irrigation rules at a regional scale has not been quantified. Moreover, these comparisons between IWR simulations are usually based on annual or monthly scales, while regulatory constraints and objectives are usually defined on the basis of shorter time steps (e.g., day(s)) and on small catchment scale as

is the case, for example, in France (Mazzega et al. 2014; MEDDTL 2011).

The present study aims to fill these gaps in IWR assessment by comparing the impact of different automatic irrigation rules with other sources of potential variability on which many researchers focus their efforts, such as crop evapotranspiration estimation, or root growth estimation. In an operational perspective and for integrated hydrological modeling, it is important to identify the strongest source of uncertainty in IWR assessment. Two types of modeling approaches involving different levels of simplification of farmers' practices are compared with the MAELIA benchmark in a French southwestern water basin with a significant water deficit. MAELIA has already been calibrated and validated on this study area in a previous work (Martin et al. 2016; Murgue et al. 2016). Different versions of these approaches are explored and compared with the MAELIA outputs. To this end, indicators characterizing irrigation hydrographs at the daily time step are used. The impact of modeling hypotheses was quantified with variance decomposition.

The following research questions are investigated in the present study:

1. What is the sensitivity of daily IWR assessment to simplifying modeling assumptions at different spatial scales? How should this sensitivity be taken into account by hydrological modelers and water managers?
2. Is it possible to adequately reproduce simulations of a high-accuracy agent-based model with simplified approaches?

Study area and data

Study area

The study focuses on an 840-km^2 downstream portion of the Aveyron River basin, a tributary of the Garonne River, located in southwestern France (Fig. 1). This area is mostly agricultural, with 58,500 ha of cropland, 22,000 ha of forests and semi-natural areas, and only 3500 ha of artificialized soils. Irrigated crops comprise 8000 ha. Maize is by far the main irrigated crop, followed by wheat and orchards. Murgue et al. (2016) estimated that mono-cropping of grain maize in alluvial soils reached an annual average irrigation amount of 255–305 mm during the 2003–2007 period in the study area.

This area is highly water-stressed and agricultural withdrawal restrictions are common in summer. These restrictions are aimed at avoiding ecological degradation of the

Fig. 1 Study area location (**a**) and land use (**b**)
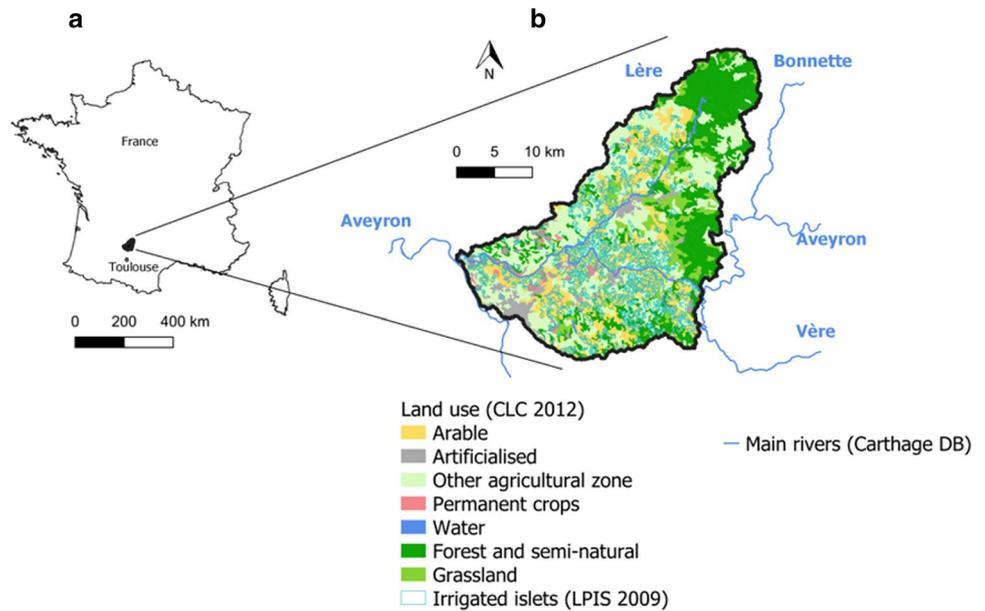
aquatic environment and ensuring water is available for domestic and industrial use.

The climate is temperate with an annual mean air temperature of 13 °C and mean annual precipitation of approximately 750 mm. However, summers are dry and hot, when maize water needs are high, leading to a high irrigation dependency. Monthly precipitations are less than 50 mm in July and August, while monthly evapotranspiration is more than 115 mm during the same period.

Data

The following data were available:

- Crop rotation sequences and irrigated surfaces from the French Land Parcel Identification System (LPIS) database created in 2006, based on European Union Common Agricultural Policy declarations of cultivated plots;
- Soil characteristics from the Soil Geographical Data Base of France (SGDBF) (INRA 2018);
- Daily data of past climate conditions (precipitation and air temperature) from the SAFRAN reanalysis (Vidal et al. 2010).

Data were previously completed and adjusted through a survey among local farmers and stakeholders (see Murgue et al. 2015).

The major irrigated crops in the study area are cereals (other than maize), maize (six cultivars from very early to very late), maize seeds, maize silage, rapeseed, peas, soybean, sunflower, orchards, and grassland.

Modeling protocol

Irrigation modeling at regional scale

In the present study, we compare two approaches of varying complexity:

- The MAELIA platform, combining the soil–crop water balance model AqYield (Constantin et al. 2015) at plot scale and a high-accuracy agent-based automatic irrigation modeling. This modeling approach is called "MAELIA" (M);
- The soil–crop water balance model CropWat (Smith 1992) combined with two simpler regional automatic irrigation approaches called "Conceptual" (C) and "Semi-plot" (S).

These different approaches are described below and summarized in Fig. 2. Details about the soil–crop water balance models, CropWat and AqYield, are given in Appendix "Soil–crop water balance models". Their parameter calibration procedure is detailed in Appendix "Parameter calibration". The beginning of the simulation period is January 2008 and the end is December 2014. The year 2007 is used for initialization.

The MAELIA approach benchmark

MAELIA (Therond et al. 2014) is a high-accuracy platform modeling explicitly farmers' practices at a daily time step in each plot (*n* = 15,224) individually for each farm (*n* = 1143) described in the LPIS database of the study area. It provides

Fig. 2 The three modeling approaches used to assess irrigation water requirements (IWRs). The MAELIA (M) irrigation approach distinguishes 232 pedo-climatic zones and each individual plot and farm. The AqYield soil–crop water balance model is coupled to an agent-based model in MAELIA to assess IWR. A Conceptual approach (C) is used to simulate daily irrigation amounts on the basis of data aggregated on 200 pedo-climatic zones crossed with existing crops based on CropWat outputs. A Semi-plot approach (S) in which the simulation units of the C approach are surface-equally divided into irrigation water turn groups irrigated successively. At simulation unit scale, the S approach leads to irrigation events on singular days followed by several days without irrigation represented by peaks in the figure. AqYield outputs are used to calibrate the CropWat parameters
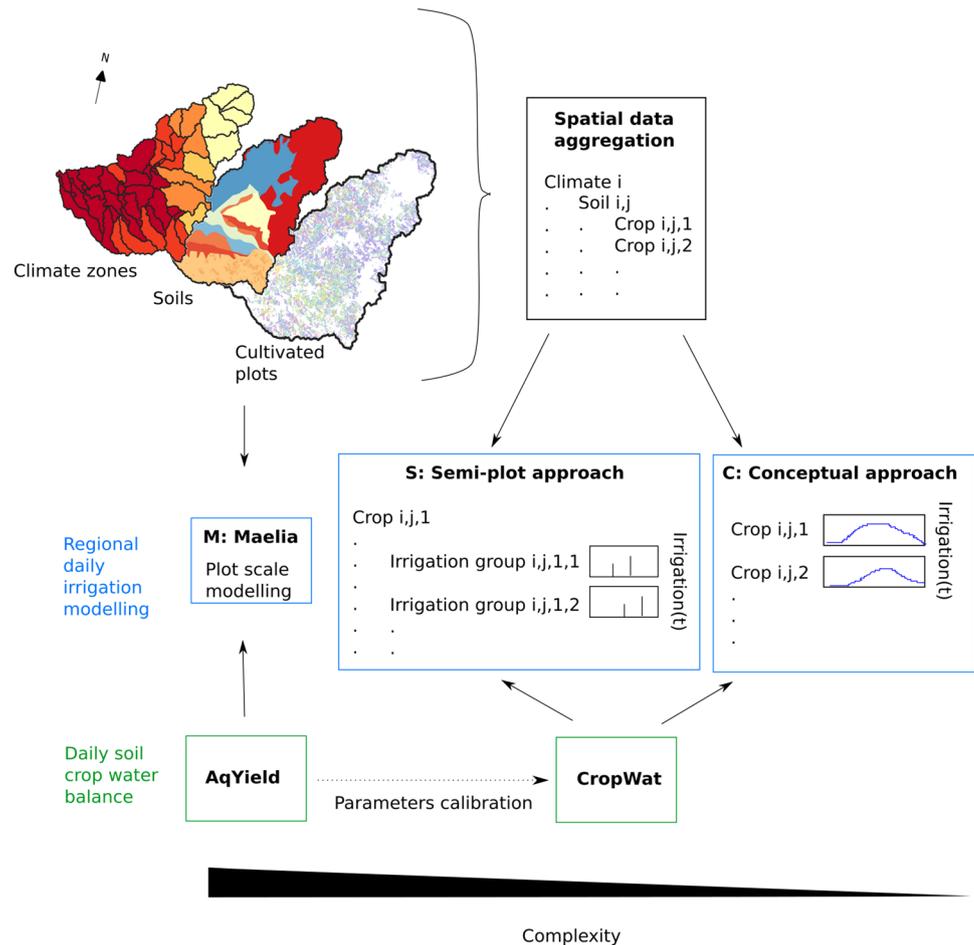
a plot-scale modeling of irrigation practices. Technical operation durations are taken into account to constrain the number of farmers' actions within a single day. Irrigation management strategies described through IF–THEN decision rules are defined for different combinations of crops, soils, irrigation equipment, farm types, etc. Each strategy defines a possible period for irrigation, the dose for each irrigation (mm), the conditions triggering irrigation (e.g., soil moisture and past and future rainfall thresholds, crop water stress), and the minimal temporal interval between irrigation applications in the same field (hereafter called "water turn"). Details regarding these decision rules are provided by Murgue et al. (2014). The irrigation strategies in our study area stem from a farm survey performed and described by Murgue et al. (2015).

The soil–crop model AqYield runs on each plot (Fig. 2), characterized by crop, technical management, soil properties, and climate. For the study area, 51 climatic zones (CZs) and 14 soils were differentiated. Crossing soils and CZs generate 232 pedo-climatic areas.

Unfortunately, irrigation data are very coarse in space, time span and time resolution, and their exactitude is highly questionable in France and particularly in the South-west

region, where this information is highly sensitive. The only existing information is irrigation declared by farmers to the French Water Authority at an annual time step. Moreover, actual irrigation withdrawals cannot be directly compared with IWR, because withdrawals can be limited by water availability and restrictions. A comparison between simulated irrigation withdrawals with MAELIA, taking into account water availability and restriction rules, and annual individual farmer reports to French water authorities showed a very good fit (Martin et al. 2016). The temporal distribution of irrigation over weeks was also assessed through local expert interviews (Murgue et al. 2016). Therefore, we consider in our work that the MAELIA irrigation demand estimation, without taking into account water availability and restriction rules, is probably the best assessment of daily IWR that one can afford for this region given the available data and it will represent our reference in this study.

Conceptual approach

In many studies (Collet et al. 2015; Smith et al. 2012), regional irrigation modeling consists of bringing the amount of water (Irr, mm) to fill the soil reservoir, to maintain the

soil water deficit (Dr, mm) to a prefixed threshold (θ, mm) for each simulation unit, as expressed in Eq. (1). In this configuration, irrigation is triggered when Dr exceeds θ. A similar approach is to bring the amount of water needed to compensate for the lack of soil water to evapotranspirate at the crop maximal evapotranspiration (CET, mm day^{-1}) level, maintaining water at the readily available water (RAW, mm) level equivalent to a θ value (Funes et al. 2021):

$$\begin{cases} \text{if } \ Dr(d) < \theta(d), \text{Irr}(d) = 0 \\ \text{else, Irr}(d) = Dr(d) - \theta(d) \end{cases}. \tag{1}$$

In this simplified approach, individual plots are not explicitly represented. Simulation units to calculate daily irrigation are defined for homogeneous crop, soil, and climate types (Fig. 2). In this study, 200 pedo-climatic zones were defined, aggregating MAELIA spatial units characterized by the same climate and water content characteristics.

Semi-plot approach

We developed an intermediate approach in this study, called the "Semi-plot" approach. It aims at reproducing a more realistic modeling of irrigation over plots, but in a more simplified way than the reference (MAELIA). In this approach, pedo-climatic zones are the same as in the Conceptual approach but the crop simulation units of the Conceptual approach are divided into irrigation water turn groups of equal area and are irrigated successively (Fig. 2). For example, for a 5-day water turn, a simulation unit would be divided in 5 groups, and the first group could be irrigated on days 1, 6, 11, etc., the second group could be irrigated on days 2, 7, 12, etc., and so on. The number of groups for each crop type was defined based on the number of water turns simulated by the reference experiment. This approach simulates more explicitly the dynamics of irrigation at the plot scale as each simulation unit can receive a high amount of water on a particular day followed by several days without irrigation (Fig. 2).

Indicators characterizing irrigation

While most studies only consider monthly or even annual IWR amounts, this study explores numerous indicators to characterize the temporal variability of withdrawals under different simulations. Indeed, water crises can occur in short time intervals, and a monthly estimation of IWR might not be sufficient to identify them (Mazzega et al. 2014). Indicators were selected to characterize seven features of irrigation:

- irrigation volumes (I, I_m),
- irrigation frequency (N, N_m),
- period of inter-annual mean highest irrigation (Max_regime, Max_regime_date),
- mean annual highest irrigation (Max_10, Max),
- irrigation daily variability (Q_dispersion, Var2),
- accuracy compared with reference irrigation simulation (KGE, KGE_10),
- crop water stress (ET_S, ET_S_m).

Details on these indicators are provided in Appendix "Indicator calculation". In particular, the Var2 indicator was developed to compare narrow temporal variabilities of irrigation.

Table 1 Mean, minimal, and maximal values of annual indicators ("Indicators characterizing irrigation") for Conceptual, Semi-plot and reference experiments (as described in "Irrigation modeling at regional scale" and "Sensitivity analysis experiments") for lumped outputs at the scale of the study zone

| Indicator	Conceptual			Semi-plot			Reference
	Mean	Min	Max	Mean	Min	Max	
I (m^3)	1.40E+07	6.08E+06	2.48E+07	1.54E+07	4.83E+06	2.99E+07	1.41E+07
N (days)	120	79	188	148	83	269	154
Max_regime (m^3)	1.05E+05	7.20E+04	1.47E+05	1.10E+05	5.40E+04	1.72E+05	1.16E+05
Max_regime_date (DOY)	197 (16 July)	139 (19 May)	201 (20 July)	194 (13 July)	140 (20 May)	230 (18 August)	201 (20 July)
Max (m^3)	5.10E+05	2.81E+05	1.41E+06	4.21E+05	1.91E+05	8.08E+05	3.29E+05
Max_10 (m^3)	3.10E+05	1.94E+05	4.31E+05	3.22E+05	1.46E+05	5.07E+05	1.47E+05
Q_dispersion (–)	3.7	2.4	6.4	4.3	2.2	13.7	5.1
Var2 (–)	0.0021	0.0019	0.0027	0.0010	0.0006	0.0016	0.0009
ET_S (–)	0.97	0.87	1.00	0.97	0.83	1.00	0.93
KGE (–)	0.57	− 0.1	0.81	0.56	− 0.26	0.91	–
KGE_10 (–)	0.70	0.17	0.95	0.62	− 0.21	0.96	–

Sensitivity analysis experiments

Balanced simulation plans were developed for both the Conceptual and Semi-plot approaches. They aim at studying the impact of modeling simplifications and at identifying sensitive parameters for each soil–crop water balance and regional irrigation modeling chain. The chosen variation factors are:

- Soil water deficit threshold θ. Many studies fix θ at a hypothetical RAW level (Neilsen et al. 2018; Rinaudo et al. 2013), corresponding to the value optimizing the amount of water brought to crops. Some studies fix various values of θ, e.g., at a value of 0 mm (Collet 2013), at a threshold of 50% of total available water (TAW, mm; Bouras et al. 2019), or at a threshold of $0.8 \times RAW + 0.2 \times TAW$ (Smith et al. 2012). Moreover, deficit irrigation amounts ($\theta > RAW$) are also possible, particularly for crops resistant to water stress. Because

irrigation is calculated at a daily time step, contrary to Collet et al. (2013), who considered a 10-day time step, we consider that θ cannot be equal to 0 in this modeling configuration. We also include a value higher than RAW to explore a deficit irrigation hypothesis. Accordingly, we explore a range of values for θ from $0.25 \times RAW$ to $RAW + 0.25 \times (TAW - RAW)$;

- Irrigation amounts (IA). For Semi-plot experiments, different quantification methods of irrigation in simulation units are tested: one similar to the Conceptual approach simulation units (Dr − θ), one with a fixed amount for each crop (FixMeanC), as done by Bouras et al. (2019) or Rouhi Rad et al. (2020), and one to fill the soil water reservoir (Dr), as done by Hori et al. (2008);

- Seasonal variation of depletion factor p_var. Simulations were made with variable p or constant p to evaluate the importance of taking into account this seasonal variability (see Appendix "The CropWat model");
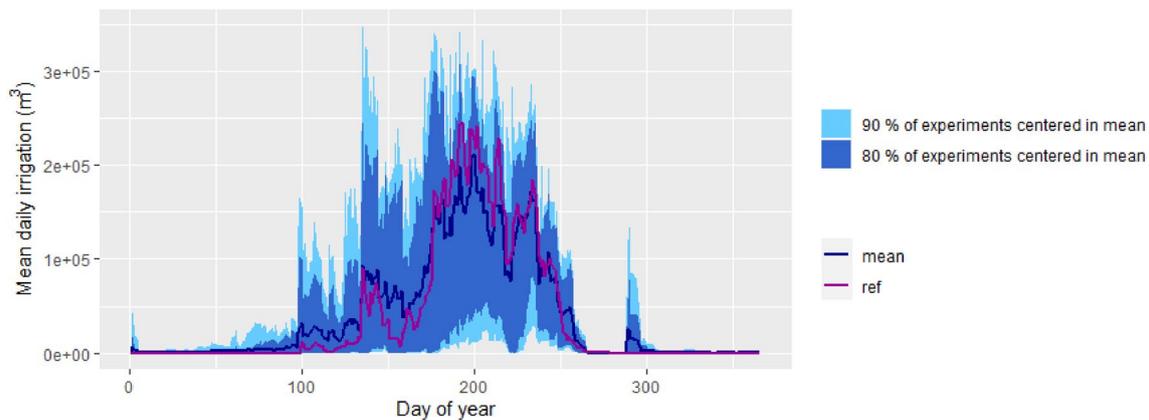
Fig. 3 Daily regimes of irrigation obtained at the study zone scale from the reference experiments (purple) and from the ensemble, the mean and the 80% and 90% envelopes of all C and S experiments (blue), as described in "Irrigation modeling at regional scale" and "Sensitivity analysis experiments" (color figure online)

Fig. 4 Partial variance explained by the factors of annual indicators. On the left, the Conceptual (C) experiments, on the right, the Semi-plot (S) experiments. A higher partial variance indicates that the variability of the indicator is more affected by this factor
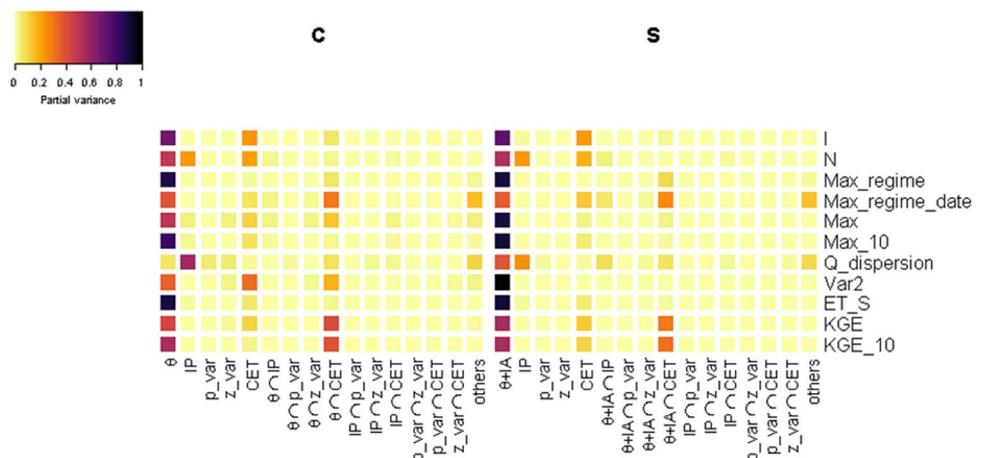
Table 2 Characteristics of the "best experiments" compared to the reference (MAELIA) for Conceptual and Semi-plot approaches

	Conceptual (96 experiments)			Semi-plot (256 experiments)		
				Number of experiments: 7		
				Factor	Modality	Number
KGE > 0.9	Number of experiments: 0			θ	varCrop	7
				IA	varCrop	7
				IP	0	3
					1	4
				CET	1	7
	Number of experiments: 1			**Number of experiments: 58**		
	Factor	Modality	Number	Factor	Modality	Number
KGE > 0.8	θ	varCrop	1	θ	0.25×RAW	8
	IP	0	1		0.5×RAW	16
	CET	1	1		0.75×RAW	10
					RAW	8
					varCrop	16
				IA	Dr-θ	21
					FixMeanC	21
					varCrop	16
				IP	0	28
					1	30
				CET	0	19
					1	39
	Number of experiments: 36			**Number of experiments: 100**		
	Factor	Modality	Number	Factor	Modality	Number
KGE > 0.7	θ	0.5×RAW	8	θ	0.25×RAW	8
		0.75×RAW	8		0.5×RAW	17
		RAW	8		0.75×RAW	32
		varCrop	16		RAW	20
	IP	0	18		RAW+0.25 (TAW-RAW)	7
		1	18		varCrop	16
	CET	0	12	IA	Dr-θ	41
		1	24		Dr	3
					FixMeanC	40
					varCrop	16
				IP	0	48
					1	52
				CET	0	45
					1	55

For three thresholds of performant KGE (best potential performance for KGE = 1), modalities of corresponding experiments are indicated, aimed at identifying modalities that clearly result in an improvement of KGE

- Root growth z_var. Simulations were made with increasing rooting depth between initial and maximal rooting depth or constant rooting depth equal to maximal rooting depth (see Appendix "The CropWat model");
- Irrigation period (IP). MAELIA defines precise irrigation periods for each crop. However, in the context of inter-annual climate variability increasing with climate change, it seems important to let the model calculate irrigation potential needs outside the usual irrigation periods. For this, we simulated experiments following irrigation periods for each crop defined in the reference
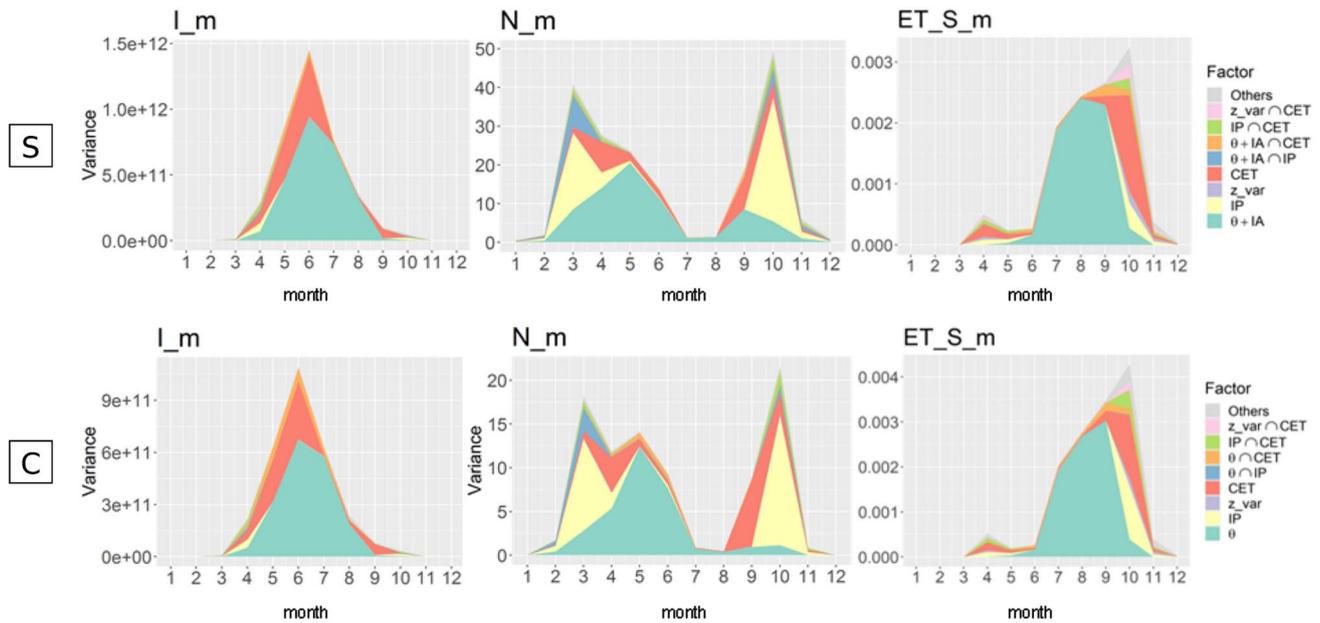
Fig. 5 Partial variance of monthly indicators related to different factors. For each month, partial variances are cumulated, and show the monthly variation in the contribution of each factor

Table 3 Mean, minimal, and maximal experiment values of mean CZ value for each indicator ("Indicators characterizing irrigation") for Conceptual, Semi-plot and reference experiments (as described in "Irrigation modeling at regional scale" and "Sensitivity analysis experiments")

| Indicator	Conceptual			Semi-plot			Reference
	Mean	Min	Max	Mean	Min	Max	
I (m³)	2.98E+05	1.29E+05	5,28E+05	3.27E+05	1.03E+05	6.37E+05	3.01E+05
N (days)	75	47	127	85	33	165	76
Max_regime (m³)	4.53E+03	3.14E+03	6.28E+03	4.90E+03	2.39E+03	7.40E+03	4.86E+03
Max_regime_date (DOY)	198 (17 July)	143 (23 May)	218 (6 August)	196 (15 July)	142 (22 May)	222 (10 August)	197 (16 July)
Max_10 (m³)	6.71E+03	4.31E+03	9.43E+03	7.29E+03	3.27E+03	1.29E+04	6.20E+03
Max (m³)	1.12E+04	5.83E+03	3.01E+04	9.89E+03	4.00E+03	2.38E+04	8.80E+03
Q_dispersion (–)	1.47	1.09	1.87	2.21	1.26	3.68	1.45
Var2 (–)	0.0024	0.0021	0.0031	0.0018	0.0007	0.0031	0.0027
KGE_10	0.59	− 0.03	0.86	0.47	− 0.36	0.87	–
KGE	0.38	− 0.39	0.64	0.28	−0.48	0.68	–

and compared them with experiments able to trigger irrigation at any time during the crop cycle;

- Crop maximal evapotranspiration calculation (CET) (see Appendix "The CropWat model"). The impact of the evapotranspiration calculation method has already been studied and quantified (Multsch et al. 2015). To identify the main sensitivity sources of regional irrigation uncertainty including evapotranspiration, we integrate experiments into our modeling scheme with a classic evaluation

of CET and with experiments considering CET equal to PET-PM.

The modalities for each factor are summarized in Appendix "Varying factors in C and S experiments".

Some complementary experiments were conducted to evaluate the added value of defining different irrigation rules (θ and IA) between crops. For each crop, for each crossing of p_var, z_var, CET and IP hypotheses conditions, θ (for C experiments), and θ and IA (for S experiments), the
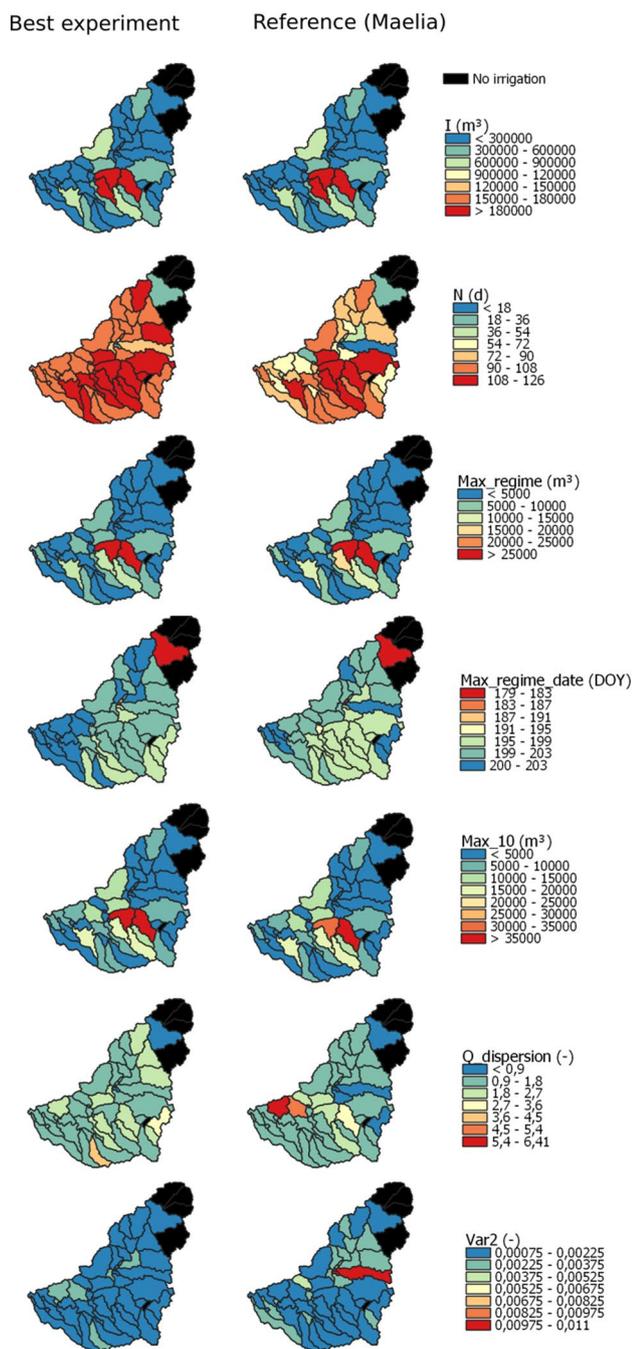
Fig. 6 Comparison of indicator values at the CZ scale between the reference (MAELIA) and the best experiment. This experiment corresponds to a Semi-plot approach, with irrigation rules defined specifically for each crop, no irrigation period delimitation, and root growth as well as seasonal variation of p and Kc taken into account (modalities varCrop, 0, 1, 1, 1 for θ + IA, IP, z_var, p_var, CET, respectively)

best-performing experiments in reproducing the reference experiment outputs at crop level were selected using the KGE-10 criterion (see "Indicators characterizing irrigation" and Appendix "Indicator calculation"). The resulting modality of θ and IA is called "varCrop."

The variance decomposition procedure we used to estimate the sensitivity of indicators to variation factors is detailed in Appendix "Variance decomposition".

Results

In this section, we assess the irrigation obtained from the reference, Conceptual and Semi-plot experiments at the basin scale as well as the factors explaining the variability. Then, we analyze the best experiments in terms of KGE and assess the experiments at the CZ scale.

Sensitivity of simulation to variation factors at the scale of the total study zone

General analysis of indicators

According to the results from the reference experiment, irrigation can start in April, is maximal in July (mean value of 6 million m^3), and ends in October. The results of the reference, Conceptual (C) and Semi-plot (S) simulations are summarized in Table 1, presenting values of annual indicators aggregated for the total study zone. With higher mean values of Q_dispersion, the S experiments show mean higher dephasing between daily values of high and low irrigation. However, with higher values of Var2, daily temporal variations of irrigation are globally higher in the C experiments. For almost all factors, the C results are within the envelope of the S results, which might be caused by the larger number of factors (IA) explored in the S experiments. Reference values of indicators are contained within the range of the C and S results except for the higher values reached by Max_10 and Var_2, which are not included within the range explored in the C experiments, showing that C experiments have a narrow higher daily variability than reference and S experiments (Appendix "Annual irrigation hydrographs") The inclusion of the reference experiment in the CropWat-based experiments is confirmed in Fig. 3, showing that the reference regime of irrigation is contained within the simulations produced by our experiments.

Distribution of the total variance in indicators between factors

The variance of annual indicators explained by different factors is plotted in Fig. 4. For the Semi-plot experiments, the six modalities of θ (0.25 × RAW, …, varCrop) and the four modalities of IA (Dr, …, varCrop) were merged into one factor θ + IA of 16 modalities to avoid an unbalanced experimental plan, because the varCrop modality for θ was run only with the varCrop modality of IA.
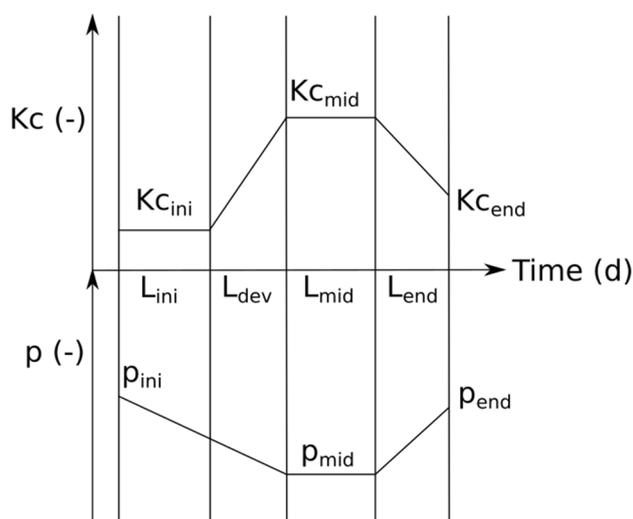
Fig. 7 Example of Kc (–) and p (–) curves for a set of parameters: crop coefficients (Kc_{ini}, Kc_{mid} and Kc_{end}), depletion factor parameters (p_{ini}, p_{mid} and p_{end}), and length of growth stages (L_{ini}, L_{dev}, L_{mid} and L_{end})

First, it is clear that the automatic irrigation parameters (θ for C experiments and $\theta + IA$ for S experiments) override the effects of the other factors for most indicators. CET is also very impactful for both the Conceptual and Semi-plot experiments, particularly on indicators I, N, Max_regime_date, Var2, and ET_S, while IP is also very impactful on indicators N and Q_dispersion. Factors p_var and z_var are systematically not impactful, for each indicator of the Conceptual and Semi-plot experiments. Second, we note that the interaction effects might be high. The interaction between automatic irrigation parameters (θ and $\theta + IA$) and CET has a strong impact on the Max_regime_date and on KGE and KGE_10. Impacting factors on indicators are often the same between the C and S experiments, except for daily irrigation variability indicators, i.e., Var2, Q_dispersion. This difference between the C and S experiments is explained by the integration in the S experiments of several modalities of IA, leading to large variations between experiments for these indicators (Appendix "Impact of IA modalities on Var2 and Q_dispersion").

The evaluation of the impact of each modality on each indicator is detailed in Appendix "Impact of factor modalities on indicators". It is a necessary additional step after variance decomposition to select accurate modalities for modeling purposes and to identify the strengths and weaknesses of the chosen modalities. Notably, we naturally observed that higher θ leads to a decrease in annual irrigation and in irrigation maxima, and to a delay in irrigation. For the S experiments, the modality Dr of IA leads to higher amounts of irrigation.

Characterization of best performing configurations

Table 2 summarizes modalities of experiments that reach high KGE values. First, we observe that the Semi-plot experiments clearly outperform Conceptual experiments in KGE performance in reproducing the reference experiment daily irrigation. Moreover, varCrop experiments are overrepresented, particularly among experiments with an excellent KGE (> 0.9). This observation is not surprising, because the selection of the modalities for automatic irrigation rules (θ and IA for S experiments) was based on their KGE_10 performance. However, some experiments with homogeneous automatic irrigation rules among crops also reach good KGE values. KGE does not reveal a strong difference between IP modalities among the performant experiments. However, among the performant experiments, those with modality 1 of CET are clearly more frequent than experiments with modality 0 of CET. This shows a clear and constant benefit of taking into account crop coefficients for IWR assessment, albeit the resulting variability is not as high as with other tested factors.

A look at the monthly time step

In Fig. 5, partial variances of factors in monthly indicators are presented. The reactions of Semi-plot and Conceptual experiments with respect to the variation factors are relatively similar. The area under the curve for monthly variance of automatic irrigation parameters (θ and $\theta + IA$) shows that these parameters are the most impactful parameters on each monthly indicator. Their impact reaches a peak in July for each indicator. Consequently, the June–July period appears to be the period with the highest variance for I_m between experiments. However, some factors have a strong impact in other months. CET and IP have a strong impact in spring months until the beginning of summer and in autumn. Under the influence of these last two factors cumulated with automatic irrigation factors, the periods of the highest variance for N_m are spring and autumn, and autumn for ET_S_m. IP has a strong impact on N_m in winter and autumn months. Indeed, the irrigation periods defined for each crop often exclude those months, leading to large differences between experiments of modality 1 or 0 of IP factor. However, the IP factor is not as impactful on I_m during these periods. That can be explained by small amounts of irrigation applied in these periods, because cultivated surfaces are low, evapotranspiration is low, and rainfall is high. The variance of N_m is low at the end of autumn and winter because conditions for triggering irrigation are not reached and the modality 0 of IP is not sufficient to trigger irrigation in those extreme periods. The impact of CET is particularly

strong on ET_S in autumn. Indeed, in this season, the crop coefficient is supposed to be low, but with the modality 0 of CET, the crop coefficient is constantly equal to 1, which is a high value.

Impact of spatial resolution on experiment outputs

For each experiment, each indicator was calculated at the CZ scale. Then the mean CZ value was computed for each experiment (Table 3). Experiments at the CZ scale reach similar values as the reference for indicators, similarly to what was observed at the lumped scale. Indeed, reference values are still contained within intervals explored by our CropWat experiments. However, we observe that KGE values at the CZ scale are overall lower than KGE for lumped outputs (Table 1), which can be explained by a higher irrigation sporadicity at the CZ scale. The best mean KGE at the CZ scale reaches 0.68, while a value of 0.91 reached at the lumped scale. There was a greater deterioration in the performance of KGE for Semi-plot experiments than for Conceptual experiments.

To complete this analysis, we drew maps showing values of indicators for different CZs for the reference experiment and the experiment reaching the best KGE_10 (Fig. 6), called the "best experiment" below. This experiment corresponds to a Semi-plot approach, with irrigation rules defined specifically for each crop, no irrigation period delimitation, and root growth as well as seasonal variation of p and Kc taken into account (modalities varCrop, 0, 1, 1, 1 for θ + IA, IP, z_var, p_var, CET, respectively). The spatial variability of indicators between CZs is linked to climatic (temperature and precipitations), pedologic and agronomic spatial variabilities. The spatial variability of the reference experiment is almost perfectly reproduced by the best experiment for I and Max_regime. Some CZs show different values for Max_10. More important differences are observed in the other indicators. For some indicators, we observe a bias in comparison with the reference, but this bias is spatially homogeneous. For example, Max_regime_date seems to occur globally a few days later for the best experiment than for the reference. The best experiment has more difficulties to fit reference values for N, Q_dispersion, and Var_2. For these three indicators, the best experiment seems to produce more spatially homogeneous results than the reference experiment, showing that the simplified approaches tested here might face more difficulties in reproducing spatial heterogeneity in daily irrigation variability than the spatial heterogeneity in the other factors. Despite these differences, all spatialized indicator values of the best experiment remain globally consistent with those of the reference experiment.

Discussion

Impact of tested variation factors on irrigation simulations

Our results showed that irrigation modeling choices have an impact on irrigation modeling outputs, not only on annual irrigation volumes, but also on the seasonal distribution of irrigation and high variations in irrigation in short time periods. For example, the date of the maximal irrigation period (Max_regime_date) varies greatly between 13 May and 10 August among our experiments.

Impact of modeling approaches

Tables 1 and 3 show that the ranges explored with both the Conceptual and Semi-plot approaches are quite similar and consistent with the reference experiment for most of indicators at lumped and CZ scales. However, the Semi-plot experiments are able to approach the results of the reference for the Var2 indicator, which represents daily variability, at the lumped scale, unlike Conceptual experiments. This difference leads to lower values of KGE for the Conceptual approach, because the daily variability of irrigation is different from the daily variability simulated by MAELIA. Indeed, the Conceptual approach can trigger irrigation in all simulation units, which can lead to high irrigation peaks and dips, which are not consistent with irrigation simulated by the reference and Semi-plot approaches at the lumped scale. As a consequence, taking into account water turns, which reproduce equipment availability constraints, might be decisive. Nevertheless, several simulations of both the Conceptual and Semi-plot approaches manage to approximate the reference experiment, reaching high KGE_10 and KGE values at the lumped scale: 37.5% of Conceptual experiments and 39% of Semi-plot experiments reach a KGE higher than 0.7.

The ability to obtain good performances for both the Semi-plot and Conceptual experiments in reproducing reference irrigation leads to the conclusion that calibration, particularly of irrigation rules, can be more impactful than the choice of the modeling approach among the approaches tested. However, although adequately reproducing irrigation at the lumped scale is possible, reproducing the daily irrigation simulated by the reference at the CZ scale is clearly more difficult (see "Impact of spatial resolution on experiment outputs"). This is easily explained by the sporadic behavior of irrigation at the local scale.

However, we applied an approach using a fixed Kc curve for CropWat experiments compared to an approach estimating crop growth based on a degree.day approach (Appendix "Soil–crop water balance models") for AqYield. Although this difference did not seem to be very impactful for the

study period, the change of crop growth dynamic in a context of climate warming might be very impactful in future. In this context, it will become necessary to adjust Kc curves, or to use models such as AqYield, to estimate irrigation needs.

Impact of variation factors

The impact of automatic irrigation factors (θ, IA) is very strong among the factors tested. The impact of CET is also important, confirming the value of taking into account uncertainties in evapotranspiration estimation. Although the impact of IP is not strong according to the KGE_10 indicator, it has an important impact on the number of days of irrigation. However, in a climate change context, restraining or not restraining irrigation to specific periods might be more impactful. Concerning the depletion factor and root depth curves, the modalities evaluated in this work were to take into account the variation in the parameters according to crop growth on the one hand (modality 1), or to fix a constant value on the other hand (modality 0). For example, concerning the rooting depth, the maximal value could be directly reached when the crop was sown (modality 0), or progressively increased with crop growth for other experiments (modality 1; Fig. 7). The maximal rooting depths resulting from the crossing of crops and soils were maintained for all experiments. Consequently, our results show that the dynamics of the evolution of these is not a key process for irrigation assessment at catchment scale, and their calibration should not be a priority. However, maximal root depth might be a key factor of interest to evaluate in future studies.

Beyond the statistical performance of the experiments, we can question their agronomic relevance and robustness. For example, extreme values of the modalities of factors investigated here can produce high KGE and KGE_10 values for some experiments while they might also lead to unrealistic simulations when combined with other modalities of other factors. To reinforce the probability of modeling choices to represent realistic irrigation over space and time, we advise selecting realistic modalities of each variation factor represented. Following the same logic, our study also reveals the importance of interactions between some variation factors. Hence, with the modality 0 of IP but a high value of θ, irrigation can be triggered late enough in the year to reproduce the reference scenario adequately.

There are numerous impacts related to the variation factors tested. Our study shows that evaluating and comparing irrigation modeling based on a single indicator, for example, annual irrigation, is not enough. Some modalities can lead to a decrease in annual irrigation (I), but without changing irrigation peaks in IWR (Max, Max_10, Max_regime_date) and thereby without an impact on extreme values of hydrologic droughts.

Many studies approximate irrigation inputs and withdrawals by calculating optimized values of irrigation, which would correspond, for our CropWat simulations, to the use of a θ equal to RAW (Funes et al. 2021; Neilsen et al. 2018; Rinaudo et al. 2013). However, in our study site, more experiments with a θ fixed at $0.5 \times$ RAW or $0.75 \times$ RAW were able to reproduce the reference simulations very well. Our results might be linked to the fact that farmers in our case study tend to implement an over-irrigation strategy (Allain et al. 2018), as in other catchments (Battude 2017; Tan 2019). To take into account this uncertainty, we would advise modelers using automatic irrigation algorithms to use several irrigation thresholds of θ to represent uncertainty linked to farmers' practices. Finally, defining irrigation parameters adapted to each crop (varCrop) can lead to significantly more accurate irrigation modeling. However, it leads to a complexification of calibration while some experiments with homogeneously calibrated irrigation for the different crops were still able to reach high scores.

Potential consequences for hydrological modeling and water management

Simulating dynamics of irrigation is of particular interest when considering the impact of irrigation during low-flow periods. Irrigation has two main impacts on hydrology: on the one hand withdrawals impacts, i.e., taking out water from the system, and on the other hand, irrigation rain impacts, bringing water to the system. Periods of irrigation, periods of maximal irrigation, and daily irrigation variations can change significantly between simulations obtained from different model configurations. A model bringing high amounts of irrigation in short periods could have an impact on hydrological modeling that is different from a model bringing low but regular amounts of irrigation.

Finally, similarly to Multsch et al. (2015), our results showed that the evapotranspiration estimation method might be an impactful variation factor between irrigation simulations, even if this factor might be less important than the irrigation rules. If an exhaustive coupling between crops and hydrological modeling is intended, evapotranspiration estimation might also be important as a direct input for hydrological models.

Our simplified approaches (Conceptual and Semi-plot) seem to be able to reproduce adequately the spatial variability of most indicators and should be compatible with semi-distributed and distributed hydrological modeling. However, we observed difficulties in reproducing irrigation at a daily time step and at the local scale, showing the difficulty of mimicking farmers' behavior regarding irrigation at these scales.

Limitations to this work and other variation factors to explore

We can identify several limitations of our study. First, the benchmark irrigation data we used correspond to modeling outputs. As a consequence, these data are distinct from reality, even if they represent the best reference data existing in our study area and even if MAELIA showed a very good capacity to simulate irrigation withdrawals. Therefore, we could assume that some of our experiments, even if not identified as the best ones, could be more realistic than MAELIA simulations. This supports the need to keep several modeling hypotheses and even to keep modalities that were less performant to reproduce reference simulations if they are considered as realistic and robust.

Furthermore, this work was carried out in only one study zone. This choice is notably justified by the availability of MAELIA outputs and the complexity of the modeling protocol used, which cannot be easily generalized to other areas. Consequently, conclusions drawn in this area should be carefully used for other areas, particularly in very different agroclimatic zones and cropping systems.

The modeling approaches tested here aimed at studying different levels of modeling simplifications. However, more simplified models exist. For example, the impact of spatio-temporal aggregation of input data and the reduction in the number of simulated crops could also be explored in further studies. Moreover, the reference model, MAELIA, itself relies on several simplifications, and not all processes are described in detail. For example, the run-on of water and its impact on the redistribution of water between crop simulation units is not taken into account.

Climate data are deterministic in this study. However, for operational purposes (prediction, projection, generic characterization of irrigation distribution), climate inputs might result from hypotheses, simulations or estimations, which might also bring additional uncertainty. For example, Jie et al. (2022) considered precipitation and evapotranspiration statistical distributions as sources of variability to evaluate generic irrigation variability. Moreover, even deterministic precipitation amounts and spatio-temporal distribution carry unavoidable uncertainty. Comparing the relative impacts of climate modeling uncertainty and irrigation modeling uncertainty might be very informative. This is however not in the scope of this study.

Last but not least, coupling these simulations with hydrological modeling is necessary to confirm or contest the significance of the differences between irrigation simulations for water management and resource issues. Indeed, the differences between outputs might seem significant, but they may have a moderate impact on hydrology.

Conclusion

This work described the methodology and the results of a sensitivity analysis of irrigation modeling at the local to river-basin scale. Two simplified modeling approaches (Conceptual: lumping irrigation simulation for homogeneous crop, soil, and climate conditions; Semi-plot: dividing simulation units into water turns groups) were compared with a more complex, agent-based, benchmark (MAELIA). For the two simplified approaches, the impacts of several modeling hypotheses regarding irrigation variation factors were analyzed. A sensitivity analysis based on variance decomposition was performed. The relative impacts of variation factors were measured based on several indicators of irrigation dynamics, with the objective of exploring the irrigation modeling effect beyond the simplistic annual sum of irrigation. This work highlighted that calibration of variation factors is more crucial than the choice of a given modeling approach. It showed the strong impact of irrigation-triggering rules and quantification of nominal irrigation amount parameters on regional irrigation assessment. It also confirmed that the definition of evapotranspiration and irrigation periods can have an important impact on irrigation modeling, a key issue for simulation under future climatic conditions. Several configurations of simpler approaches (Conceptual and Semi-plot) managed to reproduce adequately the simulations of the more complex approach (MAELIA). Experiments managing to reproduce adequately MAELIA were actually quite heterogeneous, showing a multiplicity of possible performing modeling configurations and the ability of the modalities tested to offset each other. Finally, this work enabled us to identify the following recommendations that might be followed for irrigation modeling: using multi-parameter simulations of irrigation; including different rules for triggering and quantifying irrigation; and evaluating irrigation with diverse indicators capturing its levels, frequency, and dynamics.

Appendices

Soil–crop water balance models

Soil water content mainly results from the balance between rain and irrigation inputs and evapotranspiration outputs. Evapotranspiration on cropland can be estimated with soil–crop water balance models. However, many of these models are complex, which makes them too computationally and data demanding for regional applications. On the other hand, semi-empiric crop coefficient methods

described by the FAO (Allen et al. 1998) are still largely used in research work and their performance and robustness, if well calibrated, have been demonstrated. The single crop coefficient (Kc) approach was implemented in the CropWat model and is used in this study.

The CropWat model

In a single crop coefficient (Kc) approach, crop maximal evapotranspiration (CET, mm day^{-1}) is calculated at each time step (t) using Eq. (2) with the crop coefficient Kc (–) and potential evapotranspiration (PET, mm day^{-1}) estimated through the Penman–Monteith equation:

$$CET(t) = Kc(t) \times PET(t). \tag{2}$$

In CropWat, three values of Kc are defined for each crop corresponding to the initial, mid-, and end stage of the crop cycle, linked by linear interpolation and associated with length of growth stages (Fig. 7). Water balance is calculated at a daily time step (d). Soil water availability for crops consists of a single bucket. Total available water (TAW, mm), describing the depth of the bucket, is calculated using Eq. (3), with ω_{fc} the water content at field capacity (m^3 m^{-3}), ω_{wp} the water content at wilting point (m^3 m^{-3}), and Z_r the rooting depth (mm):

$$TAW(d) = \left(\omega_{fc} - \omega_{wp}\right) \times Z_r(d). \tag{3}$$

The rooting depth is estimated at each time step by a linear interpolation between initial root depth and maximal root depth, the latter being reached at mid-stage. Readily available water (RAW) is calculated as follows in Eq. (4), with p (–) the depletion factor:

$$RAW(d) = p(d) \times TAW(d). \tag{4}$$

In CropWat, p is represented by a curve with p_{ini}, p_{mid}, p_{end} defined for each crop associated with length of growth stages (Fig. 7).

Water level is estimated at a daily time step by the root zone depletion Dr (mm), i.e., the gap between TAW and soil water content. Soil water content is updated with daily rain, irrigation and evapotranspiration amounts. If Dr exceeds the RAW value, evapotranspiration is reduced because of water stress, leading to the calculation of actual evapotranspiration (AET, mm day^{-1}). AET is estimated with Ks (–), the water stress coefficient, as shown in Eq. (5). Ks is calculated through Eq. (6):

$$AET(d) = Ks(d) \times CET(d), \tag{5}$$

$$Ks(d) = \begin{cases} \frac{(TAW(d) - Dr(d))}{(TAW(d) - RAW(d))} & \text{if } Dr(d) > RAW(d) \\ 1 & \text{if } Dr(d) \leq RAW(d) \end{cases}. \tag{6}$$

The AqYield model

The MAELIA platform includes its own soil–crop water balance model, AqYield. Like CropWat, it is based on a Kc approach. The main differences are:

- Transpiration and evaporation are calculated separately. Transpiration takes water from the root zone, while evaporation takes water from the shallow soil horizon. Maximal crop transpiration (MT, mm day^{-1}) is calculated as follows in Eq. (7), with evaporation (E, mm day^{-1}):

$$MT(d) = Kc(d) \times (PET(d) - E(d)). \tag{7}$$

- Developments of Kc and roots are represented by smooth functions depending on crop parameters and sum of degree day, with thresholds corresponding to flowering and maturity stages;
- Water stress impact on transpiration is a smooth function of the soil water amount, without any break between Dr ≤ RAW and Dr > RAW, and is influenced by the clay rate.

Parameter calibration

MAELIA crop parameters were calibrated by experts of the AqYield model to fit the Aveyron basin context. To avoid bias linked to the crop parameters, CropWat parameters were estimated based on the MAELIA outputs. Hence, Kc curves were built on the basis of AqYield detailed outputs. However, Kc curves were kept fixed inter-annually unlike AqYield simulations. Moreover, AqYield detailed outputs were obtained for only one CZ due to constraints on data storage and computation time. As a consequence, Kc curves were built to correspond to AqYield evapotranspiration in one CZ and applied to the entire study area for CropWat experiments. A detailed explanation of CZ choice and Kc calibration methodology is given hereafter ("Choice of reference AqYield data for calibration", "CropWat crop coefficients adjustment").

Depletion factor p was adjusted locally with CET using the following FAO formula presented in Eq. (8):

$$p = pFAO + 0.04 \times (5 - CET), \tag{8}$$

p_{ini}, p_{mid}, and p_{end} values were calibrated to correspond to daily p values calculated with the FAO formula. Minimal root depths were set to 30 cm for each crop and maximal root depths were taken from FAO report no. 56.

### Choice of reference AqYield data for calibration

AqYield detailed outputs were obtained in the CZ 2031 (Fig. 8).

The selection of this CZ was made with different criteria:

– each simulated crop is present;
– number of plots for every irrigated crop is high;
– number of different soils on which cultivated crops are present is high.
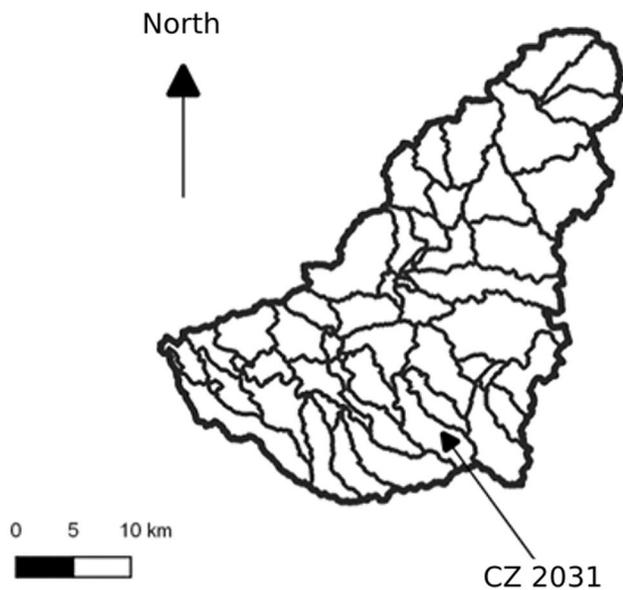
Fig. 8 Location of the reference CZ used for CropWat coefficients calibration
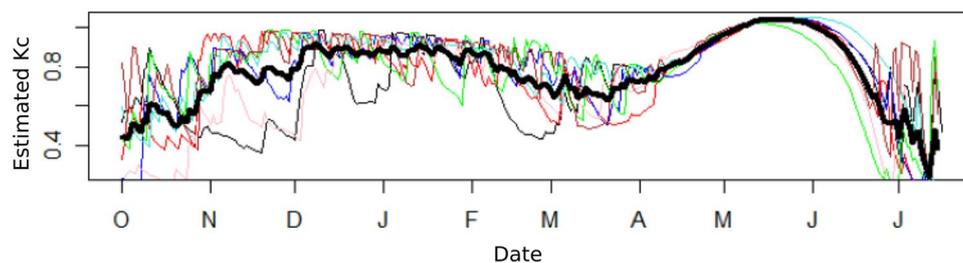
In CropWat, crop coefficients aim at calculating maximal crop evapotranspiration, cumulating evaporation, and transpiration, while in MAELIA, crop coefficients are designed to be proportional to maximal transpiration only. That is why we compiled for each plot the sum of maximal transpiration and evaporation simulated by AqYield between 2008 and 2014, considered as maximal evapotranspiration. Then, this maximal evapotranspiration was divided by potential evapotranspiration to obtain a crop coefficient curve comparable to the CropWat crop coefficient curve.

Finally, for each crop type, a mean daily inter-annual crop coefficient curve was calculated by the weighted mean of the crop coefficient curve of plots based on their surfaces (Fig. 9).

CropWat crop coefficients adjustment

Each crop Kc curve was calibrated manually with the objective of reproducing adequately MAELIA outputs (Fig. 10). The intercrop and initial-stages Kc calibrated value (Kc_{ini}) is lower than the optimal value for this crop stage, but fits the crop Kc curve during the development stage. This choice was made to avoid overestimation of evapotranspiration during the transition between the initial and development stages, which would lead to an overestimation of soil reservoir depletion. This choice results in an underestimation of maximal evapotranspiration during the end of winter and spring, leading to a possible underestimation of water stress, but it does not have a strong impact on soil water depletion. Indeed, the water level is maintained near field capacity during this period (explaining high values of evapotranspiration in AqYield). Excess water in CropWat is not integrated in the soil water reservoir and is not converted into evapotranspiration, but is simply considered as lost water.

Fig. 9 Inter-annual variability of crop coefficients for wheat for CZ 2031. Each colored curve corresponds to a mean crop coefficient curve weighted by the surfaces of plots for a specific year. The bold curve corresponds to the inter-annual mean of the colored curves (color figure online)

Fig. 10 Annual crop coefficient curve calculated with AqYield (black line) and calibrated for CropWat (red line) for wheat (color figure online)
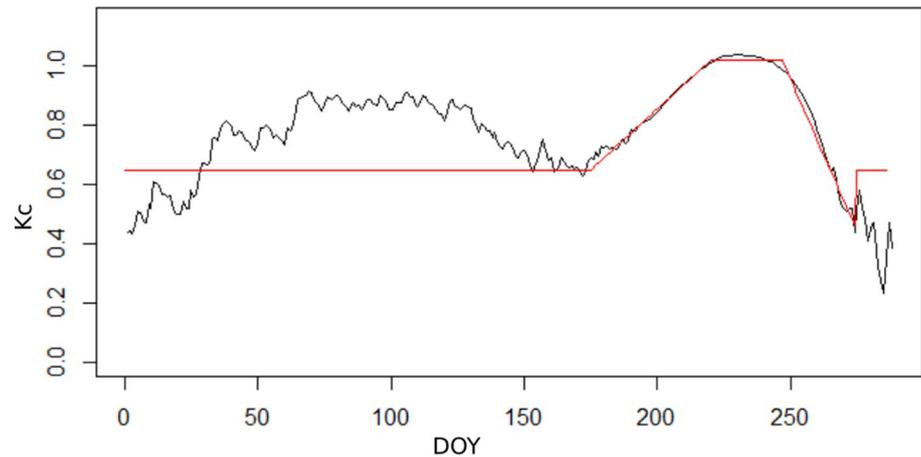
Indicator calculation

Indicator name	Unit	Definition	Scale of calculation	Calculation	Variables
I	m³	Mean annual irrigation	Lumped, CZ	$I = \frac{\sum_{d=1}^{N_d} I_d}{N_Y}$	N_d: number of days (–) d: day index (–) I_d: daily irrigation (m³) N_Y: number of years (–)
I_m	m³	Mean monthly irrigation	Lumped	For each month m, $I\_m = \frac{\sum_{d=1}^{N_{d,m}} I_{d,m}}{N_Y}$	$N_{d,m}$: number of days in month m (–) d: day index (–) $I_{d,m}$: daily irrigation of day d in month m (m³) N_Y: number of years (–)
N	(–)	Mean annual number of days of irrigation	Lumped, CZ	$N = \frac{N_{d,I>0}}{N_Y}$	$N_{d,I>0}$: number of days with $I_d > 0$ (I_d: daily irrigation (m³)) (–) N_Y: number of years (–)
N_m	(–)	Mean monthly number of days of irrigation	Lumped	For each month m, $N\_m = \frac{N_{d,I>0,m}}{N_Y}$	$N_{d,I>0,m}$: number of days of month m with $I_{d,m} > 0$ ($I_{d,m}$: daily irrigation of month m (m³)) (–) N_Y: number of years (–)
Max_regime	m³	Maximum of irrigation for 10-day rolling periods on mean annual regime curve	Lumped, CZ	$\text{Max}_{\text{regime}} = \max\left(I_{10d}\right)$	I_{10d}: vector of 10-day rolling mean annual regime of irrigation (m³,…,m³) max(): maximal value (m³)
Max_regime_date	DOY	Day of year of maximum of irrigation for 10-day rolling periods on mean annual regime curve	Lumped, CZ	$\text{Max\_regime\_date} = \text{DOY\_max}\left(I_{10d}\right)$	I_{10d}: vector of 10-day rolling mean annual regime of irrigation (m³,…,m³) DOY_max(): date of maximal value (DOY)

Indicator name	Unit	Definition	Scale of calculation	Calculation	Variables
Max	m^3	Mean annual maximum of daily irrigation	Lumped, CZ	$Max = \frac{\sum_{Y=1}^{N_Y} \max(I_{d,Y})}{N_Y}$	$I_{d,Y}$: vector of daily irrigation for year Y (m^3,…,m^3) $\max()$: maximal value (m^3) N_Y: number of years (–)
Max_10	m^3	Mean annual maximum of 10-day mean rolling irrigation	Lumped, CZ	$Max\_10 = \frac{\sum_{Y=1}^{N_Y} \max(I_{10d,Y})}{N_Y}$	$I_{10d,Y}$: vector of 10-day rolling mean of daily irrigation for year Y (m^3,…,m^3) $\max()$: maximal value (m^3) N_Y: number of years (–)
Q_dispersion	(–)	(Q75–Q25)/Q50 of daily irrigation	Lumped, CZ	$Q\_dispersion = \frac{Q_{75}(I_{d,I_d>0}) - Q_{25}(I_{d,I_d>0})}{Q_{50}(I_{d,I_d>0})}$	$I_{d,I_d>0}$: vector of daily irrigation I_d, with $I_d > 0$ (m^3,…,m^3) Q_x: quantile $X\%$ (m^3)
Var2	(–)	Mean of absolute second derivative of daily irrigation (m^3), divided by mean annual irrigation	Lumped, CZ	$Var2 = \frac{\sum_{d=2}^{N_d-1} |(I_{d+1}-I_d)-(I_d-I_{d-1})|}{I}$	N_d: number of days (–) d: day index (–) I_d: daily irrigation (m^3) I: see indicator I (m^3)
KGE	(–)	Kling–Gupta efficiency comparing irrigation obtained from experiments with reference irrigation	Lumped	$KGE = 1 - \sqrt{(1 - r(I_d))^2 + (1 - \beta(I_d))^2 + (1 - \alpha(I_d))^2}$	r: the Pearson product–moment correlation coefficient between experiment values and reference values (–) β: the ratio between the mean of the experiment values and the mean of the reference values (–) α: the ratio between the standard deviation of the experiment values and the standard deviation of the reference values (–) I_d: vector of daily irrigation for experiment and reference (m^3,…,m^3)
KGE_10	(–)	Kling–Gupta efficiency comparing 10-day rolling irrigation obtained from experiments with reference 10-day rolling irrigation	Lumped	$KGE\_10 = 1 - \sqrt{(1 - r(I_{10d}))^2 + (1 - \beta(I_{10d}))^2 + (1 - \alpha(I_{10d}))^2}$	r: the Pearson product-moment correlation coefficient between experiment values and the reference values (–) β: the ratio between the mean of the experiment values and the mean of the reference values (–) α: the ratio between the standard deviation of the experiment values and the standard deviation of the reference values (–) I_{10d}: vector of 10-day rolling mean of daily irrigation for experiment and reference (m^3,…,m^3)

Indicator name	Unit	Definition	Scale of calculation	Calculation	Variables
ET_S	(–)	Sum of AET divided by sum of CET of cultivated surfaces during crop growth cycles	Lumped	$\text{ET\_S} = \dfrac{\sum_{d=1}^{N_d} AET_d}{\sum_{d=1}^{N_d} CET_d}$	N_d: number of days (–) d: day index (–) AET_d: daily actual evapotranspiration of all cultivated simulation units (between sowing date and harvesting date) (m^3) CET_d: daily crop maximal evapotranspiration of all cultivated simulation units (between sowing date and harvesting date) (m^3)
ET_S_m	(–)	ET_S calculated monthly	Lumped	$\text{ET\_S} = \dfrac{\sum_{d=1}^{N_{d,m}} AET_{d,m}}{\sum_{d=1}^{N_d.^m} CET_{d,m}}$	$N_{d,m}$: number of days in month m (–) d: day index (–) $AET_{d,m}$: daily actual evapotranspiration of all cultivated simulation units (between sowing date and harvesting date) in month m (m^3) $CET_{d,m}$: daily crop maximal evapotranspiration of all cultivated simulation units (between sowing date and harvesting date) in month m (m^3)

Varying factors in C and S experiments

Factor name	Definition	Values
θ	Deficit threshold for irrigation	$0.25 \times \text{RAW}$ $0.5 \times \text{RAW}$ $0.75 \times \text{RAW}$ RAW $\text{RAW} + 0.25 \times (\text{TAW} - \text{RAW})$
IA[a]	Irrigation amounts	$Dr - \theta$: equivalent to C approach Dr: irrigation amount is equal to Dr and soil is totally refilled FixMeanC: irrigation amount is equal to a value defined for the crop based on MAELIA parameters
p_var	Depletion factor variation	1: depletion factor varies along time according to p_{init}, p_{mid}, p_{end} (See Appendix "The CropWat model") 0: depletion factor is constantly equal to p_{mid}
z_var	Root depth variation	1: root depth varies along time from minimal to maximal root depth 0: root depth is constantly equal to maximal root depth
IP	Irrigation period delimitation	1: irrigation period delimitation is injected for each crop and crops cannot be irrigated before and after this irrigation period delimitation 0: crops can be irrigated at any time during their crop cycle if θ is reached
CET	Crop modulation of potential evapotranspiration	1: CET is calculated as a modulation of Penman–Monteith PET 2: CET is considered equal to Penman–Monteith PET

[a]IA variations were simulated only for S experiments

Variance decomposition

Conceptual and Semi-plot approaches consist of balanced simulation plans, allowing for simple variance decomposition. Variance decomposition is used to estimate the sensitivity of IWR indicators to variation factors (θ, IP, etc.). For each indicator I and each factor F, we calculate partial variance $V_{I,F}$ with Eq. (9), with $N_{F,\exp}$ the number of experiments for each modality of F, N_F the number of modalities of F, $\overline{X_i}$ the mean value of F for modality I, $\overline{X_.}$ the mean value of F, and $N_{\exp}$ the total number of experiments:

$$V_{I,F} = N_{F,\exp} \frac{\sum_{i=1}^{N_F} \left(\overline{X_i} - \overline{X_.}\right)^2}{N_{\exp} - 1}. \tag{9}$$

Moreover, sensitivity to first-order interactions is also calculated with Eq. (10). For a factor F_1 and a factor F_2, the sensitivity to their interaction is V_{I,F_1,F_2}, with $N_{F_1 \cap F_2,\exp}$ the number of experiments for each crossing modality of F_1 and F_2:

$$V_{I,F_1,F_2} = N_{F_1 \cap F_2,\exp} \frac{\sum_{j=1}^{N_{F_2}} \sum_{i=1}^{N_{F_1}} \left(\overline{X_{i,j}} - \overline{X_{.j}} - \overline{X_{i,\bullet}} + \overline{X_{.,.}}\right)^2}{N_{\exp} - 1}. \tag{10}$$

Then partial variance can be divided by the total variance to get the contribution of a factor to total variability.

Annual irrigation hydrographs

To complete our work based on inter-annual indicators, annual hydrographs are produced for dry–hot (2009) and wet–cold (2013) years globally over the basin. First, we observe the impact of inter-annual variability on the duration of crop cycles in MAELIA, which is not taken into account in other approaches: in a dry–hot year, MAELIA irrigation ends before the other experiments (Fig. 11), contrary to a cold–wet year (Fig. 12). We observe a higher difficulty to reproduce MAELIA irrigation in spring when irrigation is low. The same difficulty might be found at the CZ scale. We observe that the Conceptual experiments produce abrupt dips contrary to the Semi-plot experiments, explaining the lower KGE values and the higher Var2 values for the Conceptual experiments at the lumped scale. Irrigation during a wet–cold year seems to be more sporadic for all experiments, which can probably be explained by summer rain events limiting the irrigation needs during some short periods.
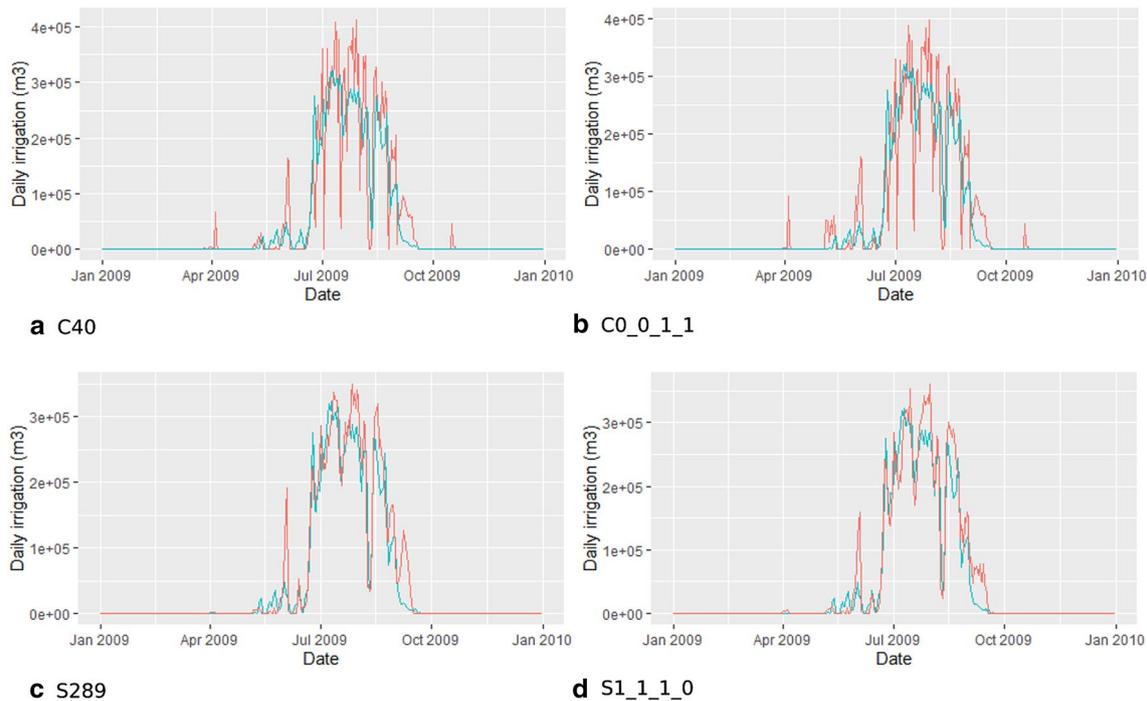
Fig. 11 Comparison between CropWat experiments daily irrigation (salmon) and MAELIA reference irrigation (turquoise) for the year 2009 (dry) globally over the basin. C40 (**a**) corresponds to the Conceptual experiment yielding the best KGE value without varCrop modality; C0_0_1_1 (**b**) corresponds to the Conceptual experiment yielding the best KGE value with varCrop modality; S289 (**c**) corresponds to the Semi-plot experiment yielding the best KGE value without varCrop modality; S1_1_1_0 (**d**) corresponds to the Semi-plot experiment yielding the best KGE value with varCrop modality
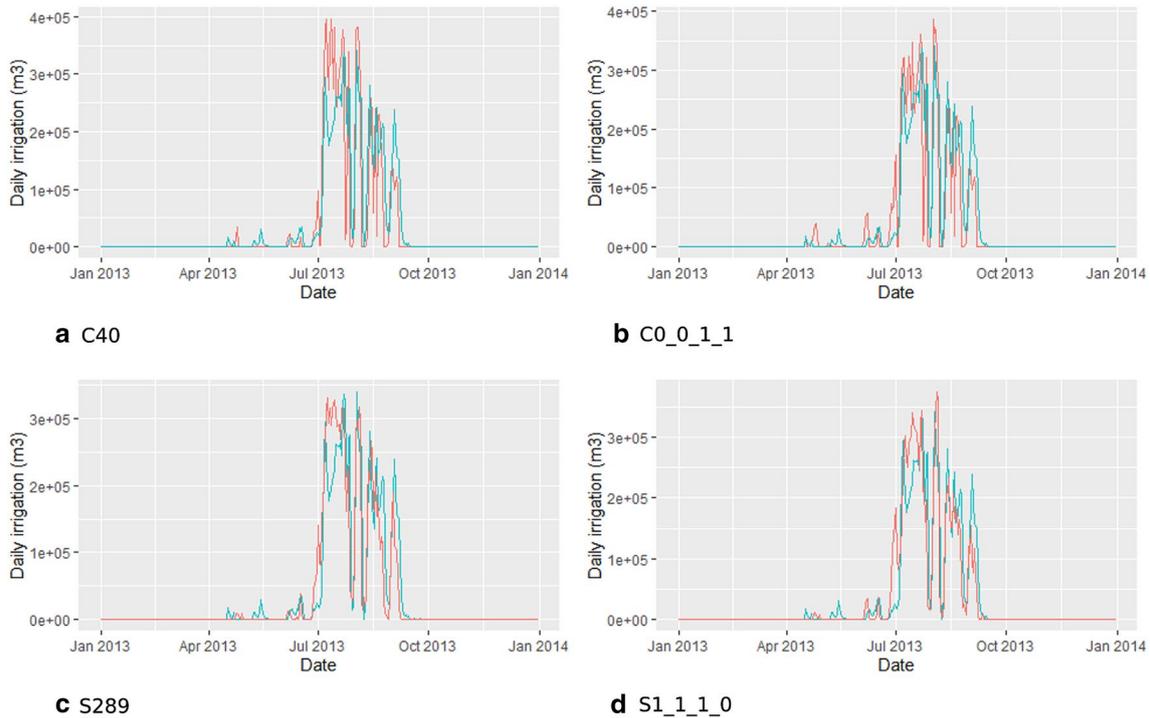
Fig. 12 Comparison between CropWat experiments daily irrigation (salmon) and MAELIA reference irrigation (turquoise) for the year 2013 (wet) globally over the basin. C40 (**a**) corresponds to the Conceptual experiment yielding the best KGE value without varCrop modality; C0_0_1_1 (**b**) corresponds to the Conceptual experiment yielding the best KGE value with varCrop modality; S289 (**c**) corresponds to the Semi-plot experiment yielding the best KGE value without varCrop modality; S1_1_1_0 (**d**) corresponds to the Semi-plot experiment yielding the best KGE value with varCrop modality

Impact of IA modalities on Var2 and Q_dispersion

Figure 13 shows the high influence of IA variation factor on Var2 and Q_dispersion indicators.

Impact of factor modalities on indicators

The impact of the different modalities of each factor on indicators is summarized in Fig. 14, compared with the MAELIA benchmark indicator values. The indicators for annual irrigation (I) and number of irrigated days (N) increase if θ decreases. Indeed, if θ is higher, irrigation is triggered for higher values of Dr. As a consequence, irrigation is triggered less frequently in simulation units and later in the year. I and N are lower for modality 1 of IP than for modality 0, since for modality 1, irrigation can only be triggered during specific periods for each crop. *I* and *N* are lower for modality 1 of CET. Indeed, the Kc curves for modality 1 of CET result in globally lower evapotranspiration than evapotranspiration estimated from PET directly in modality 0. A higher evapotranspiration leads to an increase in instantaneous IWR, resulting in increased annual irrigation and number of

Fig. 13 Impacts of automatic irrigation parameters on daily irrigation variability for Semi-plot experiments. IA modalities have a strong impact on Var2 (**a**) and Q_dispersion (**b**) values
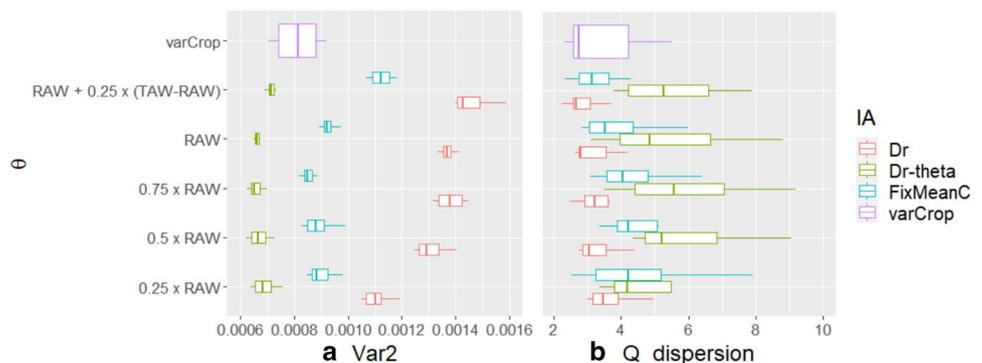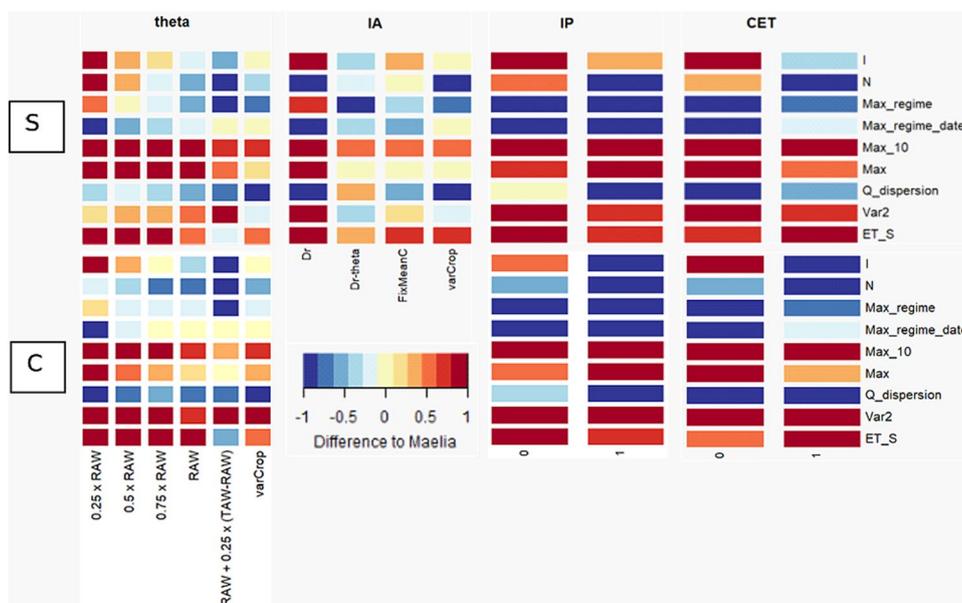
Fig. 14 Impact of the modalities of each factor on indicators compared with their reference values. The mean indicator value was calculated for each modality of each factor, then compared with the reference value (MAELIA). Differences between mean values for each modality and the reference value were then divided by the maximum absolute difference value for each indicator to get a relative variation between − 1 and + 1. Red: the mean modality value exceeds the reference value; blue: the mean modality value is below the reference value; yellow: the mean modality value is equal to the reference value. The color intensities are related to the variance of each factor separately, not to the total variance of all experiments. Consequently, some colors might be intense, but the total impact of this modality might remain relatively low compared to total variance. For the evaluation the partial effect of a variation factor, please refer to Fig. 4 (color figure online)

days of irrigation. For IA modalities, *I* is minimal and below the reference for Dr-*θ*, followed by varCrop near the reference value, by FixMeanC, and finally by Dr, both exceeding the reference value. It is clear that nominal amounts are higher for the Dr modality than for the Dr-*θ* modality, and this result shows that irrigation amounts brought with the Dr modality are globally higher than FixMeanC irrigation amounts. *N* is maximal for FixMeanC, followed by Dr-*θ*, by VarCrop, and by Dr. This observation can be linked to the explanation given for *I*: If nominal irrigation amounts are higher in simulation units, the frequency of irrigation is lower. Indeed, after an irrigation event in a simulation unit, if the irrigation amount was low, Dr after irrigation remains relatively high, and *θ* will be reached again after a shorter time than for a higher irrigation amount.

The maximum of irrigation for 10-day rolling periods on the mean annual regime curve (Max_regime) and its date of occurrence (Max_regime_date) are analyzed here. Max_regime_date is reached later for high values of *θ*. Indeed, with higher *θ*, irrigation is triggered later in simulation units, which results in a lag for the period of maximal irrigation. Max_regime decreases if *θ* increases. For lower values of *θ*, *θ* might be reached by more simulation units simultaneously, leading to higher values of irrigation during the maximum

irrigation period. Max_regime is higher than the reference value for the Dr modality of IA, and lower than the reference value for the other modalities, particularly the Dr-*θ* modality. As for annual irrigation, it is clear that nominal amounts are higher for the Dr modality than for the Dr-*θ* modality, leading to higher lumped irrigation amounts during the period of maximal irrigation. Again, as for annual irrigation, the difference in Max_regime between the Dr and FixMeanC modalities can be explained by higher irrigation amounts with the Dr modality than with the FixMeanC modality during the period of maximal irrigation. Finally, we observe that Max_regime is slightly higher for modality 1 of CET. During the annual maximal irrigation period, some major crops have a Kc value higher than 1.0, leading to higher evapotranspiration than modality 0 of CET, which might lead to an increase in IWR during this specific period. Max_regime_date is seen to occur later for modality 1 of CET. During the period preceding the maximal irrigation period, evapotranspiration is globally lower with modality 1 of CET than evapotranspiration estimated with modality 0 of CET, leading to a temporal dephasing of irrigation-triggering conditions.

The mean annual maximum of daily (Max) irrigation and 10-day (Max_10) irrigation indicators are both globally

higher than the reference. Max_10 and Max slightly decrease with higher values of θ, in a similar manner to the Max_ regime. For S experiments, Max_10 and Max are higher for the Dr modality than for the other three modalities.

Regarding daily variability, indicators Var2 and Q_dispersion have opposite behavior, showing that these indicators measure different aspects of temporal variability. For C experiments, Var2 remains globally superior to the reference value, showing that C experiments have a narrow higher daily variability than reference and S experiments (Appendix "Annual irrigation hydrographs"). However, Q_ dispersion is globally lower than for the reference experiment. This result can be obtained for simulation showing unstable variations between successive days, for example, increasing and decreasing very frequently, but keeping lumped irrigation values in the same order of magnitude. On the contrary, a theoretical experiment with a regular increase in irrigation from day to day would lead to a low value of Var2, but a high value of Q_dispersion.

Regarding crop water stress, the ET_S indicator decreases (meaning higher crop water stress) with higher modalities of θ. Obviously, with higher values of θ, Dr can be higher and as a consequence crop water stress too. However, we notice that only the modality $RAW + 0.25 \times (TAW - RAW)$, consisting of deficit irrigation, leads to lower ET_S (higher crop water stress) than the reference experiment. This can be explained by the difference in AET formulation between AqYield and CropWat. In AqYield, water stress is a smooth function of soil water deficit, with crop water starting for a zero deficit and progressively accelerating with an increasing deficit. In CropWat, there is a threshold effect since crop water stress begins when the deficit reaches RAW and is quickly high. Moreover, the calibration methodology of the Kc curve might also partly explain these differences (see Appendix "CropWat crop coefficients adjustment"). ET_S is higher (lower crop water stress) with modality 1 of CET. Indeed, in this case, the Kc curves result in globally lower evapotranspiration than evapotranspiration estimated from PET directly, and a lower evapotranspiration might lead to a lower crop water stress if conditions of irrigation are not triggered. ET_S is lower (higher crop water stress) for modality 1 of IP. Indeed, for this modality, irrigation cannot be triggered outside irrigation periods, leading to higher crop water stress. For IA impacts, ET_S is minimal for Dr-θ but still higher than the reference, followed by varCrop, Fix_ Mean_C, and then Dr: the higher the irrigation amounts for the same crop evapotranspiration, the lower the crop water stress.

Declarations

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