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1 **Multicriteria evaluation of the AquaCrop crop model in a hilly rainfed Mediterranean**  
2 **agrosystem**

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11 **Abstract**

12 Exploring crop spatial organizations within landscapes is a promising solution for agroecolog-  
13 ical transitions and climate change adaptation in Mediterranean rainfed hilly agrosystems. A  
14 prerequisite is to ensure that crop models can simulate a range of agrohydrological processes  
15 in such agrosystems. The current study deepened the evaluation of the AquaCrop model by  
16 conducting a multicriteria evaluation (canopy cover CC, dry aboveground biomass AGB, ac-  
17 tual evapotranspiration  $ET_a$ , runoff R, soil water content SWC) for a range of crop and soil  
18 combinations, and for contrasted hydroclimatic years in northeastern Tunisia. The data were  
19 collected in the Kamech catchment (OMERE Observatory) during nine measurement cam-  
20 paigns on predominant soils and crops. AquaCrop simulations were based on field observations  
21 and parameters from the literature.

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22 AquaCrop could simulate plant dynamics and water fluxes for contrasted hydroclimatic years,  
23 with a slight dependence on soil class and a significant dependence on crop type. Model simu-  
24 lations were of moderate quality for CC ( $R^2$  of 0.45, RMSE of 0.24 on average) and of accepta-  
25 ble quality for AGB ( $R^2$  of 0.81, RMSE of 0.85 ton ha<sup>-1</sup> on average). AquaCrop acceptably  
26 simulated water transfer across the soil–plant continuum ( $R^2$  of 0.62, RMSE of 0.77 mm day<sup>-1</sup>  
27 on average for ET<sub>a</sub>;  $R^2$  of 0.68, RMSE of 0.75 mm day<sup>-1</sup> on average for R;  $R^2$  of 0.86, RMSE  
28 of 27.4 mm on average for SWC). The model performances were satisfactory for most cases,  
29 with p values larger than 5% for the Student’s t test on linear regressions of validation. Our  
30 results were similar to those reported in previous studies over flat terrain, including delayed  
31 senescence by model simulations with subsequent overestimation of CC and AGB observa-  
32 tions. Additionally, soil cracks likely altered the AquaCrop ability to simulate runoff. Despite  
33 these limitations, our results support the application of AquaCrop to evaluate water productiv-  
34 ity in hilly agrosystems.

### 35 **Keywords**

36 AquaCrop model; Rainfed agrosystems; Hilly terrains; Multicriteria evaluation; Mediterranean  
37 soils and crops; Soil water balance

## 38 1. Introduction

39 Mediterranean agriculture is an important sector from economic, social and environmental per-  
40 spectives, especially for the southern and eastern Mediterranean countries. It is a significant  
41 contributor to gross domestic product (GDP) in these countries; it ensures food security, and it  
42 helps reduce rural migration by providing local jobs (Tanyeri-Abur, 2015). Rainfed agriculture  
43 covers 80% and 75% of cultivated lands in the world and North Africa, respectively  
44 (Bhattacharya, 2019; Wani et al., 2009). It is generally based on family systems, and it has  
45 significant room for improvement in water productivity (Ruben and Pender, 2004). In hilly  
46 areas, the productivity of rainfed agriculture depends not only on the rainfall regime but also  
47 on the spatiotemporal distribution of surface water and sediment flows (Norouzi et al., 2010).  
48 Until now, Mediterranean public policies within hilly areas have mainly focused on mobilizing  
49 blue water resources for irrigated agriculture through the planning of hydroagricultural infra-  
50 structures (e.g., dams, reservoirs) and have focused less on optimizing the use of green water  
51 for rainfed agriculture (Nouri et al., 2020).

52 Despite of numerous benefits for Mediterranean hilly areas, rainfed agriculture undergoes sev-  
53 eral pressures (Brun et al., 2016), either climate-driven (floods and erosion, heat waves, rainfall  
54 shortages) or anthropogenic-driven (population growth, increasing agricultural activities and  
55 hydroagricultural infrastructures). From a sustainability perspective, it is important to quanti-  
56 tatively manage agricultural water, where some of the numerous solutions to be explored in-  
57 volve the spatiotemporal modulation of anthropogenic actions, individually or in combination  
58 (IAASTD, 2008). These solutions imply processes (fluxes, storages and transformations) and  
59 several components (e.g., root zone, aquifer, vegetation, hydroagricultural infrastructures, ag-  
60 ricultural practices) within agrosystems. The exploration of these solutions must account for  
61 two key points. First, in situ scientific experiments are not suitable for both large agricultural  
62 areas and forecasts in a climate change context, which makes necessary the use of process

63 modelling for numerical simulations (Jones et al., 2017). Second, the water cycle and crop  
64 dynamics are strongly linked. Vegetation cover drives the rainfall repartition between runoff  
65 and infiltration in relation to fluxes within hydrographic networks towards lakes and reservoirs,  
66 to soil water storage and to aquifer refill. The water cycle drives root zone water content and  
67 crop water consumption, with consequences on agricultural yields. It is therefore important to  
68 properly characterize the interactions between the water cycle and crop functioning within ag-  
69 rosystems (Kanda et al., 2018).

70 Integrated process modelling should be able to simulate, within hilly catchments, crop func-  
71 tioning and the water cycle along with their interactions. This requires parsimonious crop mod-  
72 els that (1) minimize the number of parameters for realistic simulations with spatialization pur-  
73 poses and (2) simulate crop functioning in relation to water dynamics within the root zone layer  
74 and underlying shallow aquifer. The literature provides a large number of crop models that  
75 describe plant functioning and growth along with crop yield (Weiss et al., 2020). Well known  
76 examples are APSIM (Keating et al., 2003), DSSAT (Jones et al., 2003), EPIC (Williams et  
77 al., 1984), STICS (Brisson et al., 2003), WOFOST (Todorovic et al., 2009; de Wit et al., 2019),  
78 AquaCrop (Raes et al., 2009; Steduto et al., 2009), CropSyst (Stöckle et al., 2003), or AqYield  
79 (Constantin et al., 2015; Tribouillois et al., 2018). Based on the primary factors that describe  
80 crop functioning, Todorovic et al. (2009) classified crop models into (1) carbon-driven models  
81 such as WOFOST, CROPGRO, and DSSAT, (2) solar radiation-driven models such as  
82 CERES, EPIC, STICS, and APSIM, and (3) water-driven models such as AquaCrop and  
83 CropSyst in which biomass production is proportional to the amount of transpired water.  
84 CropSyst is a model based on water and solar radiation. When the vapour pressure deficit  
85 (VPD) is very low, the transpiration-biomass relationship is replaced by a radiative approach  
86 in which biomass is determined on the basis of intercepted photosynthetically active radiation

87 (IPAR, Stöckle et al., 2003; Kanda et al., 2018). Among the aforementioned crop models, AquaCrop is therefore the unique water-driven model (Kanda et al., 2018). It is thus an interesting model for addressing the coupling of crop functioning and the water cycle within Mediterranean hilly catchments typified by rainfed agriculture. In addition, it provides a trade-off between robustness and simplicity, since it requires a moderate number of input parameters.

92 The literature includes numerous studies that involve AquaCrop. These studies can be classified into four main groups, according to their content: (1) calibration, validation, and performance evaluation of the model in specific contexts (Mkhabela and Bullock, 2012; Zeleke, 2019); (2) cropping system management on the basis of model simulations: estimation of crop water requirements, sowing dates and crop yields, as well as consequences of fertilization, salinity, and irrigation regimes on crop yield (Araya et al., 2010; Qin et al., 2013; Nyakudya and Stroosnijder, 2014; El Mokh et al., 2017; Er-Raki et al., 2021); (3) impact of climate change on crop production and evaluation of different adaptation strategies (Muluneh, 2020; Raoufi and Soufizadeh, 2020; Rashid et al., 2019); and (4) economic impact of cropping practices and climate change on productivity (Cusicanqui et al., 2013; Bird et al., 2016). Meanwhile, AquaCrop has been used across the five continents, under different climates (Mediterranean, tropical, continental, temperate) and within both irrigated and rainfed agrosystems (Geerts et al., 2009; García-Vila and Fereres, 2012; García-López et al., 2014; Vanuytrecht et al., 2014; Ahmadi et al., 2015; Deb et al., 2015; Shrestha et al., 2016; Silvestro et al., 2017; Xing et al., 2017; Sandhu and Irmak, 2019; Lu et al., 2021). Overall, AquaCrop has been tested and validated on a wide range of agroenvironmental conditions.

108 Some of the aforementioned AquaCrop-based studies focused on variables describing crop growth, such as canopy cover CC, dry aboveground biomass AGB and yield (Todorovic et al., 2009; Mkhabela and Bullock, 2012; Silvestro et al., 2017). Other studies addressed actual evapotranspiration ( $ET_a$ ) (Geerts et al., 2009; Katerji et al., 2013) as well as soil water content

112 (SWC) (Nyakudya and Stroosnijder, 2014; Sghaier et al., 2014). Similar to most crop models,  
113 AquaCrop was designed and evaluated for local applications at the plot level over flat terrains.  
114 More recently, the model was evaluated on hilly terrains, either in a multilocal way that disre-  
115 garded interplot water exchanges (Alaya et al., 2019; Han et al., 2019) or in a distributed way  
116 that accounted for interplot water exchanges (Van Loo and Verstraeten, 2021). However, more  
117 research is needed to address the diversity of situations induced by Mediterranean rainfed hilly  
118 agrosystems in relation to cropping, soil and topographic conditions. In addition, AquaCrop  
119 was evaluated on only a few variables simultaneously, whereas any multicriteria evaluation is  
120 likely to provide a better assessment of model capacities.

121 The objective of this study is to deepen the evaluation of the capabilities of the AquaCrop  
122 model for rainfed crops within hilly Mediterranean catchments. We propose (1) to consider  
123 little-studied crops (e.g., faba bean and oats) under subhumid to semiarid climates, (2) to con-  
124 sider combinations of crops (faba bean, oats, wheat, barley) and soils (Vertisols, Cambisols  
125 and Luvisols) for contrasted hydroclimatic years, and (3) to conduct a more substantial mul-  
126 ticriteria analysis that includes simultaneously vegetation canopy (CC, AGB), soil water con-  
127 tent integrated over topsoil and root zones, and water fluxes ( $ET_a$ , runoff as infiltration excess).  
128 We focus here on the evaluation of AquaCrop without addressing calibration issues. The cur-  
129 rent paper is structured as follows. We briefly present the AquaCrop model. We introduce the  
130 study area and the datasets used, as well as the strategy for evaluating the model. Thereafter,  
131 we analyse the comparison of the simulations against the observations by exploring the possible  
132 influences of soil and crop type. We finally discuss these results in light of former studies, and  
133 we conclude with our contribution to the assessment of AquaCrop performances, along with  
134 further perspectives.

## 135 2. Presentation of the AquaCrop model

136 Detailed presentations of AquaCrop (<https://www.fao.org/aquacrop/en/>) are given by Steduto

137 et al., (2009), Raes et al. (2009) and Salman et al. (2021). We detail here the specificities related

138 to the methodological choices on which the current study relies. Developed by FAO, AquaCrop

139 is a parsimonious (reduced number of parameters) crop model that aims to simulate crop bio-

140 mass and yield by considering water as the main driver of crop functioning (Kanda et al., 2018).

141 Operating at a daily time step, AquaCrop simulates the vertical exchanges between the different

142 components of the soil–plant–atmosphere continuum.

143 AquaCrop describes the soil as a reservoir split into several horizons (5 maximum). Each hori-

144 zon is characterized by texture or related hydrodynamic properties: soil moisture at field ca-

145 pacity (HFC), soil moisture at wilting point (HWP), soil moisture at saturation (HSAT), satu-

146 rated hydraulic conductivity (KSAT) and drainage coefficient ( $\tau$ ).

147 The model calculates soil evaporation ( $E_s$ ) and crop transpiration ( $T_r$ ) separately, which per-

148 mits the quantification of the amount of water unused by vegetation (Steduto et al., 2009).

149 Another feature of the model is the description of canopy growth by using canopy cover (CC)

150 instead of leaf area index (LAI). The model calculates  $T_r$  as a function of CC, and biomass is

151 determined as a function of both  $T_r$  and normalized water productivity ( $WP^*$ ). The yield is

152 finally calculated by multiplying biomass by harvest index (HI). Water productivity ( $WP^*$ )

153 accounts for atmospheric concentration [ $CO_2$ ] and therefore permit to apply AquaCrop in pro-

154 spective climate contexts related to precipitation, air temperature, evaporative demand and

155 [ $CO_2$ ].

156 The soil water content at each time step results from the balance of drainage, infiltration from

157 rainfall/irrigation, soil evaporation and crop transpiration. AquaCrop accounts for four types

158 of stress that affect crop growth: water stress, heat stress, fertilization stress and salinity stress.



159 Depending on the type of stress, the target parameters of the model change. For example, water  
160 stress affects leaf and CC expansion, root zone expansion, transpiration and the harvest index.  
161 The main variables simulated by the model relate to crop productivity (canopy cover, dry  
162 aboveground biomass and yield) and water balance (soil water content, runoff, infiltration,  
163 drainage, capillary rise, soil evaporation and vegetation transpiration). The model parameters  
164 are related to the crop (conservative parameters, fixed for a given species and nonconservative  
165 parameters, varying according to the varieties), the soil (horizon number, texture or hydrody-  
166 namic parameters), and the groundwater table (depth). The forcing variables of the model are  
167 the climatic variables: reference evapotranspiration ( $ET_0$ ), air temperature, rainfall and mean  
168 annual  $[CO_2]$ . Agricultural practices include sowing date, fertilization and irrigation. Finally,  
169 the initial conditions include the initial soil water and salinity content.

### 170 **3. Materials and methods**

#### 171 **3.1. Study site**

172 The study was conducted within the Kamech catchment, which is the southern site of the Med-  
173 iterranean Observatory of Rural Environment and Water (French acronym OMERE, Molénat  
174 et al., 2018) that has collected multiple observations over the last 30 years. Kamech is a small  
175 hilly catchment area (2.6 km<sup>2</sup> size) located within the Cap-Bon Peninsula, northeastern Tunisia  
176 (10°52'-10°53'E and 36°52'-36°53' N, 108 m above sea level - asl.). It is representative of the  
177 climatic and cropping conditions of the region. The climate is Mediterranean subhumid/semi-  
178 arid. The rainy season spans from October to March (Mekki, 2003) with a cumulative rainfall  
179 of 635 mm (annual average over the [1994-2020] period) and an annual reference evapotran-  
180 spiration of 1366 mm (Molénat et al., 2018). The area is 70% agricultural, combining crops  
181 and livestock, with significant spatiotemporal variability in land cover and spatial heterogene-  
182 ity in soil types (Mekki, 2003; Mekki et al., 2006).

183 The Kamech catchment is typified by a diversified land cover that encompasses rainfed and  
184 fodder crops (Mekki, 2003; Zitouna-Chebby et al., 2018). The dominant crops are winter cereals  
185 (durum wheat, barley, oats and triticale) and legumes (chickpeas, faba bean and peas). Altitudes  
186 range from 80 m to 200 m, and terrain slopes vary between 0 and 30%. The geological substratum  
187 is from the Miocene epoch, and it is mainly made of marl and clay (Mekki, 2003; Molénat  
188 et al., 2018). The four dominant soils are Cambisols, Luvisols, Vertisols and Regosols. They  
189 cover 46%, 26%, 10% and 18% of the catchment area, respectively (Mekki et al., 2018b). The  
190 soil depth varies from a few millimetres to 2 m.

191 Kamech is also typified by a large occurrence of swelling clay soils with shrinkage cracks that  
192 occur from March to December (Mekki, 2003; Inoubli, 2016). The closing of cracks heavily  
193 depends on rainfall at the beginning of the wet season and completely ends after cumulative  
194 rainfalls of approximately 200 mm  $\pm$  50 mm (Mekki, 2003). At their maximum opening, they  
195 have a water storage capacity of approximately 70 mm. Runoff occurs from December to  
196 March, when cracks are closed (Mekki, 2003; Inoubli, 2016).

### 197 **3.2. Datasets**

198 The current study benefits from a large database collected over the last three decades in the  
199 framework of the OMERE Observatory. This database includes meteorological, pedological,  
200 hydrological and agronomic observations (Mekki et al., 2006, 2018; Zitouna-Chebby et al.,  
201 2018; Inoubli et al., 2017). This permitted to perform a thorough, multicriteria evaluation of  
202 the AquaCrop model.

203 We chose wheat/barley, oats and faba bean as representative species of grain cereals, fodder  
204 cereals and legumes, respectively. For each of these crops, some datasets were available be-  
205 tween 2001 and 2013. Each of these datasets included a range of observations collected  
206 throughout a crop cycle on a given plot from September to August that also corresponded to a

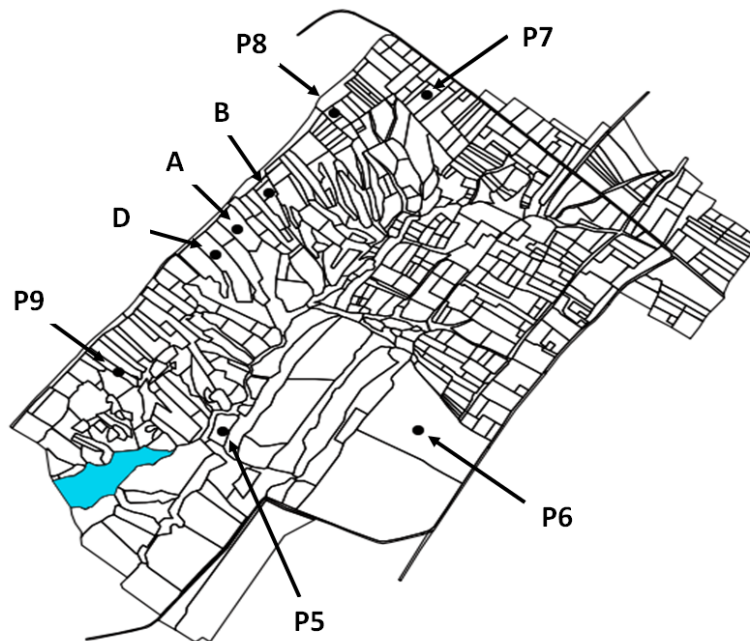
207 hydrological year. We selected the nine most complete datasets for conducting the AquaCrop  
208 multicriteria evaluation. This resulted in the combination of five years and eight plots. Table 1  
209 shows the available datasets, including the panel of data available in each of the nine datasets  
210 for the AquaCrop multicriteria evaluation. Fig. 1 shows the location of the plots within the  
211 Kamech catchment. In the panel of plots presented in Fig. 1, plot A differs from the others.  
212 Indeed, this plot has been dedicated for two decades to regular monitoring as part of the  
213 OMERE Observatory. This monitoring included meteorological forcing, surface and subsur-  
214 face hydrological monitoring, vegetation monitoring and soil characterization.

215 In the remainder of this section, we present the climatic, pedological, agronomic and hydrolog-  
216 ical data, by distinguishing between (1) the data used as inputs to the AquaCrop model and  
217 (2) the data used for the multicriteria evaluation of the model simulations.

218

219 **Table 1.** The nine available datasets for the multicriteria evaluation of AquaCrop. *LAI\_plan*,  
 220 *CC\_visu*, *ET<sub>a</sub>*, *R* and *SWC* stand for LAI from planimetric measurements, canopy cover from  
 221 visual quantification, actual evapotranspiration, runoff and soil water content, respectively.  
 222 The value *Y* of the label Year is related to harvesting year, and thus corresponds the crop cy-  
 223 cle that spreads from September of year *Y-1* to August of year *Y*.

Crop	Dataset		Available data					
	Year	Plot	LAI_plan	CC_visu	ET <sub>a</sub>	R	SWC	AGB
Wheat	2001	P7	x			x	x	x
	2002	P9	x			x	x	x
	2013	A	x		x	x	x	x
Barley	2006	D	x				x	
Oats	2002	P6	x			x	x	x
	2005	B	x		x		x	x
Faba	2001	P5		x		x	x	x
	2001	P8		x		x	x	x
	2002	P7		x		x	x	x



224  
 225 **Fig. 1.** Map of the Kamech catchment with the location of the plots A, B, D, P5, P6, P7, P8  
 226 and P9. The meteorological station is located near the outlet of the catchment area, down-  
 227 stream limit of the hilly lake.

### 228 3.2.1. AquaCrop input data

### 229 3.2.1.1. Climatic data

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2  
3 230 The climatic data were collected by the meteorological station located near the outlet of the  
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5 231 catchment area (see Fig. 1). First,  $ET_0$  was calculated at the half-hourly time step by using the  
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7 232 FAO-56 method along with measurements of solar radiation, air temperature, air humidity and  
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9 233 wind speed. Next, estimates calculated at the half-hourly time step were integrated at the daily  
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11 234 timescale.

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15 235 All rainfall data were collected at a daily time step. The rain gauge for each of the plots P5, P6,  
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17 236 P7, P8 and P9 was located downstream of the plot. For plots A, B and D, we used the data  
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19 237 collected by the rain gauge located downstream of plot A, thanks to their spatial proximity. In  
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21 238 the case of missing data, we used average values across all rain gauges within the catchment  
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23 239 area.

### 240 3.2.1.2. Soil hydrodynamic parameters

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28 241 AquaCrop inputs include soil depth and soil moisture at wilting point (HWP) and at field ca-  
29  
30 242 pacity (HFC). We consider three soil classes: Vertisols for plots A, B, D and P5, Cambisols for  
31  
32 243 plots P6, P7, and P8 and Luvisols for plot P9. Soil depth and hydrodynamic parameters for  
33  
34 244 each plot are shown in Table 2.

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39 245 We summarize in this section the estimation of HWP and HFC; a detailed description is pro-  
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41 246 vided in Section 1 of the supplementary materials. We used the laboratory measurements (Cas-  
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43 247 sel and Nielsen, 1986) conducted within the framework of the OMERE Observatory, and the  
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45 248 agroclimatic method (Sreelash et al., 2017) with discrete soil moisture measurements con-  
46  
47 249 ducted at specific dates. The comparison of the estimates resulting from these two approaches  
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49 250 showed relative differences of approximately 15% on average (Table SP1 in supplementary  
50  
51 251 materials), which corresponds to the precision and spatial representativeness of local field  
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53 252 measurements, approximately 15% (Susha Lekshmi et al., 2014; Walker et al., 2004; Robinson  
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253 et al., 2008). Next, we verified the consistency of the HWP and HFC estimates with the time  
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 2 254 series of SWC (SWC data are presented in Section 3.3.6). This led to the use of the estimates  
 3  
 4  
 5 255 from the laboratory measurements for plot A, and to the estimates from the agroclimatic  
 6  
 7 256 method for the other plots.

10 257 **Table 2.** *Soil characteristics of the plots. Soil classes are taken from Mekki et al. (2006). We*  
 11  
 12  
 13 258 *used the same values of soil depth for plots A, B and D thanks to their spatial proximity.*

Plot	Class	Soil depth	Soil hydrodynamic parameters (m <sup>3</sup> /m <sup>3</sup> )	
			HWP	HFC
P5	Vertisol	1.60	0.23	0.45
P6	Cambisol	1.50	0.21	0.35
P7	Cambisol	1.60	0.23	0.44
P8	Cambisol	1.20	0.19	0.46
P9	Luvisol	1.60	0.25	0.47
A	Vertisol	1.15	0.34	0.43
B	Vertisol	1.15	0.26	0.44
D	Vertisol	1.15	0.23	0.44

### 30 260 3.2.1.3. Crop parameters

31  
 32  
 33 261 We chose wheat/barley, oats and faba bean as representative species of grain cereals, fodder  
 34  
 35 262 cereals and legumes, respectively. In the literature, there are some annual crops for which Aq-  
 36  
 37  
 38 263 uaCrop parameterizations are not representative of various agro-environmental conditions. In-  
 39  
 40 264 deed, some parameterizations are proposed in the literature for chickpeas (Mubvuma et al.,  
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 42  
 43 265 2021), leafy vegetables (Nyathi et al., 2018), table grape (Er-Raki et al., 2021), oats and faba  
 44  
 45 266 bean (Yuan et al., 2013; Zeleke, 2019), but they need to be tested and confirmed in other geo-  
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 48 267 climatic contexts and for other crop varieties to ensure that they are reliable, as is the case for  
 49  
 50 268 those related to wheat or corn crops.

51  
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 53 269 For wheat, barley and faba bean, we used parameters proposed in the literature that were rather  
 54  
 55 270 suitable for the local varieties of our study site, as indicated in Table 2 of Alaya et al. (2019).

56  
 57  
 58 271 For oats, we used the values proposed by Yuan et al. (2013) for the conservative parameters

272 (invariant from one variety to another), and we used values related to wheat for the noncon-  
273 servative parameters that describe the phenological stages throughout the crop cycle, due to the  
274 lack of data.

### 275 **3.2.2. AquaCrop multicriteria assessment**

#### 276 **3.2.2.1. Actual evapotranspiration (ET<sub>a</sub>)**

277 For actual evapotranspiration, two datasets were available (Table 1): the first dataset was col-  
278 lected in plot A in 2013 for wheat, and the second dataset was collected in plot B in 2005 for  
279 oats. The time series were collected at the plot scale, with a 30 min timescale throughout the  
280 crop cycle. The daily ET<sub>a</sub> measurements were derived from the energy balance closure method  
281 in 2005 (Zitouna-Chebbi et al., 2015) and from the eddy covariance method in 2013 (Boudhina  
282 et al., 2017a). For 2013, the missing latent heat flux data were reconstructed using the REddy-  
283 Proc gap-filling method (Reichstein et al., 2005). The experimentation, calibration, data pro-  
284 cessing and gap-filling are discussed in detail by Zitouna-Chebbi (2009); Zitouna-Chebbi et  
285 al., (2012; 2015; 2018), and Boudhina et al., (2017a, 2017b, 2018). ET<sub>a</sub> data were finally ag-  
286 gregated at the daily timescale.

#### 287 **3.2.2.2. Crop variables (CC, AGB)**

288 When dealing with vegetation growth throughout the crop cycle, we used planimetric meas-  
289 urements of the leaf area index (LAI) for cereals (wheat, barley, oats) and visual estimates of  
290 canopy cover (CC) for faba bean (Table 1). Nevertheless, AquaCrop simulates CC to describe  
291 crop growth. For cereals, we therefore converted LAI measurements into CC estimates by using  
292 Equation 1, as done in numerous studies (Katerji et al., 2013; Yuan et al., 2013; Pereira et al.,  
293 2015):

$$294 \quad CC = 1 - e^{-k \times LAI} \quad (\text{Equation 1})$$

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295 Coefficient  $k$  is an extinction coefficient that quantifies the light interception by canopy cover  
296 (Pereira et al., 2015). We used a  $k$  value equal to 0.57 for all cereals. The determination of this  
297  $k$  value is discussed in Section 2 of the supplementary materials.

298 We also used measurements of dry aboveground biomass (AGB), except for barley in plot D  
299 in 2006. For each of the eight datasets, AGB was determined throughout the crop cycle using  
300 a destructive method (i.e., field samples to be weighed before and after oven drying). Spatial  
301 sampling varied across datasets, ranging from three to 10 replicates (Mekki, 2003; Boudhina  
302 et al., 2019). For each crop, the number of observation dates also varied across datasets, be-  
303 tween three and 11 dates at maximum.

### 304 **3.2.2.3. Soil water content (SWC)**

305 Time series of SWC measurements were available for all datasets (Table 1). For 2001, 2002  
306 and 2013, measurements were made using a neutron probe with a weekly frequency. For 2005  
307 and 2006, measurements were made by the gravimetric method, with a biweekly frequency  
308 throughout the crop cycle and with a bimonthly frequency during summer with bare soil. All  
309 measurements were carried out across 1 m depth profiles. To account for spatial variability in  
310 SWC, the samples were collected at different landscape positions (distributed across the top,  
311 middle and bottom of each plot), except for 2001 and 2002, with one measurement only per  
312 plot. The moisture values were obtained by plot-scale averaging of measurements. Detailed  
313 descriptions of the measurements are given in Mekki (2003); Zitouna-Chebbi (2009); Boudhina  
314 et al. (2019).

### 315 **3.2.2.4. Runoff (R)**

316 Runoff measurements were included in each of the datasets listed in Table 1, apart from oats  
317 in 2005 and barley in 2006. Runoff data were collected at the daily timescale.



- 318 • For 2001 (end of December) and 2002 (November), runoff was measured in each plot using  
 319 a 2 m<sup>2</sup> size harvesting frame that was connected to a tank with a 20-litre capacity (Mekki  
 320 et al., 2006).
- 321 • For 2013, runoff was measured by the hydrological station located at the outlet of plot A.  
 322 The experimental protocol is detailed in Inoubli et al. (2017).

### 323 3.3. Determination of initial soil moisture and fertilization degree

324 To obtain reliable AquaCrop simulations throughout the crop cycle for each of the nine datasets  
 325 (Table 1), it was necessary to set the initial soil water content (SWC<sub>i</sub>). It was also necessary to  
 326 set the fertilization rate (FR) for cereal crops, while no fertilization rate was required for faba  
 327 bean that is a nitrogen-fixing legume crop (FR represents the effect of the soil nutrient level on  
 328 canopy development and biomass production, and AquaCrop expresses the lack of soil nutrient  
 329 from soil fertility stress, by means of stress coefficients). Given that no information was avail-  
 330 able for either SWC<sub>i</sub> or FR, we determined them by minimizing the differences between ob-  
 331 servations and simulations of CC, AGB and SWC (time series of ET<sub>a</sub> were available for only  
 332 two datasets).

333 For each of the nine datasets, we choose 15 SWC<sub>i</sub> values between HWP and HFC and 30 FR  
 334 values ranging from 70 to 100% according to expert knowledge. We then created pairs (SWC<sub>i</sub>,  
 335 FR) and generated the corresponding AquaCrop simulations. The optimal (SWC<sub>i</sub>, FR) pair was  
 336 selected using two criteria. First, the NRMSE (normalized root mean square error) had to be  
 337 lower than 15% for SWC, which corresponds to measurement error on soil moisture (Susha  
 338 Lekshmi et al., 2014). Second, we minimized the quadratic error between the observations and  
 339 simulations of CC and AGB simultaneously using the objective function F defined by Equation  
 340 2 (Montes et al., 2014):

$$341 \quad F = \text{NRMSE}_{\text{CC}}^{1/2} + \text{NRMSE}_{\text{AGB}}^{1/2} \quad (\text{Equation 2})$$

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342 AquaCrop tends to overestimate CC observations during the senescence phase in the case of  
343 heat waves (Andarzian et al., 2011), while early senescence is recurrent in Kamech. To avoid  
344 the influence of any overestimation when minimizing the quadratic error, we calculated F over  
345 a simulation period that spread from the beginning of the crop growth to the maximum plant  
346 cover ( $CC = CC_{max}$ ). Across the selected AquaCrop simulations, the obtained  $SWC_i$  values  
347 were larger than  $0.75 \times HFC$ , and those retained for FR were approximately 85%. According  
348 to expert opinions, the FR values are representative of actual field conditions in the Kamech  
349 watershed.

### 350 3.4. Model evaluation

351 AquaCrop was evaluated by comparing simulations against observations throughout the crop  
352 cycle related to each of the nine datasets by considering the variables listed in Table 1 and  
353 related to vegetation (AGB, CC), water fluxes ( $ET_a$ , runoff as infiltration excess), and water  
354 storage (SWC). Table 1 details the available data used for each crop, year and plot.

355 For the statistical evaluation of the simulations against observations, we selected the following  
356 indicators: coefficient of determination ( $R^2$ ), root mean square error (RMSE), normalized root  
357 mean square error (NRMSE) and mean bias error (MBE). These are commonly used in the  
358 literature for evaluating numerical models (Kustas et al., 1996; Jacob et al., 2002), including  
359 hydrological (Moriassi et al., 2015) or crop (Yang et al., 2014) models. We also used the Stu-  
360 dent's t test for linear regressions on model validation, to test the null hypothesis (slope and  
361 offset can be equal to 1 and 0, respectively). If the critical values (p value) were larger than  
362 5%, then the null hypothesis could not be rejected with 95% confidence, and model perfor-  
363 mances could be considered satisfactory.

$$R^2 = \frac{\sum_{i=1}^n (P_i - \bar{O})^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (\text{Equation 3})$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (P_i - O_i)^2}{n}} \quad (\text{Equation 4})$$

$$NRMSE = \frac{RMSE}{\bar{O}} \times 100 \quad (\text{Equation 5})$$

$$MBE = \frac{\sum_{i=1}^n (P_i - O_i)}{n} \quad (\text{Equation 6})$$

where  $P_i$  and  $O_i$ , are the simulated and observed variables at time step  $i$ , respectively.  $\bar{O}$  is the averaged value of the observations, and  $n$  is the observation number.

MBE indicates whether the model simulations underestimate or overestimate the observations.

NRMSE gives an indication of the relative difference between simulations and observations.

According to Jamieson et al. (1991), a crop model is classified as excellent if  $NRMSE < 10\%$ ,

good if  $NRMSE \in [10\% - 20\%[$ , acceptable if  $NRMSE \in [20\% - 30\%[$  and poor if  $NRMSE >$

$30\%$ . Likewise, simulations are considered acceptable if the coefficient of determination  $R^2$  is

greater than 0.5. For runoff, we did not consider the NRMSE in the evaluation of the AquaCrop

simulations because of the low values of this variable, which give very high NRMSE values ( $>$

$100\%$ ) that are difficult to interpret.

## 4. Results

### 4.1. Canopy cover (CC)

According to the comparison between AquaCrop simulations and in situ measurements of CC

(Fig. 2 and Table 3), for each crop type, AquaCrop simulations overestimated observations for

cereals and underestimated them for faba bean, with a positive MBE ranging between 0.03 and

0.23 for cereals and a negative MBE (-0.02) for faba bean. The  $R^2$  values did not exceed 0.4,

apart from faba bean (0.9). The RMSE values varied between 0.11 (29% relative) and 0.37

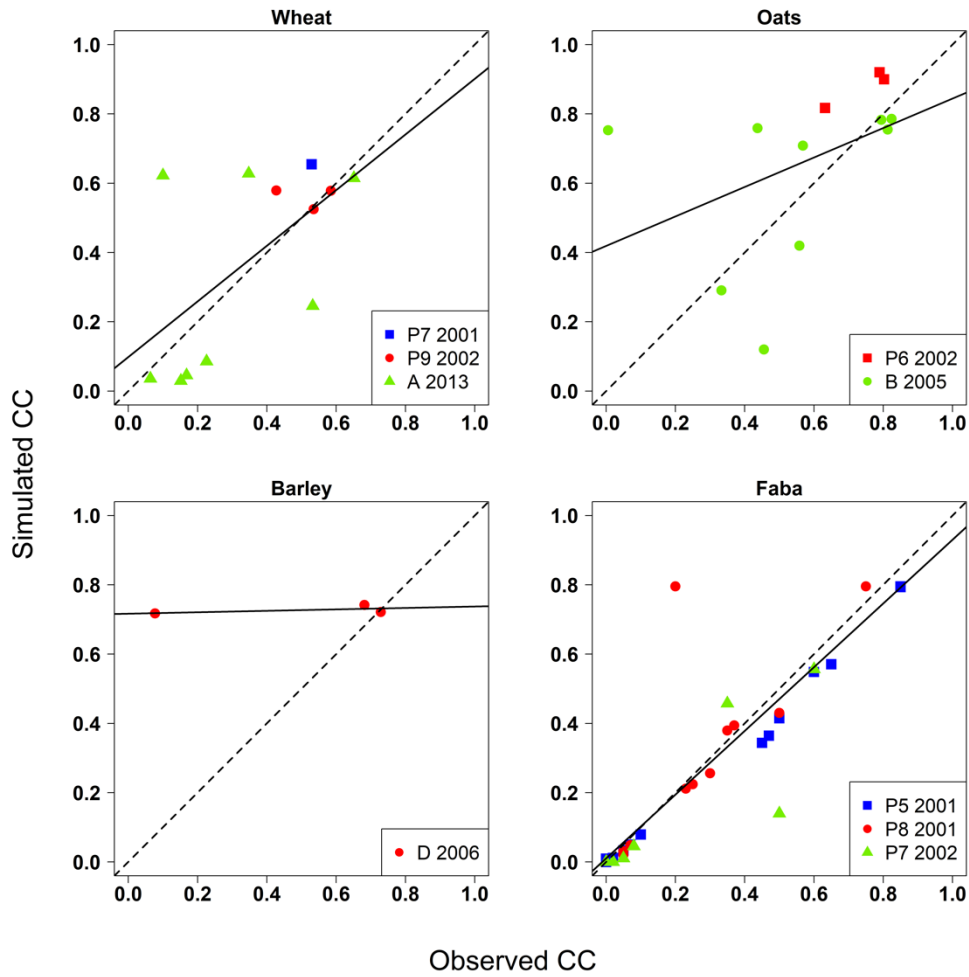
(75% relative), with the lowest values being observed for faba bean. For wheat and faba bean,

the t test provided p values larger than 5% on slope and offset. For barley, the t test provided p

1 383 value lower than 5% on slope and offset. For oats, the t test provided a p value lower than 5%  
2 384 on offset only.

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5 385 To study these results in detail, we analysed the temporal evolution of CC for each simulation  
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7 386 throughout the corresponding crop cycle (Fig. SP2 in Section 3 of the supplementary materi-  
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9 387 als). For wheat in 2002, oats in 2005, and barley in 2006, the temporal evolution of the canopy  
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11 388 cover simulated by the model showed acceptable estimates during the crop growth phase, de-  
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13 389 spite an overestimation of CC observations during the senescence phase. For wheat in 2013,  
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15 390 AquaCrop underestimated observations between DAS (day after sowing) 25 and DAS 120, and  
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17 391 it overestimated them at the end of the crop cycle. For oats in 2002, the model underestimated  
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19 392 observations throughout the crop cycle. Most time series suggested that AquaCrop simulated  
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21 393 senescence with delay compared to observations.  
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**Fig. 2.** Comparison between simulated and observed canopy cover (CC) on a crop type basis.

Each scatterplot corresponds to a crop type for several years and/or several plots. Each dataset is indicated by a different marker and a different colour. Px, A, B, D relates to plots and YYYY to years. The black line corresponds to the regression line, and the black dashed line corresponds to the 1:1 line.

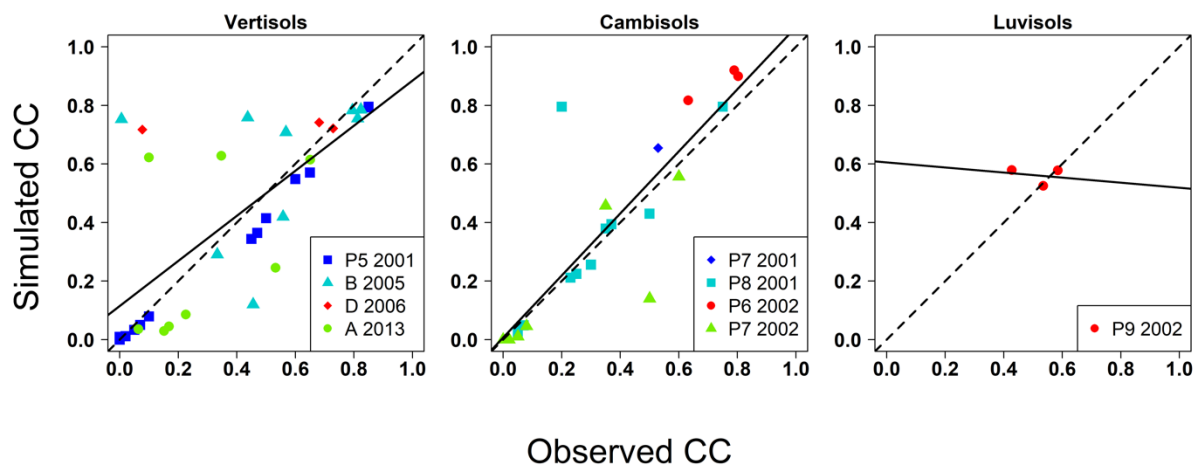
**Table 3.** Statistical indicators when comparing simulations against observations for canopy cover (CC) on a crop type basis. n is the observation number.  $R^2$  is the correlation coefficient. The t test corresponds to the p value of the Student's t test. The statistical indicators RMSE, NRMSE and MBE are defined in Section 3.4.

Crop	Var	n	$R^2$ (-)	Offset	Slope	RMSE (-)	NRMSE (%)	MBE (-)
				(-)	(-)			
				Value	t test	Value	t test	

<b>Wheat</b>	CC	12	0.39	0.10	0.47	0.80	0.55	0.21	58	0.03
<b>Oats</b>		12	0.18	0.42	0.04	0.43	0.08	0.27	46	0.08
<b>Barley</b>		3	0.33	0.72	0.02	0.02	0.02	0.37	75	0.23
<b>Faba</b>		38	0.86	0.01	0.73	0.92	0.21	0.12	32	-0.02

For each soil class, the comparison between AquaCrop simulations and in situ measurements of CC (Fig. 3 and Table 4) showed that AquaCrop simulations overestimated observations for the three soil classes. Additionally, the agreement between the model simulations and in situ measurements was moderate, with either (1) large  $R^2$  values (0.59 and 0.8) but large RMSE values (0.15 and 0.21, corresponding to 41% and 48% relative, respectively) or (2) a moderate RMSE value (0.09, 18% relative) but a low  $R^2$  value (0.05). Nevertheless, it was difficult to conclude for Luvisols because of the dataset size, with only one plot and one year. Conversely, the results for both Vertisols and Cambisols were similar, with relative changes in statistical indicators of approximately 25%. Apart from t test on slope for Vertisols, all p values were larger than 5%.

Finally, we could not conclude on any possible trend to over- or under- estimation according to the magnitude of observations. Indeed, the regression slope could be larger or lower than one from one soil class to another, in contrast to results reported on a crop type basis for which the regression slope was systematically lower than one.



421 **Fig. 3** Comparison between simulated and observed canopy cover (CC) on a soil class basis.  
 422 Each scatterplot corresponds to a soil class for several plots, years and crops. Each dataset  
 423 is indicated by a different marker and a different colour. Px, A, B, D relates to plots and  
 424 YYYY to years. The black line corresponds to the regression line, and the black dashed line  
 425 corresponds to the 1:1 line.

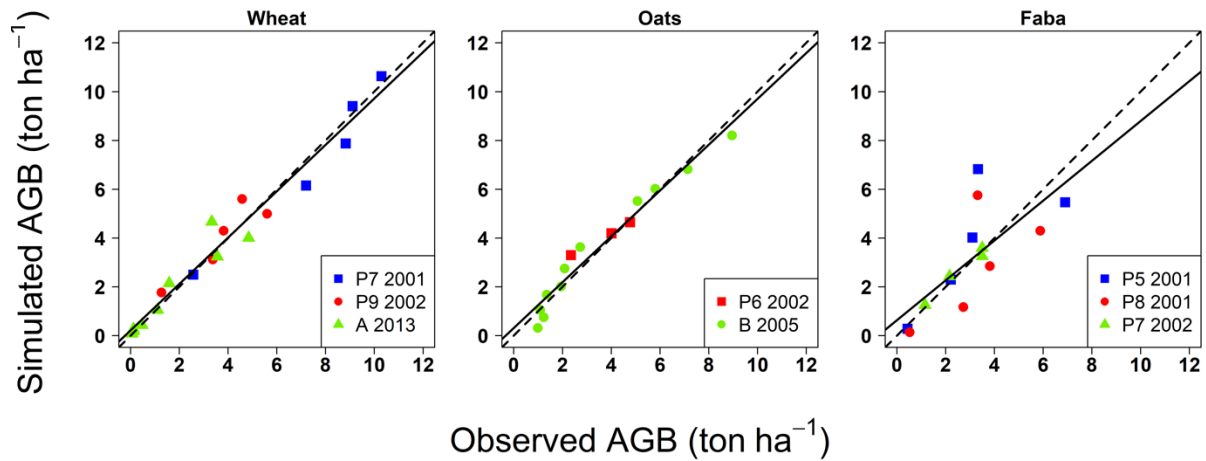
426 **Table 4.** Statistical indicators when comparing simulations against observations for canopy  
 427 cover (CC) on a soil class basis.  $n$  is the observation number.  $R^2$  is the correlation coeffi-  
 428 cient. The  $t$  test corresponds to the  $p$  value of the Student's  $t$  test. The statistical indicators  
 429 RMSE, NRMSE and MBE are defined in Section 3.4.

Soil	Var	n	$R^2$ (-)	Offset		Slope		RMSE (-)	NRMSE (%)	MBE (-)
				Value	t test	Value	t test			
Vertisols	CC	39	0.59	0.12	0.05	0.77	0.03	0.21	47	0.01
Cambisols		23	0.76	0.01	0.90	1.06	0.64	0.16	45	0.03
Luvisols		3	0.05	0.61	0.20	-0.09	0.21	0.09	17	0.05

#### 430 4.2. Aboveground biomass (AGB)

431 The comparison between simulated and observed AGB (Fig. 4 and Table 5), for each crop type,  
 432 showed a good estimation of this variable by the model for cereals, with  $R^2$  approximately 0.95  
 433 and RMSE approximately 0.6 ton ha<sup>-1</sup> (16% relative). For faba bean, the simulations were less  
 434 good, with  $R^2 = 0.52$  and RMSE = 1.4 ton ha<sup>-1</sup> (46% relative). The bias values indicated that  
 435 AquaCrop tended to overestimate AGB observations for cereals (MBE > 0) and to underesti-  
 436 mate them for faba bean (MBE < 0). For all crop types, the  $t$  test provided  $p$  values larger than  
 437 5%.

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**Fig. 4.** Comparison between simulated and observed aboveground biomass (AGB) on a crop type basis. Each scatterplot corresponds to a crop type for several years and/or several plots. Each dataset is indicated by a different marker and a different colour. Px, A, B, D relates to plots and YYYY to years. The black line corresponds to the regression line, and the black dashed line corresponds to the 1:1 line.

**Table 5.** Statistical indicators when comparing simulations against observations for aboveground biomass (AGB) on a crop type basis. *n* is the observation number.  $R^2$  is the correlation coefficient. The *t* test corresponds to the *p* value of the Student's *t* test. The statistical indicators RMSE, NRMSE and MBE are defined in Section 3.4.

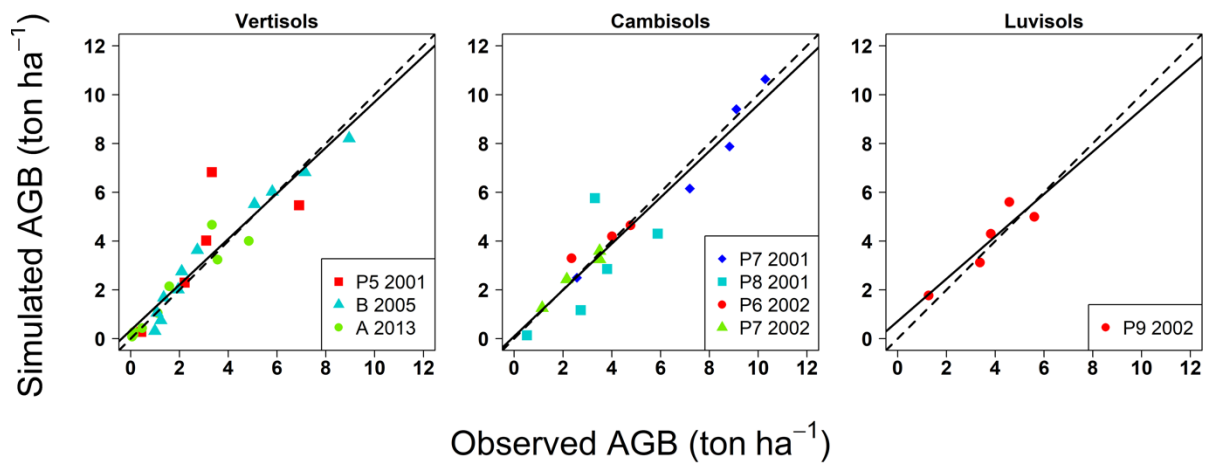
Crop	Var	n	$R^2$ (-)	Offset (ton ha <sup>-1</sup> )		Slope (-)		RMSE (ton ha <sup>-1</sup> )	NRMSE (%)	MBE (ton ha <sup>-1</sup> )
				Value	t test	Value	t test			
Wheat	AGB	19	0.96	0.22	0.34	0.95	0.30	0.61	16	0.03
Oats		14	0.95	0.31	0.25	0.94	0.33	0.53	15	0.10
Faba		14	0.52	0.64	0.44	0.82	0.43	1.40	46	0.08

To better understand the poor results for faba bean, Fig. SP3 displays the temporal evolution of AGB for both cereal crops and faba bean during the crop cycle. We noted that AquaCrop appropriately simulated AGB for 2002 in plot P7. For the year 2001 in plots P5 and P8, the model acceptably simulated AGB at the beginning of the crop cycle until Day 125 after sowing,



453 but it overestimated observations at the end of the crop cycle. This could explain the low  $R^2$   
 454 value given in Table 5.

455 The comparison between AquaCrop simulations and in situ measurements of AGB (Fig. 5 and  
 456 Table 6) for each soil class, showed that AquaCrop simulated AGB well for the 3 soil classes.  
 457 Bias values indicated that the model tended to overestimate observations for Vertisols and Lu-  
 458 visols ( $MBE > 0$ ) and to underestimate them for Cambisols ( $MBE < 0$ ). The  $R^2$  values were  
 459 above 0.84, with a small relative variation of 6% across the 3 soil classes. The RMSE values  
 460 were between  $0.62 \text{ ton ha}^{-1}$  (17% relative) and  $0.95 \text{ ton ha}^{-1}$  (21% relative). Additionally, all  
 461 regression slopes were close to one, as was the case when analysing results on a crop type basis.  
 462 This outcome agreed with the results of the t test that provided p values larger than 5% for all  
 463 soil classes.



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466 **Fig. 5.** Comparison between simulated and observed aboveground biomass (AGB) on a soil  
 467 class basis. Each scatterplot corresponds to a soil class for several plots, years and crops.  
 468 Each dataset is indicated by a different marker and a different colour. Px, A, B, D relates to  
 469 plots and YYYY to years. The black line corresponds to the regression line, and the black  
 470 dashed line corresponds to the 1:1 line.

471 **Table 6.** Statistical indicators when comparing simulations against observations for above-  
 472 ground biomass (AGB) on a soil class basis.  $n$  is the observation number.  $R^2$  is the correla-  
 473 tion coefficient. The  $t$  test corresponds to the  $p$  value of the Student's  $t$  test. The statistical in-  
 474 dicators RMSE, NRMSE and MBE are defined in Section 3.4.

Soil	Var	n	$R^2$ (-)	Offset (ton ha <sup>-1</sup> )		Slope (-)		RMSE (ton ha <sup>-1</sup> )	NRMSE (%)	MBE (ton ha <sup>-1</sup> )
				Value	t test	Value	t test			
				<b>Vertisols</b>	AGB	25	0.86			
<b>Cambisols</b>		17	0.89	0.10	0.83	0.95	0.56	0.95	21	-0.13
<b>Luvisols</b>		5	0.84	0.72	0.47	0.87	0.59	0.62	17	0.23

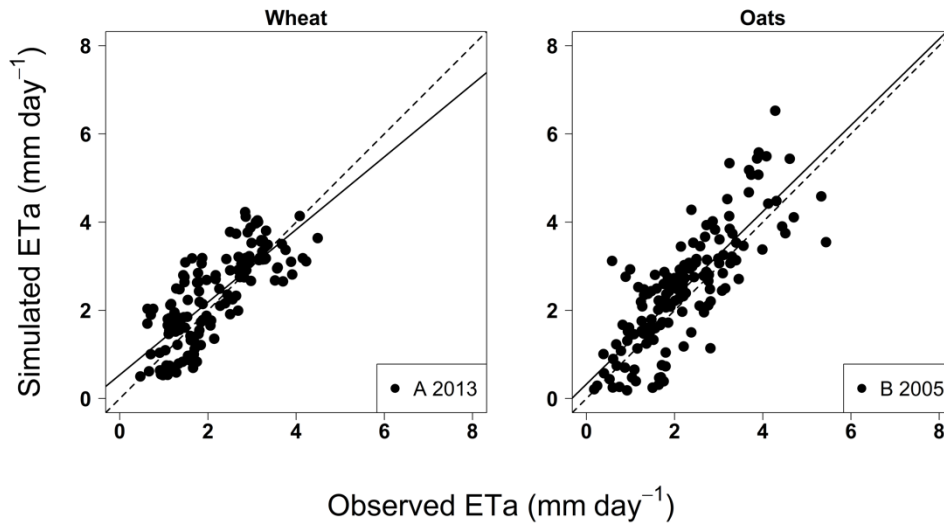
### 475 4.3. Actual evapotranspiration (ET<sub>a</sub>)

476 As shown in Table 1, ET<sub>a</sub> measurements were only available for oats in 2005 (plot B) and for  
 477 wheat in 2013 (plot A). The comparison between AquaCrop simulations and in situ measure-  
 478 ments of ET<sub>a</sub> (Fig. 6 and Table 7) showed a slight overestimation of the observations. The  
 479 overestimation was more important for oats (MBE = 0.28 mm day<sup>-1</sup>) than for wheat  
 480 (MBE = 0.17 mm day<sup>-1</sup>). The other indicators showed that the model performance was accepta-  
 481 ble for both crops, with  $R^2 \geq 0.6$  and  $RMSE \leq 0.84$  mm day<sup>-1</sup> (35% relative on average). Addi-  
 482 tionally, we noted scatterings around the regression lines that were close to the 1:1 line. Apart  
 483 from slope for wheat, the  $t$  test provided  $p$  values lower than 5%.

484 **Table 7.** Statistical indicators when comparing simulations against observations for actual  
 485 evapotranspiration (ET<sub>a</sub>) on a crop type basis.  $n$  is the observation number.  $R^2$  is the correla-  
 486 tion coefficient. The  $t$  test corresponds to the  $p$  value of the Student's  $t$  test. The statistical in-  
 487 dicators RMSE, NRMSE and MBE are defined in Section 3.4.

Crop	Var	n	$R^2$ (-)	Offset (mm day <sup>-1</sup> )		Slope (-)		RMSE (mm day <sup>-1</sup> )	NRMSE (%)	MBE (mm day <sup>-1</sup> )
				Value	t test	Value	t test			
				<b>Wheat</b>	ET <sub>a</sub>	134	0.59			
<b>Oats</b>		150	0.64	0.33	0.03	0.98	0.72	0.84	38	0.28

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490 **Fig. 6.** Comparison between simulated and observed actual evapotranspiration ( $ET_a$ ) on a  
491 crop type basis. Each scatterplot corresponds to a crop type. A, B relates to plots and YYYY  
492 to years. The black line corresponds to the regression line, and the black dashed line corre-  
493 sponds to the 1:1 line.

494 For a better understanding of the scattering around the regression line, we investigated the  
495 temporal dynamics of  $ET_a$  simulations by AquaCrop throughout the crop cycle for wheat and  
496 oats (Fig. SP4). We observed a significant similarity between the simulated and observed tem-  
497 poral evolutions of  $ET_a$  for both crops. For wheat, the overestimation of  $ET_a$  observations by  
498 model simulations was more important from DAS 130 (9 Mar 2013). For oats, we observed an  
499 overestimation of  $ET_a$  observations by the model between DAS 140 – (3 May 2005) and DAS  
500 160 - (23 May 2005) – as well as an underestimation of the observations from DAS 160 until  
501 the end of the crop cycle. Overall, we did not observe any trend to under- or overestimation  
502 according to crop phenological stages.

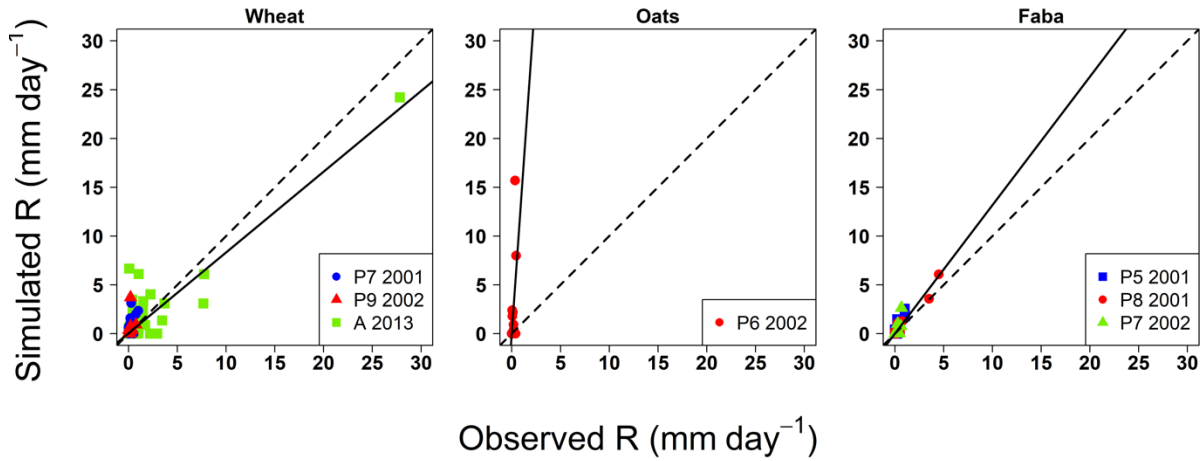
503 The two datasets of  $ET_a$  belonged to the Vertisols class. The statistical indicators we obtained  
504 when merging the scatterplots in Fig. 6 suggested good model performance in simulating  $ET_a$ ,

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505 with acceptable values for the correlation coefficient (0.62) and RMSE (0.77 mm day<sup>-1</sup>) and a  
506 slight overestimation of ET<sub>a</sub> observations by model simulations (MBE = 0.23 mm day<sup>-1</sup>).

#### 507 4.4. Runoff (R)

508 For runoff (infiltration excess), in situ measurements were available for all datasets, except for  
509 barley in plot D in 2006 and oats in plot B in 2005 (Table 1). The comparison between Aqua-  
510 Crop simulations and in situ measurements (Fig. 7 and Table 8) for each crop type showed that  
511 the model overestimated observations. The magnitude of the overestimation varied from one  
512 crop to another, and it was larger for oats (MBE = 0.2 mm day<sup>-1</sup>). AquaCrop acceptably simu-  
513 lated runoff for wheat and faba bean, with R<sup>2</sup> values larger than 0.8 and RMSE values lower  
514 than 0.63 mm day<sup>-1</sup>. The simulations were less effective for oats (R<sup>2</sup> = 0.41; RMSE =  
515 1.44 mm day<sup>-1</sup>). According to Fig. 7, the overestimation of runoff observations by AquaCrop  
516 simulations mainly occurred for low runoff values. For wheat in 2013 in plot A, the model  
517 acceptably simulated a significant runoff event (27 mm day<sup>-1</sup>) with a slight underestimation.  
518 For all crops, the t test on slope provided p values equal to 0. Apart from wheat, the t test on  
519 offset provided p values larger than 5%.

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*Fig. 7. Comparison between simulated and observed runoff (R) on a crop type basis. Each scatterplot corresponds to a crop type for several years and/or several plots. Each dataset is indicated by a different marker and a different colour. Px, A, B, D relates to plots and YYYY to years. The black line corresponds to the regression line, and the black dashed line corresponds to the 1:1 line.*

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*Table 8. Statistical indicators when comparing simulations against observations for runoff (R) on a crop type basis. n is the observation number. R<sup>2</sup> is the correlation coefficient. The t test corresponds to the p value of the Student's t test. The statistical indicators RMSE, NRMSE and MBE are defined in Section 3.4.*

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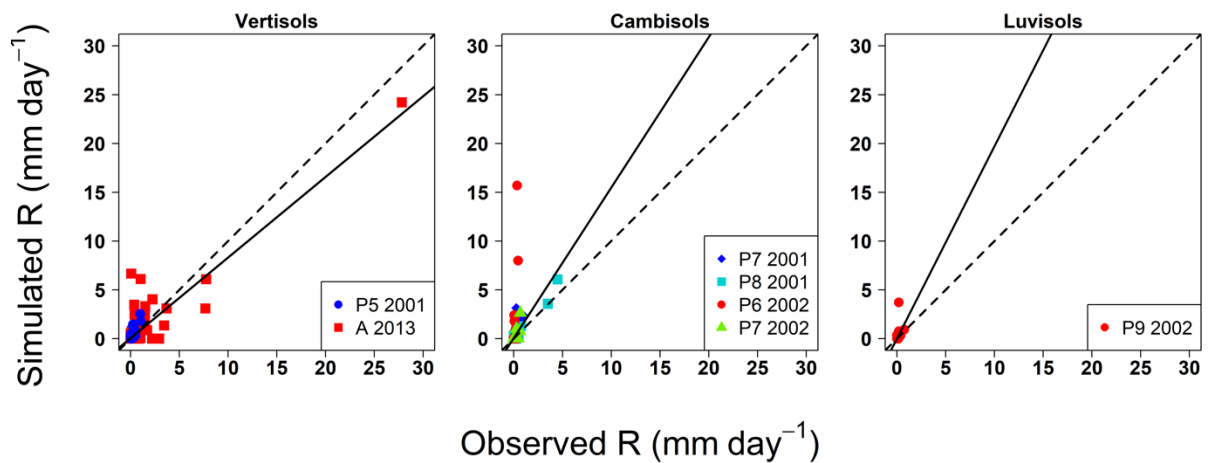
Crop	Var	n	R <sup>2</sup> (-)	Offset (mm day <sup>-1</sup> )		Slope (-)		RMSE (mm day <sup>-1</sup> )	MBE (mm day <sup>-1</sup> )
				Value	t test	Value	t test		
<b>Wheat</b>	R	478	0.80	0.06	0.03	0.83	0	0.63	0.02
<b>Oats</b>		147	0.41	-0.03	0.76	14.26	0	1.44	0.20
<b>Faba</b>		453	0.84	0.01	0.25	1.32	0	0.19	0.02

531

For a better understanding of these scatterplots, Fig. SP5 displays the temporal evolution of observed and simulated runoff for each dataset. Apart from wheat in plot A in 2013, the observed runoff was usually low, with values below 15 mm day<sup>-1</sup>. The most important differences between observed and simulated accumulations were noted for wheat in plot P7 in 2001 (12

535 mm day<sup>-1</sup>) and for oats in plot P6 in 2002 (29 mm day<sup>-1</sup>). We also noted that the model simu-  
 536 lated large runoff values at the beginning of the crop cycle compared to in situ measurements.  
 537 This was true for wheat in plot P9 in 2002 and in plot A in 2013, as well as for oats in plot P6  
 538 and faba bean in plot P7 in 2002. The same trend was also observed at the end of the crop cycle  
 539 (the last 40 days) for oats in plot P6 in 2002 and wheat in plot A in 2013.

540 From the comparison between AquaCrop simulations and in situ measurements of runoff, for  
 541 each soil class (Fig. 8 and Table 9) we noted a better performance of the model for Vertisols  
 542 ( $R^2 = 0.82$ , RMSE = 0.71 mm day<sup>-1</sup>), where the large  $R^2$  value for Vertisols likely results from  
 543 a single large runoff event. The model performed worse for Cambisols ( $R^2 = 0.22$  and  
 544 RMSE = 0.76 mm day<sup>-1</sup>) and Luvisols ( $R^2 = 0.21$  and RMSE = 0.28 mm day<sup>-1</sup>). The t test pro-  
 545 vided p values larger than 5% and lower than 5% for offset and slope, respectively.



547  
 548 **Fig. 8.** Comparison between simulated and observed runoff ( $R$ ) on a soil class basis. Each  
 549 scatterplot corresponds to a soil class for several plots, years and crops. Each dataset is indi-  
 550 cated by a different marker and a different colour. Px, A, B, D relates to plots and YYYY to  
 551 years. The black line corresponds to the regression line and the black dashed line corre-  
 552 sponds to the 1:1 line.

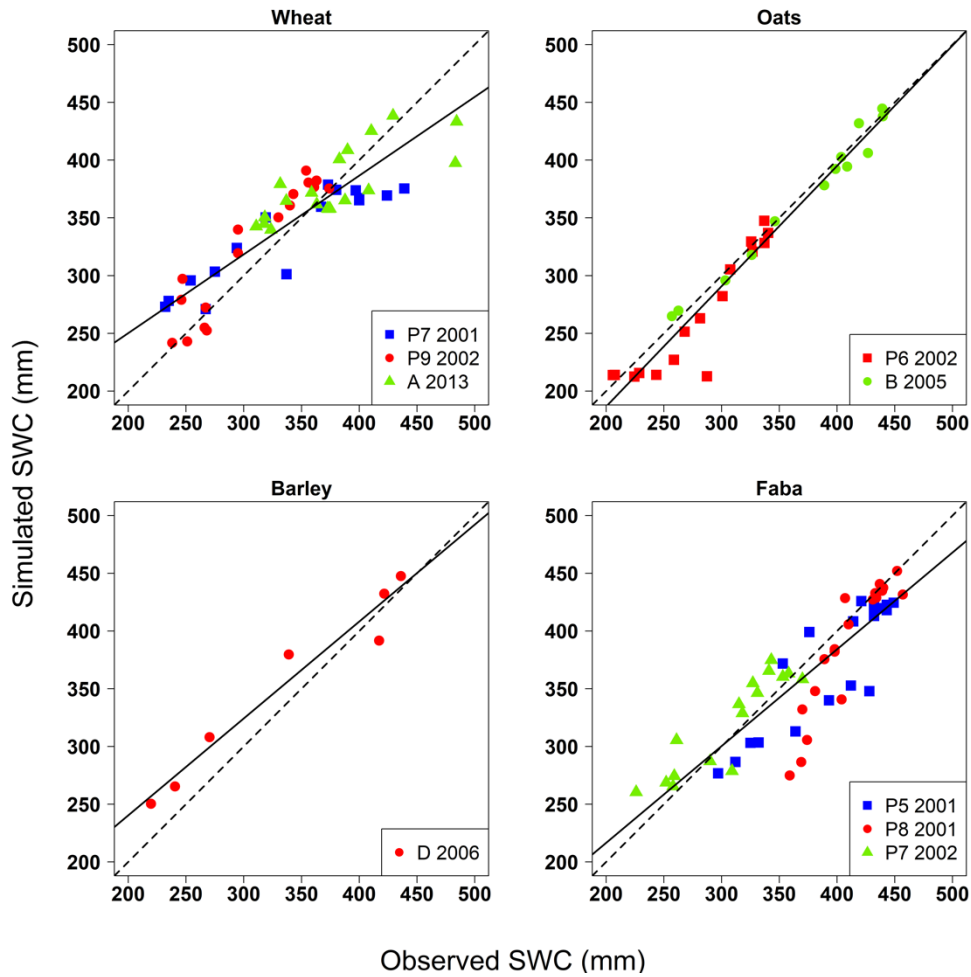
553 **Table 9.** Statistical indicators when comparing simulations against observations for runoff  
 554 ( $R$ ) on a soil class basis.  $n$  is the observation number.  $R^2$  is the correlation coefficient. The  $t$   
 555 test corresponds to the  $p$  values of the Student's  $t$  test. The statistical indicators RMSE,  
 556 NRMSE and MBE are defined in Section 3.4.

Soil	Var	n	$R^2$ (-)	Offset (mm day <sup>-1</sup> )		Slope (-)		RMSE (mm day <sup>-1</sup> )	MBE (mm day <sup>-1</sup> )
				Value	t test	Value	t test		
Vertisols	R	331	0.82	0.05	0.15	0.83	0	0.71	0.01
Cambisols		587	0.22	0.06	0.07	1.54	0	0.76	0.08
Luvisols		160	0.21	0.01	0.61	1.97	0	0.28	0.03

#### 557 4.5. Soil water content (SWC)

558 From the comparison between AquaCrop simulations and in situ measurements of soil water  
 559 content (SWC) (Fig. 9 and Table 10), for each crop type, we noted that AquaCrop simulated  
 560 this variable very well, with  $R^2$  values between 0.76 and 0.95 and RMSE values between 18.5  
 561 mm and 32 mm. The best simulations were observed with oats. The MBE values indicated that  
 562 the model simulations slightly underestimated the SWC observations for oats and faba beans  
 563 and slightly overestimated them for wheat and barley. Despite these favourable results, we  
 564 noted that the regression slope could be far from the 1:1 line for wheat. Additionally, we could  
 565 not conclude on any possible trend to over- or underestimation according to the magnitude of  
 566 in situ measurements. Indeed, the regression slopes were lower than one, apart from oats (1.04).  
 567 For oats and barley, the  $t$  test provided  $p$  values larger than 5%. For wheat, the  $t$  test provided  
 568  $p$  value lower than 5%. For faba bean, the  $t$  test provided a  $p$  value lower than 5% for slope.

569



**Fig. 9.** Comparison between simulated and observed soil water content (SWC) on a crop type basis. Each scatterplot corresponds to a crop type for several years and/or several plots. Each dataset is indicated by a different marker and a different colour. Px, A, B, D relates to plots and YYYY to years. The black line corresponds to the regression line, and the black dashed line corresponds to the 1:1 line.

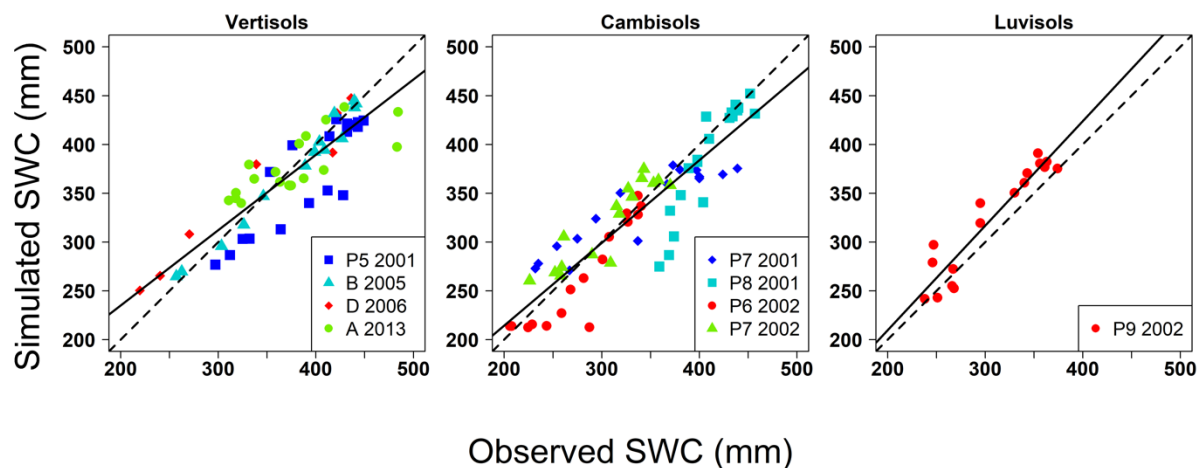
**Table 10.** Statistical indicators when comparing simulations against observations for soil water content (SWC) on a crop type basis.  $n$  is the observation number.  $R^2$  is the correlation coefficient. The  $t$  test corresponds to the  $p$  values of the Student's  $t$  test. The statistical indicators RMSE, NRMSE and MBE are defined in Section 3.4.

Crop	Var	n	$R^2$ (-)	Offset (mm)		Slope (-)		RMSE (mm)	NRMSE (%)	MBE (mm)
				Value	t test	Value	t test			



<b>Wheat</b>	SWC	52	0.77	113.86	0	0.68	0	30.93	9	5.33
<b>Oats</b>		30	0.95	-21.70	0.14	1.04	0.33	18.51	6	-8.05
<b>Barley</b>		7	0.95	72.63	0.05	0.84	0.11	28.17	8	18.71
<b>Faba</b>		55	0.76	48.99	0.05	0.84	0.01	31.98	9	-11.71

580 The comparison between simulated and in situ measurements of SWC (Fig. 10 and Table 11),  
581 for each soil class, showed that the model well simulated SWC for the 3 soil classes, with a  
582 trend to underestimate observations for Vertisols and Cambisols and overestimate observations  
583 for Luvisols. The  $R^2$  values were above 0.79, with a relative variation of approximately 12%  
584 across the three soil classes. The RMSE values ranged from 25 mm to 30 mm, and the regres-  
585 sion slopes were lower than one, apart from Luvisols. For Luvisols, the t test provided p value  
586 larger than 5%. For Vertisols and Cambisols, the t test provided p values lower than 5%.



588 **Fig. 10.** Comparison between simulated and observed soil water content (SWC) on a soil  
589 class basis. Each scatterplot corresponds to a soil class for several plots, years and crops.  
590 Each dataset is indicated by a different marker and a different colour. Px, A, B, D relates to  
591 plots and YYYY to years. The black line corresponds to the regression line, and the black  
592 dashed line corresponds to the 1:1 line.

594 **Table 11.** Statistical indicators when comparing simulations against observations for soil wa-  
 595 ter content (SWC) on a soil class basis.  $n$  is the observation number.  $R^2$  is the correlation co-  
 596 efficient. The  $t$  test corresponds to the  $p$  values of the Student's  $t$  test. The statistical indica-  
 597 tors RMSE, NRMSE and MBE are defined in Section 3.4.

Soil	Var	n	$R^2$ (-)	Offset (mm)		Slope (-)		RMSE (mm)	NRMSE (%)	MBE (mm)
				Value	t test	Value	t test			
Vertisols	SWC	59	0.79	80.77	0	0.77	0	28.41	8	-5.37
Cambisols		68	0.82	44.75	0.01	0.85	0	30.51	9	-6.69
Luvisols		17	0.89	-4.38	0.89	1.07	0.48	25.30	8	17.29

## 598 5. Discussion

### 599 5.1. Canopy cover (CC)

600 The large RMSE and NRMSE values on CC were ascribed to an overestimation of CC obser-  
 601 vations by AquaCrop simulations throughout the senescence phase. This overestimation could  
 602 result from the fact that the model disregarded the effect of high temperatures on crop func-  
 603 tioning during the senescence phase (Andarzian et al., 2011). First, AquaCrop accounted for  
 604 the effect of heat stress (low and high temperatures) on the pollination and harvest index only.  
 605 Second, the early senescence we observed was not due to water stress: the seasonal courses of  
 606  $ET_a$  and  $ET_0$  observed for wheat in 2013 in plot A (Fig. SP4) started to diverge as of DAS 140  
 607 (19 Apr 2013), while senescence began at DAS 120 (30 Mar 2013). According to local farmers,  
 608 early or sudden senescence of vegetation after heat waves has been observed in Kamech.  
 609 Other studies reported overestimations of field observations by AquaCrop for CC at the end of  
 610 the crop cycle for wheat in arid / semiarid climates, with lower magnitudes (Andarzian et al.,  
 611 2011; Sghaier et al., 2014; Toumi et al., 2016). Beyond such differences during the senescence,  
 612 the method used to convert LAI to CC for cereals might be an additional source of uncertainty,  
 613 since the conversion was calibrated on hemispherical photos and applied on planimetric meas-  
 614 urements, both observation types leading to physical differences (Jonckheere et al (2005).

## 615 5.2. Aboveground Biomass (AGB)

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2  
3 616 AquaCrop simulated AGB well, with an overestimation trend at the end of the crop cycle (e.g.,  
4  
5 617 faba bean, Fig. SP3). This could be ascribed to the overestimation of CC observations by Aq-  
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7  
8 618 uaCrop simulations during the senescence phase in relation to a possible delay in senescence  
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10 619 by model simulations. For faba bean plot P5 in 2001, this could not be shown due to the lack  
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12 620 of CC measurements at the end of the crop cycle. However, Fig. SP2 indicates a recurrent  
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14  
15 621 overestimation of CC observations by AquaCrop simulations at the end of the crop cycle for  
16  
17 622 different crop types and soil classes. Other studies have reported an overestimation of AGB  
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19  
20 623 observations by AquaCrop simulations, either at the end of the crop cycle (Katerji et al., 2013;  
21  
22 624 Ahmadi et al., 2015; Sandhu and Irmak, 2019) or during the growth phase (Sghaier et al., 2014).

## 25 625 5.3. Actual evapotranspiration (ET<sub>a</sub>)

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27  
28 626 AquaCrop showed acceptable performance in simulating ET<sub>a</sub> for wheat and oats, with a trend  
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30  
31 627 to slightly overestimate observations. The overestimation of ET<sub>a</sub> from DAS 130 (9 April 2013)  
32  
33 628 for wheat and DAS 140 (3 May 2005) for oats could be related to the overestimation of CC  
34  
35  
36 629 observations during the senescence. Masasi et al. (2019) reported a similar trend for sorghum  
37  
38 630 in a semiarid climate, and they suspected large atmospheric evaporative demand and poor char-  
39  
40  
41 631 acterizations of soil hydrodynamic parameters. Despite this overestimation in ET<sub>a</sub>, AquaCrop  
42  
43 632 well reproduced the divergence between ET<sub>a</sub> and ET<sub>0</sub> courses at the end of the crop cycle.

44  
45  
46 633 The differences between simulated and observed ET<sub>a</sub> values could also be due to (1) the eddy  
47  
48 634 covariance measurements that tend to underestimate ET<sub>a</sub> (Boudhina et al., 2019; Leuning et  
49  
50  
51 635 al., 2012), and (2) the reconstruction of missing ET<sub>a</sub> data that induces uncertainties (Boudhina  
52  
53 636 et al., 2018; Zitouna-Chebbi et al., 2018). Besides, Katerji et al. (2013) recalled that the ET<sub>a</sub>  
54  
55  
56 637 calculation method in AquaCrop has been subject to several criticisms, especially when applied  
57  
58 638 in semiarid Mediterranean regions (Katerji and Rana, 2006; Lovelli et al., 2007). A first source  
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639 of error is assuming a constant surface resistance, since several studies in semiarid and arid  
640 regions have shown that it leads to underestimating  $ET_0$  compared to lysimeter measurements  
641 (Katerji and Rana 2006). A second source of error is using the default value proposed by Allen  
642 et al. (1998) for cultural coefficient  $K_c$ , since several works reported differences up to 40%  
643 between this value and those observed in situ (Katerji and Rana 2006).

644 In contrast to the present study, previous works reported an underestimation for  $ET_a$  by Aqua-  
645 Crop for maize and tomato (Katerji et al., 2013) and for wheat (Toumi et al., 2016) in a Medi-  
646 terranean climate. No explanation could be found for this contradiction. For two calibration  
647 plots, Toumi et al. (2016) reported RMSE values of  $0.47 \text{ mm day}^{-1}$  and  $0.69 \text{ mm day}^{-1}$ , which  
648 were similar to the RMSE value found in the current study for wheat in 2013 in plot A.

#### 649 **5.4. Runoff (R)**

650 For wheat in plot P7 in 2001, wheat in plot P9 in 2002, and oat in plot P6 in 2002, AquaCrop  
651 simulated significant runoff values on DAS 19 (3 Dec 2000), DAS 2 (13 Dec 2001), and DAS  
652 12 (11 Dec 2001), respectively. However, we could not evaluate AquaCrop simulations before  
653 the second half of December, due to the lack of in situ measurements. However, it was possible  
654 to verify the potential occurrence of runoff. According to Mekki (2003), rainfall greater than  
655  $20 \text{ mm day}^{-1}$  is likely to generate runoff, regardless of surface conditions. Thus, the rainfall  
656 recorded on DAS 19 for plot P7 in 2001, DAS 2 for plot P9 in 2002, and DAS 12 for plot P6  
657 in 2002 were equal to 40 mm, 20 mm, and 28 mm, respectively (data not shown), which could  
658 have produced runoff. This was also consistent with the slight increase of outlet lake level in  
659 early December (compared to mid-November, data not shown). Overall, the runoff simulations  
660 by AquaCrop early in the crop cycle were consistent with observations and expert knowledge.  
661 For wheat in plot P9 in 2002 (DAS 10, 21 Dec 2001), wheat in plot A in 2013 (DAS 9, 09 Dec  
662 2012), and oats in plot P6 in 2002 (DAS 20, 19 Dec 2001), we noted large values of model-

663 simulated runoff early in the crop cycle, but we did not observe coincident runoff events from  
664 field observations. We observed the same difference between simulated and unobserved peak  
665 runoff at the end of the crop cycle, for wheat in 2013 in plot A and for oats in 2002 in plot P6.  
666 This could be explained by the presence of shrinkage cracks, which are known to generate  
667 preferential infiltration at the expense of runoff (Inoubli et al., 2017).

668 Wolka et al (2021) reported one of the few assessments on the ability of AquaCrop to simulate  
669 runoff. They noted that AquaCrop simulated runoff with RMSE values ranging from 9.8 mm  
670 to 61.5 mm. However, it was difficult to compare these results with ours, because of larger  
671 rainfall and runoff accumulations for Wolka et al. (2021).

## 672 **5.5. Soil water content (SWC)**

673 AquaCrop showed good performance in simulating soil water content. For oats, the underesti-  
674 mation of SWC observations was ascribed to the overestimations of  $ET_a$  and runoff. The dif-  
675 ferences between simulations and observations could be due to (1) inaccurate soil moisture  
676 initialisations, (2) poor characterizations of soil hydrodynamic properties (HWP and HFC) and  
677 (3) inadequate AquaCrop formalisms when simulating water fluxes ( $ET_a$ , runoff, drainage).  
678 Additionally, disregarding capillary rise was not critical because most plots were located at  
679 slope tops and therefore relatively far from possible shallow aquifers. Overall, the errors in  
680 SWC simulations were ascribed to the characterization of soil hydrodynamic properties (HWP  
681 and HFC), given the accuracies of AquaCrop simulations for water fluxes and crop variables.  
682 Previous studies reported overestimations of SWC observations by AquaCrop simulations, no-  
683 tably for wheat (Andarzian et al., 2011), maize (Nyakudya and Stroosnijder, 2014) and barley  
684 (El Mokh et al., 2017). These overestimations were often noticed during dry periods, which  
685 can be explained by constraints on SWC, since the latter cannot drop below HWP.

## 686 **5.6. Analysis by crop type and soil class**

687 When dealing with AquaCrop performance according to crop type, AquaCrop could be used  
688 for predicting crop growth and biomass production. Oat crops could be used as animal fodder,  
689 which is a common practice within Kamech and the surrounding region, with subsequent graz-  
690 ing and cutting operations throughout the crop cycle. However, AquaCrop does not account  
691 for the dynamics of the crop canopy induced by such agricultural practices. Nyathi et al (2018)  
692 tried to parameterize this practice for leafy vegetables, by performing independent simulations  
693 for any crop and assuming that the initial canopy cover (CC0) was reset according to the re-  
694 maining canopy cover (from 1 to 2%) after each harvest.

695 When dealing with AquaCrop performance according to soil class, the analysis of model sim-  
696 ulations permitted us to draw partial conclusions only. The analysis of the model outputs for  
697 the AGB and SWC showed an acceptable performance in simulating these two variables across  
698 all soil classes. For runoff and CC, the best results were observed with Vertisols and Cambisols,  
699 respectively. For  $ET_a$ , for which we had measurements on Vertisols only, no conclusion can be  
700 drawn regarding AquaCrop performance according to soil class.

701 When dealing with linear regressions on validation for both crop types and soil classes, the  
702 t test provided p values larger than 5% for most cases (e.g., AGB, CC, SWC), which indicated  
703 that AquaCrop performances could be considered satisfactory. For some crop/soil combina-  
704 tions, the t test provided p values lower than 5% (e.g.,  $ET_a$ , R, SWC), although the offset re-  
705 mained relatively low (e.g.,  $ET_a$  and SWC offset for oats and Cambisols, respectively).

## 706 **5.7. Main outcomes**

707 To our knowledge, the present work is the first study using AquaCrop for faba bean and oats  
708 in a semiarid Mediterranean climate. According to the results we obtained, AquaCrop can ac-  
709 ceptably simulate the functioning of these two crops by using crop parameters available in the

1  
2 710 literature. Additionally, AquaCrop simulations are acceptable for various combinations of soils  
3 711 and crops across contrasted hydroclimatic years.  
4

5 712 Although there were gaps in database on which the current study relied, it was rich enough to  
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7 713 draw several lessons. According to the results we obtained, the model performance was closely  
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9 714 related to the formalism used for simulations. AquaCrop showed good performance in simu-  
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11 715 lating biomass and soil water content for all crops, on the basis of parameterizations and forcing  
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13 716 (1) that were as adequate as possible for the crops and soils to be studied, and (2) that were in  
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15 717 line with literature recommendations. The performance of the model was moderate for the sim-  
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17 718 ulation of CC, with a possible delay in senescence for most of the crops we addressed. The  
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19 719 model showed acceptable performance in simulating  $ET_a$ , although it was delicate to conclude  
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21 720 according to the dataset size (2 years - plots).  
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27 721 Runoff was poorly simulated at both the beginning and end of the crop cycle because of shrink-  
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29 722 age cracks for clay soils. Soil cracking is a complex phenomenon that is very difficult to include  
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31 723 in numerical modelling, especially in simplified models. Runoff simulations were acceptable  
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33 724 for the other stages of the crop cycle when the cracks were closed. Despite this, the simulations  
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35 725 were acceptable to simulate the dynamics of soil water content and crop variables (AGB), as  
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37 726 shown in Figs. 4-5-9-10 and Tabs 5-6-10-11, which was ascribed to the moderate influence of  
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39 727 runoff on the soil water balance. However, in the perspective of agro-hydrological studies that  
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41 728 require the consideration of lateral fluxes between the different components of the cultivated  
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43 729 landscape (Van Loo and Verstraeten, 2021), the runoff modelling by AquaCrop was no longer  
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45 730 acceptable for our study site, and it will be necessary to consider a more realistic runoff-infil-  
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50 731 tration partitioning model.  
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## 54 732 **6. Conclusion**

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1 733 For some soil/crop combinations that have been little studied to date, AquaCrop can acceptably  
2 734 simulate their functioning in terms of vegetation growth and water consumption, as well as in  
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4 735 terms of soil water balance, by using parameters available in the literature. Additionally, Aq-  
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7 736 uaCrop can simultaneously simulate several variables in an acceptable manner, namely, above-  
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10 737 ground biomass, evapotranspiration, and soil water content. We highlight some limitations of  
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12 738 AquaCrop in terms of vegetation cover and runoff in relation to delayed senescence and disre-  
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15 739 gard of swelling soils, respectively.

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17 740 The results of the current study are in good agreement with those reported in the literature,  
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20 741 knowing that the previous studies mainly addressed flat terrains. Our study also showed that  
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22 742 AquaCrop was able to acceptably simulate crop dynamics and water fluxes for contrasted hy-  
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25 743 droclimatic years, with a slight dependence on soil class and a significant dependence on crop  
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27 744 type, including large differences from one variable to another.

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30 745 Our results open the path for further use of AquaCrop in the Mediterranean context, on which  
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32 746 we focused, with forthcoming efforts on water availability and water productivity in relation  
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34  
35 747 to plot hydrological connectivities within hilly terrains.

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## 1 **Supplementary materials - Section 1: materials and methods - soil parameters**

2 Different approaches are proposed in the literature to determine soil moisture at wilting point  
3 (HWP) and at field capacity (HFC), including (1) pedotransfer functions (e.g., Saxton and  
4 Rawls, 2006) based on the texture of different soil horizons, (2) direct laboratory measurements  
5 from soil samples (Cassel and Nielsen, 1986) and (3) the agroclimatic method which determines  
6 HFC and HWP from soil moisture time series throughout the crop growth cycle (Sreelash et al.,  
7 2017).

8 According to expert knowledge about the soil conditions within our study site (Revaillot et al.,  
9 2021), the pedotransfer functions are not suitable for the Kamech soils, since the latter are  
10 typified by large instability due to poor silt structure. Therefore, we determine HWP and HFC  
11 using the laboratory method and the agroclimatic method, and we compared the resulting  
12 estimates in order to choose the most reliable ones.

13 For all plots, we had laboratory measurements of HFC and HWP carried out either on the plots  
14 or on neighbouring plots, along with soil moisture data. For the agroclimatic method proposed  
15 by Sreelash et al. (2017), HFC corresponds to the maximum soil moisture value without  
16 considering measurements after rainfalls or irrigation events, and HWP corresponds to the 5<sup>th</sup>  
17 percentile of the minimum soil moisture measured throughout the crop growth cycle. To  
18 determine HFC and HWP by the agroclimatic method, we used all soil moisture data available  
19 for each of the eight plots, beyond the datasets used for AquaCrop evaluation. This led to  
20 include additional soil moisture data from 2002 on plot P5 and P8, from 2001 and plot P6 and  
21 P9, and from 2006 on plot A. All the soil moisture measurements we considered were collected  
22 using the same protocol described in the Section 3.3.6 of the article. For HFC, we assumed that  
23 a rainfall accumulation lower than 10 mm does not have a large influence, and we therefore  
24 excluded all measurements for which a rainfall accumulation larger than 10 mm was recorded  
25 in the previous 48 hours. For HWP, we take the 5th percentile of the minimum value measured  
26 throughout the crop growth cycle.

27 Table SP1 presents, for each plot, HWP and HFC estimates by laboratory measurements (Lab),  
28 and by the agroclimatic method (AC), as well as the relative difference  $\Delta$  calculated as:

$$29 \quad \Delta = \frac{AC - Lab}{Lab} \quad (\text{Equation SP1})$$

30 where AC (respectively Lab) represents the HWP or HFC estimates by the agroclimatic method  
31 (respectively the laboratory method).

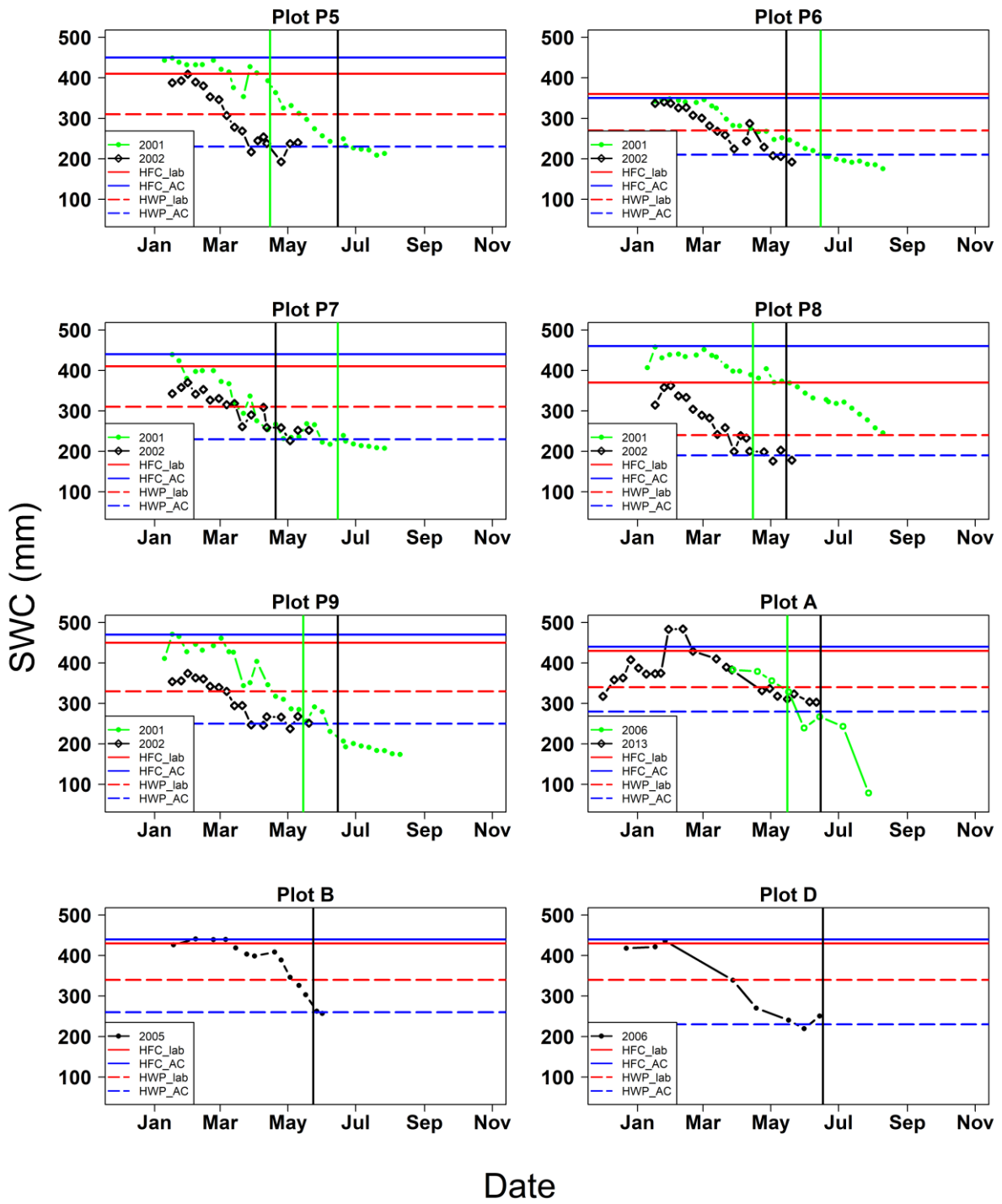
32 Table SP1 shows that HWP estimates from the agroclimatic method underestimated those from  
 33 the laboratory method, with values of relative difference  $\Delta$  between -26% and -18%, apart from  
 34 plot D (32%). For HFC, the differences between the two methods were small, with values of  
 35 relative difference  $\Delta$  between -3% and 10%, apart from plot P8 (24%). In this case, HFC  
 36 estimates from the agroclimatic method overestimated those from the laboratory method, apart  
 37 from plot P6.

38 **Table SP1.** Comparison between soil moisture at wilting point (HWP) and soil moisture at  
 39 field capacity (HFC) estimates by the laboratory measurements (Lab) and the agroclimatic  
 40 method (AC) methods.

	HWP			HFC		
	AC (m <sup>3</sup> /m <sup>3</sup> )	lab (m <sup>3</sup> /m <sup>3</sup> )	$\Delta$ (%)	AC (m <sup>3</sup> /m <sup>3</sup> )	lab (m <sup>3</sup> /m <sup>3</sup> )	$\Delta$ (%)
<b>P5</b>	0.23	0.31	-26	0.45	0.41	10
<b>P6</b>	0.21	0.27	-22	0.35	0.36	-3
<b>P7</b>	0.23	0.31	-26	0.44	0.41	7
<b>P8</b>	0.19	0.24	-21	0.46	0.37	24
<b>P9</b>	0.25	0.33	-24	0.47	0.45	4
<b>A</b>	0.28	0.34	-18	0.44	0.43	2
<b>B</b>	0.26	0.34	-24	0.44	0.43	2
<b>D</b>	0.23	0.34	-32	0.44	0.43	2

41 Fig. SP1 displays the times series of soil moisture measurements, as well as the HFC and HWP  
 42 estimates from (1) the laboratory measurements (HWP-lab and HFC-lab), and (2) the  
 43 agroclimatic method (HWP-AC and HFC-AC) for each of all plots. Fig. SP1 shows that, apart  
 44 from plot A, the soil moisture measurements before the harvest dates reach lower levels than  
 45 the HWP estimates from the laboratory measurements.

46 As a result, we selected the estimates from the agroclimatic method for all plots apart from plot  
 47 A. For plot A, the differences between estimates from both methods were very low  
 48 (10% relative, comparable to measurement errors), and we selected the estimates from  
 49 laboratory measurements that were collected in the framework of the OMERE observatory.



51

52 **Fig. SP1.** Time series of soil moisture data (dotted lines) for each of the eight plots. The  
 53 horizontal lines indicate the soil moisture at wilting point (HWP) and soil moisture at field  
 54 capacity (HFC) estimates from the laboratory measurements (Lab) (red lines) and  
 55 agroclimatic method (AC) (blue lines) methods. The vertical lines indicate the harvest dates.

56



57 **Supplementary materials - Section 2: Materials and methods – Vegetation**

58 When dealing with growth cycle of cereals (wheat, barley, oats), we could use leaf area index  
59 (LAI) measurements performed with planimeters. In order to validate the AquaCrop  
60 simulations of canopy cover (CC), we used Equation SP2 to convert planimetry-based LAI data  
61 into CC, considering that this equation had been used in many studies (Araya et al., 2010; Abrha  
62 et al., 2012; Yuan et al., 2013; Pereira et al., 2015; Zeleke, 2019):

63 
$$CC = 1 - e^{(-k \times LAI)} \quad \text{(Equation SP2)}$$

64 The coefficient k is an extinction coefficient related to the interception of light by crop canopy  
65 cover (Jeuffroy and Ney, 1997; Pereira et al., 2015). It varies according to crop and variety.  
66 Different values of k have been proposed in literature for a given crop. For example, the  
67 proposed values for barley are k = 0.5 (Pereira et al., 2015), k = 0.48 (Belhouchette et al., 2008)  
68 and k = 0.65 (Abrha et al., 2012). For wheat, (Jin et al., 2014) proposed a k value of 0.65.

69 To determine a k value that was suitable to our conditions, we used hemispherical photos that  
70 permitted to simultaneously estimate LAI and CC. These photos were collected between 2018  
71 and 2020 thanks to a camera equipped with a fisheye objective. Within each plot, between 10  
72 and 15 photos were collected in a random manner. Table SP2 summarises the number of plots  
73 and measurements available per crop.

74 **Table SP2.** Number of plots and hemispherical photos available for each crop, to be used for  
75 determining the value of coefficient k in Equation SP2.

<b>Crop</b>	<b>Years</b>	<b>Plot number</b>	<b>Measurements number</b>
<b>Wheat</b>	2018 - 2019 - 2020	8	42
<b>Barley</b>	2019 - 2020	2	10
<b>Oats</b>	2020	1	4

76 The hemispherical photos were treated with the CAN-EYE software (Weiss et al., 2008) to  
77 derive first gap fraction, and then LAI and CC. CAN-EYE permitted to distinguish two types  
78 of LAI, namely (1) effective LAI that accounts for leaf aggregation, and (2) true LAI that  
79 corresponds to actual leaf surface. The different LAI estimates proposed by CAN-EYE are  
80 discussed in Weiss et al. (2008).

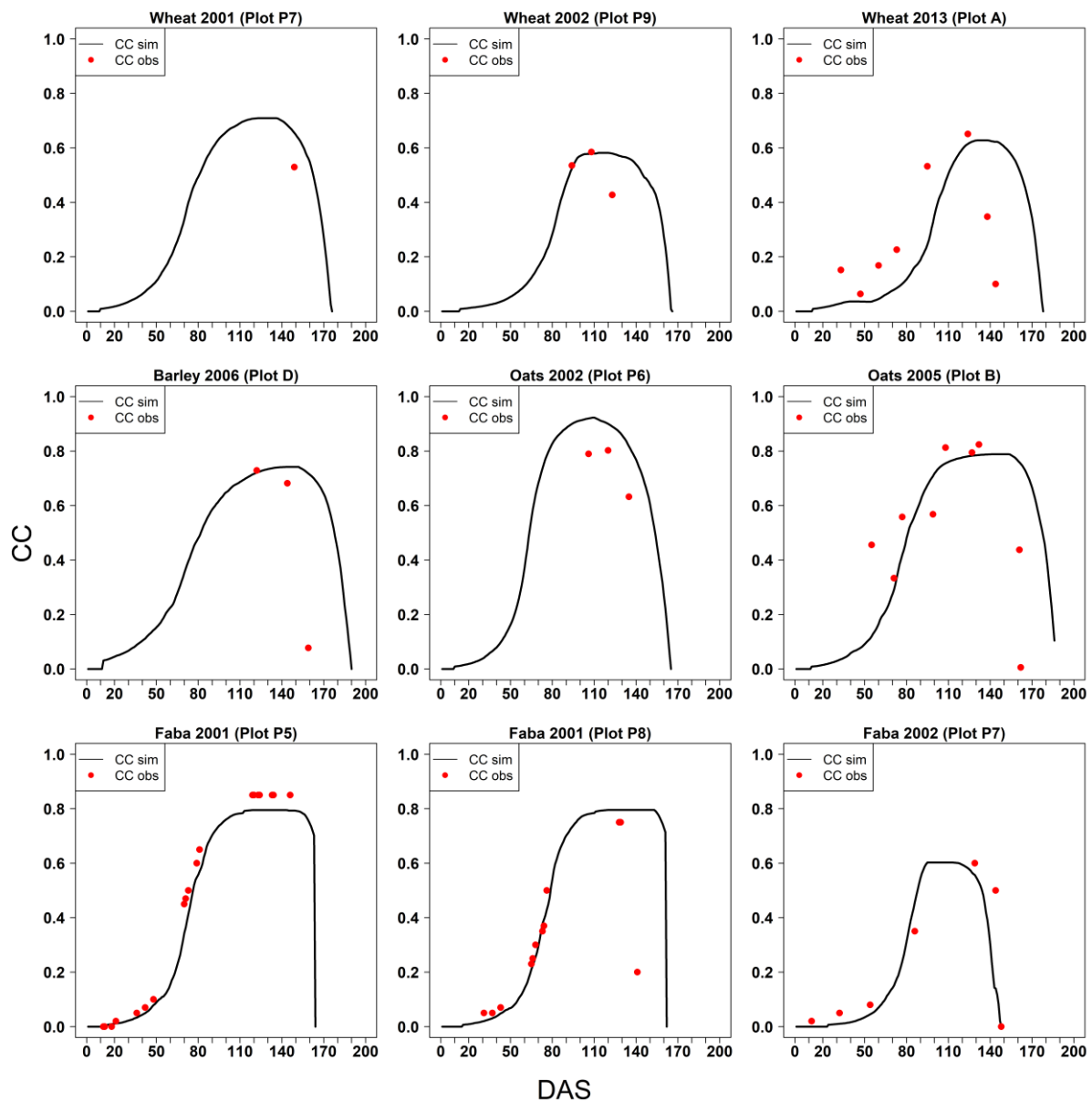
- 81 • On the one hand, planimetry is a direct and destructive technique for determining leaf area  
82 index of any crop canopy. It permits the calculation of actual LAI from direct area  
83 measurements.

- 84 • On the other hand, hemispherical photography is an indirect, non-destructive technique that  
85 permits a significant spatiotemporal sampling of crop canopy within field and throughout  
86 the crop growth cycle. It includes other plant green elements such as stems, which  
87 corresponds to Plant Area Index (PAI) rather than LAI.
- 88 • The goal here was to convert planimetric measurements of LAI into CC estimates by using  
89 Equation SP2. When estimating LAI from hemispherical photos, it was necessary to select  
90 the CAN-EYE method that provided LAI estimates as close as possible to the planimetric  
91 method. According to Weiss et al (2008), the true LAI calculated by CAN-EYE is the  
92 closest to the planimetric LAI, although the relationship between true LAI measured by  
93 CAN-EYE and planimetric LAI depends on crop and phenological stage (Demarez et al.,  
94 2008; Fang et al., 2018). Therefore, we choose true LAI for equation SP2.

95 For the present study, we decided to set a single  $k$  value for cereals (wheat, barley and oats),  
96 equal to 0.57 ( $R^2 = 0.95$ ;  $RMSE = 0.05$ ). Indeed, the coefficient of variation between the  
97 different  $k$  values across cereal crops was about 15%, thus comparable to the measurement error  
98 (Weiss et al., 2008). Moreover, the three cereal crops we considered were straw cereals with  
99 similar leaf geometry that induces similar radiative transfer processes within the canopy.

100

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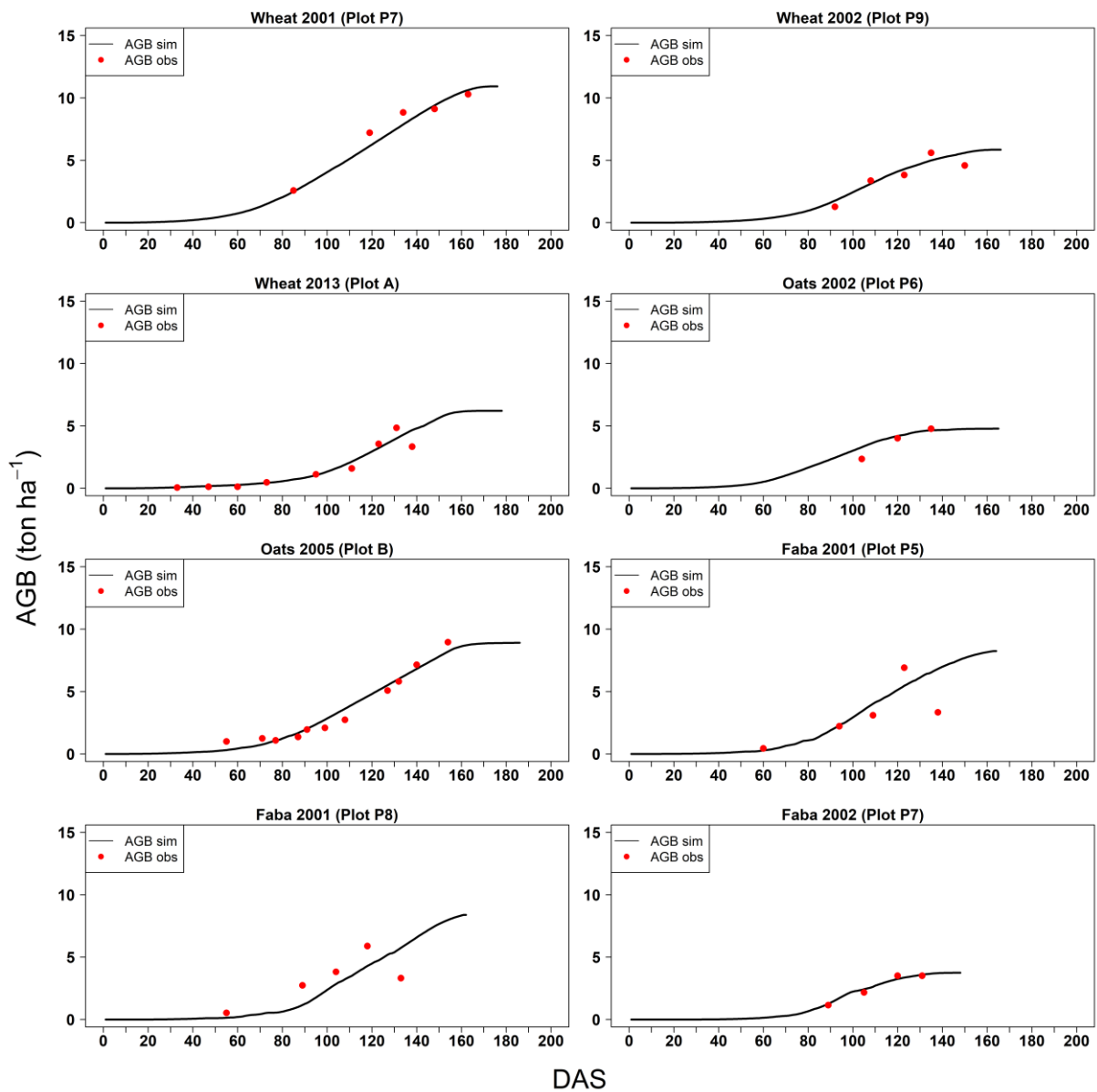


103

104 **Fig. SP2.** Temporal evolution of canopy cover (CC) for each dataset when available. The red  
 105 points correspond to the ground-based observations, and the black curves correspond to the  
 106 AquaCrop simulations. DAS stands for Day after Sowing.

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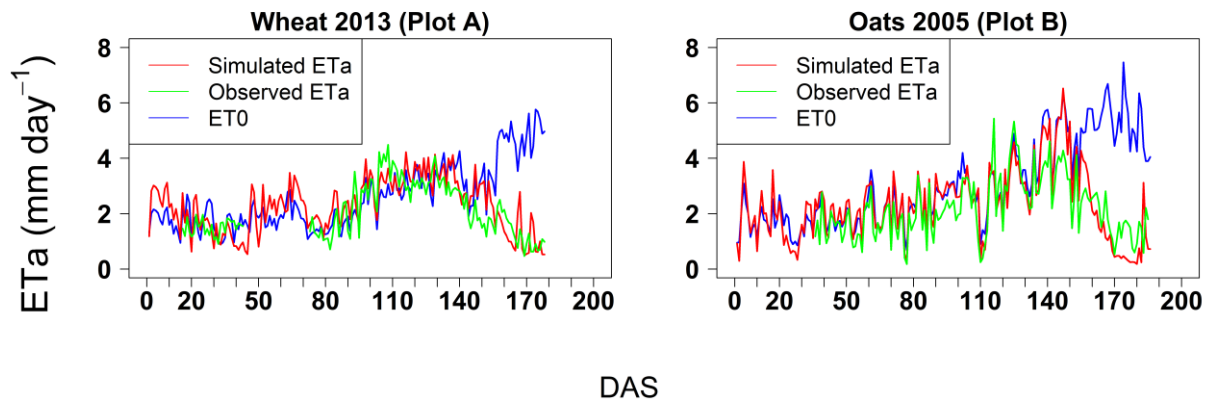
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111 **Fig. SP3.** Temporal evolution of Aboveground biomass (AGB) for each dataset when  
 112 available. The red points correspond to observations and the black curve corresponds to  
 113 AquaCrop simulations. DAS stands for Day after Sowing.

114

115 **Supplementary materials - Section 5. Results - actual evapotranspiration (ETa)**

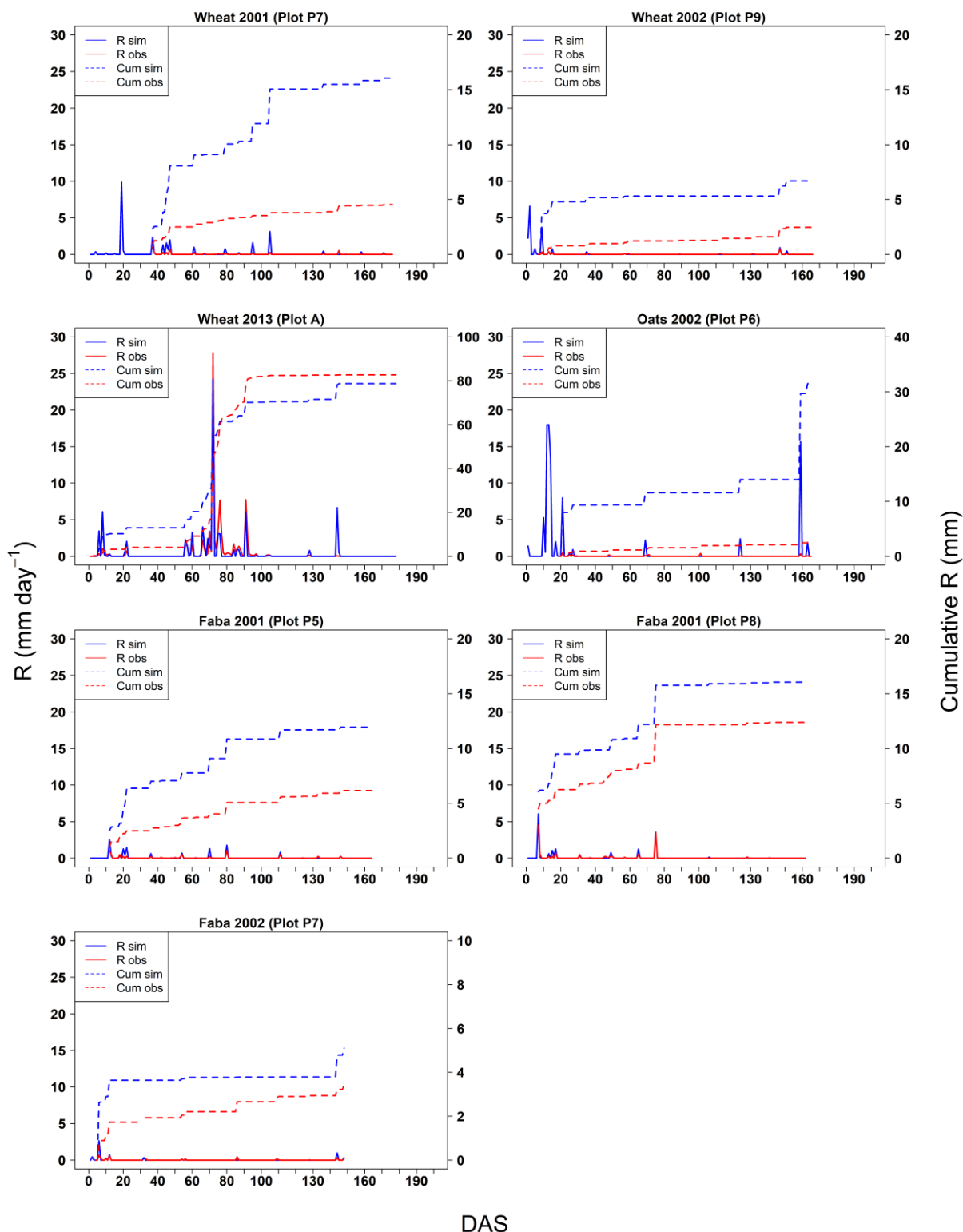
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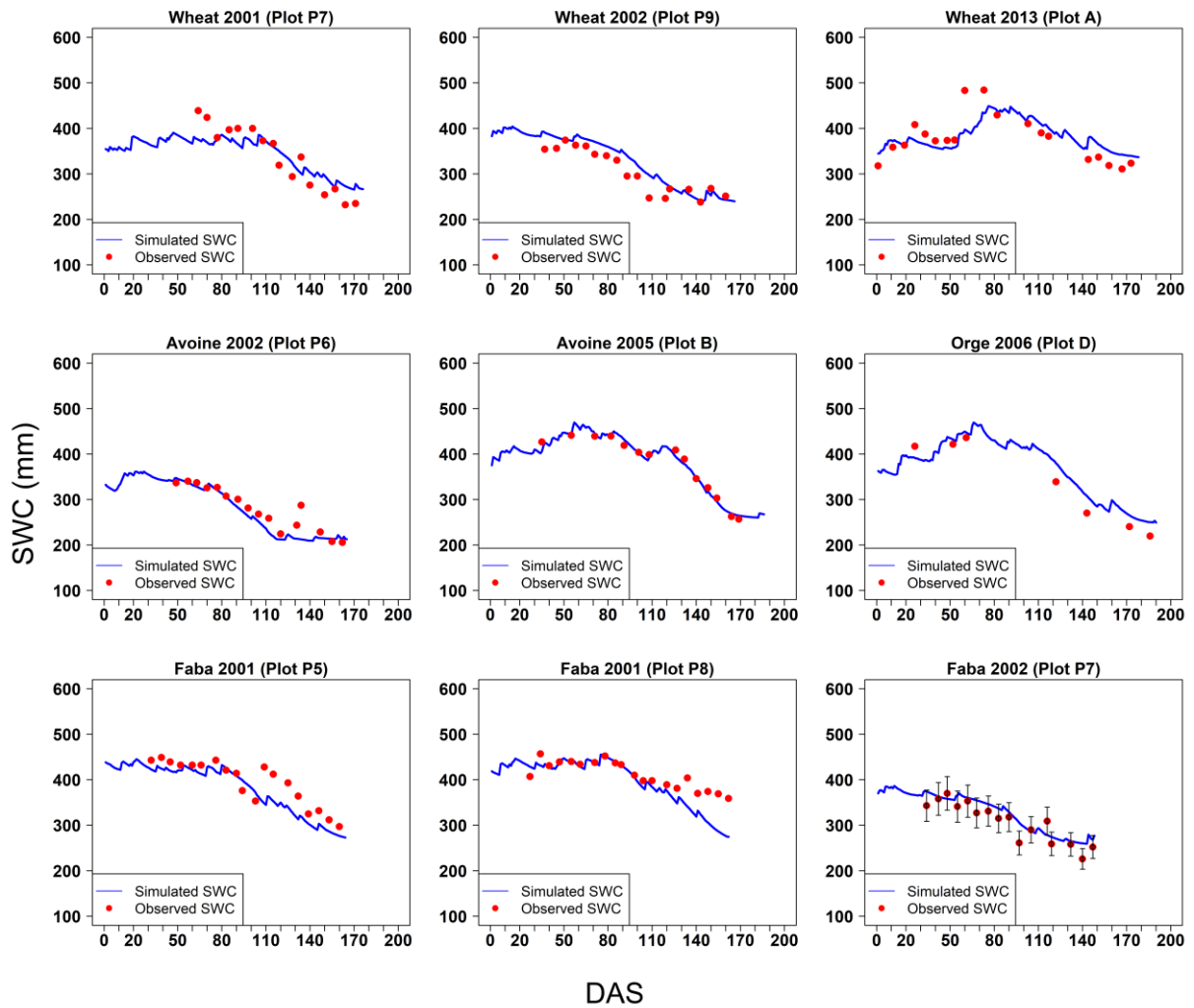
118 **Fig. SP4.** Temporal evolution of actual evapotranspiration (ETa) for each dataset when  
119 available. The red curve corresponds to ETa simulated by AquaCrop, the green curve  
120 corresponds to ETa measured in-situ by eddy covariance and the blue curve corresponds to  
121 reference evapotranspiration ET0. DAS stands for Day after Sowing.

122



124

125 **Fig. SP5.** Temporal evolution of runoff (R) for each dataset when available. The solid lines  
 126 represent the temporal evolution of R. The dashed lines represent R accumulation. The blue  
 127 colour indicates the simulations and the red colour indicates the observations. DAS stands for  
 128 Day after Sowing. Y-Scales are chosen for both reading and intercomparing.



130

131 **Fig. SP6.** Temporal evolution of soil water content (SWC) for each dataset. The red points  
 132 correspond to SWC observations, and the blue curves correspond to the AquaCrop  
 133 simulations. DAS stands for Day after Sowing.

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