water

MDPI

Article

Irrigation-Advisor—A Decision Support System for Irrigation of Vegetable Crops

José M. Mirás-Avalos [1],* , **José S. Rubio-Asensio [1]**, **Juan M. Ramírez-Cuesta [1]** ,
José F. Maestre-Valero [2] and Diego S. Intrigliolo [1,3]

[1] Centro de Edafología y Biología Aplicada del Segura (CEBAS), Consejo Superior de Investigaciones
Científicas (CSIC), Espinardo, 30100 Murcia, Spain; jsrubio@cebas.csic.es (J.S.R.-A.);
ramirezcuesta.jm@gmail.com (J.M.R.-C.); dintri@cebas.csic.es (D.S.I.)

[2] Escuela Técnica Superior de Ingeniería Agronómica, Universidad Politécnica de Cartagena, Paseo Alfonso
XIII 48, 30203 Cartagena, Spain; josef.maestre@upct.es

[3] Instituto Valenciano de Investigaciones Agrarias (IVIA), Centro Desarrollo Agricultura Sostenible (CEDAS),
Unidad asociada al CSIC "Riego en la agricultura mediterránea", Apartado Oficial, 46113 Moncada,
Valencia, Spain

* Correspondence: jose.manuel.miras.avalos@xunta.es

check for updates

Abstract: Climate change will intensify water scarcity, and therefore irrigation must be adapted
to save water. Operational tools that provide watering recommendations to end-users are needed.
This work presents a new tool, Irrigation-Advisor (IA), which is based on weather forecasts and is
able to separately determine soil evaporation and crop transpiration, and thus is adaptable to a broad
range of agricultural situations. By calculating several statistical indicators, IA was tested against the
FAO-56 crop evapotranspiration (ET_cFAO) methodology using local crop coefficients. Additionally,
IA recommendations were compared with current standard practices by experienced farmers (F).
Six field experiments with four widely cultivated species (endive, lettuce, muskmelon and potato)
were performed in Southeast Spain. Irrigation water applied, crop yield, aboveground biomass and
water productivity were determined. Crop water needs underestimations (5%–20%) were detected
when comparing IA against ET_cFAO, although the index of agreement proved reasonable adjustments.
The IA recommendations led to water savings up to 13% when compared to F, except for lettuce, with a
31% surplus in irrigation when using IA. Crop yield was not compromised and water productivity
was increased by IA. Therefore, IA mimicked the farmers' irrigation strategies fairly well without
deploying sensors on-site. Nevertheless, improvements are needed for increasing the accuracy of
IA estimations.

Keywords: evapotranspiration; modeling; soil water balance; water-use efficiency; weather forecasts

1. Introduction

Agriculture is the largest consumer of freshwater worldwide, accounting for 70% of water
withdrawals, representing 2.7 Mhm^3 annually used to irrigate 324 Mha (8300 m^3 ha^{-1}) [1]. It is
noticeable that this water volume has multiplied by three since 1950 in order to provide food for the
population, as irrigated agriculture produces 40% of the world's food while employing only 20% of
cultivated land [2]. In addition, climate change is reducing the freshwater availability, increasing the
competition for the available water resources among the different users [3]. Therefore, an accurate
determination of crop water requirements is essential to perform an optimal irrigation schedule and
increase crop yields, water use efficiency and farm profits, while reducing costs and energy use and at
the same time preventing surface and groundwater pollution [4,5].

In order to determine crop water requirements, most farmers and irrigation-advising websites have often used the one-layer methodology proposed by Allen et al. [6], Food and Agriculture Organization of the United Nations (FAO) Irrigation and Drainage paper No. 56 (FAO-56), which is based on the multiplication of the reference evapotranspiration (ET_o), calculated with the Penman–Monteith approach, by a crop coefficient (K_c) that represents the relative rate of evapotranspiration by a specific crop (ET_c). This method can be considered as a reference due to its extensive use and reliable results, as reported for a great number of crops [7–9]. However, the published K_c can result in poor estimates of crop water requirements [10] due to several reasons. First, the one-layer methodology considers the crop as a single big leaf and cases with partial vegetation cover, such as vegetable crops, might not satisfy completely such a hypothesis [11]; this could be solved by applying the dual-K_c approach that has been developed under FAO-56 [6]. Second, discrepancies exist between the actual crop characteristics (percentage of ground cover, crop height, phenological stage, etc.) and the published K_c [12], which can be overcome by applying adjustment coefficients. Third, the empirical K_c is site-specific [13], although many attempts for determining K_c at the local level have been reported for a great number of crops [14–16]. Finally, the single K_c methodology does not allow for the adaptation to different agricultural practices (e.g., mulching, cover crop) since it considers both evaporation and transpiration together. In order to take into account these issues, the dual-K_c approach [6] in which transpiration (T) is disconnected from the soil's physical conditions related to soil evaporation (E) might improve such estimations [10]. However, discrepancies between the actual crop characteristics and the published K_c and the specificity of the coefficients may still be present [12]. Therefore, modeling approaches overcoming these issues are needed.

Additionally, crop water requirements can be determined on-site by monitoring the energy exchange above the crop surface, as a residual term of the soil water balance (e.g., lysimeters and soil water budget; [11,17], or using soil and plant probes (e.g., soil water content, dendrometers, leaf temperature or sapflow probes) [18]. Overall, these methodologies have been used for research purposes as they are expensive, complex, sometimes require the installation of sophisticated equipment and depend on qualified personnel to obtain reliable results [19]. Moreover, some of these methods provide specific point-based measurements that are often linked to uncertainties, requiring models for scaling up to the whole orchard [16,20]. Consequently, they are not suitable for routine use in orchard water management [10] and hence there is a need for more mechanistic models, which can provide reliable estimates of E and T under a wide range of climatic conditions and management practices.

Nowadays, a high number of tools and decision support systems (DSS) intended for agro-system management exist. For instance, DSSAT, standing for Decision Support System for Agrotechnology Transfer, is a general crop model able to simulate growth, development and yield. There are also some more specific examples for water management such as: System of Participatory Information, Decision-support, and Expert knowledge for River-basin management (SPIDER) [21]; AquaCrop [22]; Automated Radiative Transfer Models Operator (ARTMO) [23]; AquaGIS [24]; VegSyst-DSS [25] and ArcDualKc [16]. However, some of these DSS provide information about aspects not directly related to crop water needs and, usually, they require a high number of inputs and parameters. Additionally, their complexity can limit their use by less specialized users, restricting them to scientific purposes. Furthermore, existent DSS are restricted to herbaceous crops. In this sense, the VegSyst model, which initially was developed for its use in greenhouses, has been successfully adapted to outdoor conditions [26]. This model is able to estimate ET_c for several vegetable crops; however, it is not capable of separating E from T since it uses the FAO-56 approach with a single K_c for calculating crop water requirements, with the particularity of providing K_c from a crop growth model.

One of the limitations of current DSS [22,27–30] is that they do not consider the spatial heterogeneity within the plot, and estimations are referred to a specific point location. This spatial component is captured in other existent tools by the incorporation of remote sensing technology [16,21,24]. However, remotely sensed data can be easily incorporated into some of these models by calculating inputs from satellite or drone-acquired imagery, such as the vegetated fraction cover [31].

In this context, the aim of this work was to develop a simple and operational model, Irrigation-Advisor (IA), that overcomes the issue of depending on site-specific K_c, is able to provide a separate estimation of E and T, is easily adapted to different management situations, and avoids the use of on-the-ground sensors. The viability of IA was tested in six field experiments with four different crops (endive, lettuce, muskmelon and potato) carried out in Southeast Spain.

2. Materials and Methods

2.1. Description of the Model: Irrigation-Advisor

The algorithm developed in the current study, IA, combines equations from different sources in order to avoid the use of empirical K_c (e.g., FAO-56 tabulated values) [6]. The IA model is based on the calculation of a soil water balance in the root zone (60 cm in our case), which is initiated at a given soil water content (SW_0, mm) close to field capacity, a value provided by the user and starting point for calculating the water balance within IA. This simulates a common practice for horticultural crops, namely, to over-irrigate the soil at the beginning of the growing cycle in order to optimize seedling establishment by promoting root growth and development [32]. Irrigation amounts applied aimed at re-establishing this SW_0. The main equation within the model is as follows:

$$SW_t = SW_0 + P + Irr - RO - E - T \tag{1}$$

where P is rainfall, Irr is irrigation, RO is surface runoff, E is direct evaporation from soil, T is plant transpiration and SW_t is soil water content at a given moment over the growing cycle. All variables are expressed in mm and the model runs on a daily basis.

In IA, surface runoff is calculated following the curve number methodology proposed by the United States Department of Agriculture [33]. This simple approach takes into account soil texture, slope of the terrain and the use of measures for preventing soil erosion. These parameters are introduced into the model, which assigns a curve number according to tabulated values [33]. Due to the limitations of this approach, a condition was introduced: when rainfall was less than 7 mm, RO was considered to be zero.

$$RO = \frac{(P - I_a)^2}{(P - I_a + S)} \tag{2}$$

where I_a represents soil water storage, the interception of water by the canopy and infiltration of water in the soil, and S is the retention parameter [33]. All variables are expressed in mm.

Direct evaporation from the soil (E) is computed using the approach proposed by Ritchie [34] that considers the proportion of soil covered by vegetation in order to determine the dynamics of albedo (α) over the growing season and, consequently, the amount of solar radiation falling directly upon the soil.

$$E = \frac{1}{\lambda} \cdot \frac{\Delta}{\Delta + \gamma} \cdot R_{nsoil} \tag{3}$$

where R_{nsoil} is the average net radiation over the soil surface (MJ m^{-2} day^{-1}); λ is the latent heat of evaporation (J kg^{-1}); Δ is the slope of the curve of the saturated vapor pressure versus air mean temperature (kPa °C^{-1}); and γ is the psychrometric constant (kPa °C^{-1}).

Horticultural crops do not cover the entire soil surface during their growing cycle; therefore, the standard value for α (0.23) reported in FAO-56 [6] cannot be used since solar radiation reflectance is not uniform over the field surface. Consequently, RA calculates α, for a growing crop, using this expression [6]:

$$\alpha = C \cdot \alpha_c + (1 - C) \cdot \alpha_s \tag{4}$$

where C is the fraction of soil covered by the crop at a given moment of the growing cycle (considered in FAO-56 with a cover crop adjustment factor [4], making this approach more difficult to use); α_c is the albedo for the crop (0.23) and α_s is the albedo for the bare soil (0.17) [35]. Then, short-wave net

radiation is calculated by multiplying this albedo by the radiation either forecasted or recorded at a weather station; while long-wave radiation was calculated according to Allen et al. [6]. Finally, net radiation is calculated as the difference between short- and long-wave net radiations.

In addition, the evolution of crop growth over the season and its effect on the solar radiation reaching the soil is considered in the calculation of R_{nsoil} by using the leaf area index (*LAI*) at a given moment of the growing cycle:

$$R_{nsoil} = R_n \cdot \exp^{-k \cdot LAI} \tag{5}$$

where R_n is the net radiation (MJ m^{-2} day^{-1}); k is the light extinction coefficient of the crop [36] and *LAI* is the leaf area index at a given moment of the growing cycle.

Plant transpiration (*T*) is calculated separately using the approach described by Rana and Katerji [37], in which the main equation is the following:

$$T = \frac{1}{\lambda} \cdot \frac{\Delta A + \rho c_p D / r_a}{\Delta + \gamma \left(1 + \frac{r_c}{r_a}\right)} \tag{6}$$

where $A = R_n - R_{nsoil}$ is the available energy for transpiration (MJ m^{-2} day^{-1}); ρ is air density (kg m^{-3}); c_p is the specific heat of wet air (J kg^{-1} °C^{-1}); D is air vapor pressure deficit (kPa) at a reference point z; r_c is the resistance of the canopy (s m^{-1}) and r_a is the aerodynamic resistance (s m^{-1}).

The aerodynamic resistance, r_a, is calculated between the top of the crop and a reference point z located at the boundary layer above the canopy [37]:

$$r_a(z) = \frac{\ln \frac{z-d}{z_0} \ln \frac{z-d}{h_c - d}}{k^2 u_z} \tag{7}$$

where d (m) is the zero plane displacement estimated by $d = 0.67 h_c$ [38], with h_c being crop height (m); k is the von Kármán constant (0.41); z_0 is the roughness length estimated by $z_0 = 0.1 h_c$ [38]; and u_z is the wind speed at the reference point z above the canopy. In order to determine r_c, a climatic resistance (r^*, s m^{-1}) is calculated from weather variables including relative humidity, solar radiation and air vapor pressure deficit [37]. Then, the canopy resistance (r_c) is obtained from a linear relationship between two ratios r_c/r_a and r^*/r_a, as reported by Rana and Katerji [37], including two coefficients that depend on crop species [39].

In this study, soil water balance is initiated with a soil water content close to field capacity and each irrigation event is scheduled to restore the total amount of water lost by evaporation and transpiration in order to avoid water stress situations. This is a common agricultural practice in the area, where rainfall is often scarce and the root-zone of the vegetable crops is very shallow, particularly at the beginning of the growing cycle. Therefore, combining the former equations:

$$I = SW_t - SW_0 - P + \frac{(P - I_a)^2}{(P - I_a + S)} + \frac{\Delta}{\Delta + \gamma} R_{ns} + \frac{1}{\lambda} \frac{\Delta R_{nc} + \rho c_p D / r_a}{\Delta + \gamma \left(a \frac{r^*}{r_a} + b + 1\right)}. \tag{8}$$

The result from Equation (8) provides the amount of water (mm) to apply when this is of good quality, namely its salt content is not high enough for causing yield losses. However, Irrigation-Advisor considers the negative effects that salinity may cause on crop yield and calculates a leaching fraction (*LF*) from the electrical conductivity of irrigation water and the tolerance level of the crop [6] according to the following expression:

$$LF = \frac{EC_w}{2 \times (MaxEC_s)} \tag{9}$$

where EC_w is the electrical conductivity of the irrigation water used (dS m^{-1}) and $MaxEC_s$ is the electrical conductivity (dS m^{-1}) of the soil solution that causes 100% reduction in yield. In our case, EC_w values were quite constant within a growing season and are reported in Table 1, and $MaxEC_s$

values were 9, 9, 16 and 10 dS m^{-1} for endive, lettuce, muskmelon and potato, respectively [6]. Then, the result from Equation 8 is multiplied by 1 + *LF* in order to obtain the final amount of water to apply for restoring that transpired by the crop. Leaching requirements can be computed by several approaches; the one selected here provided accurate estimations under conditions of low-frequency drip irrigation [40,41], which is the situation explored in the current study.

The model provides intermediate outputs that include evaporation (*E*), crop transpiration (*T*), irrigation amount (Irr) and leaching fraction (*LF*). From these, the users are also provided with the final irrigation time for a given event by considering the density of drippers and their flow using this expression:

$$I_t = \frac{I_v}{DD \times Flow} \cdot CU \tag{10}$$

where I_t is the irrigation time (h), I_v is the irrigation volume (mm) provided by Equation (8), *DD* is the drippers' density (emitters m^{-2}) and their flow (L h^{-1}), which are given by the user as inputs, as well as the coefficient of uniformity of the irrigation system (*CU*).

2.2. Input Data

Data describing the plantation must be introduced in the model as fixed inputs for beginning the estimations; in comparison with the inputs for the FAO-56 approach, those for IA are similar in number. These include crop species, planting date, spacings, location (latitude, longitude and elevation), irrigation system (emitter density and flow, electrical conductivity of irrigation water, coefficient of uniformity of the installation), mulching, soil texture and depth. Additionally, users can include the value for soil water stored in the soil at the beginning of the simulation as an input; otherwise, the model computes field capacity from the data on soil texture and organic matter content using pedotransfer equations [42]. These inputs allow for intermediate calculations including soil hydraulic characteristics needed for *RO* estimation [33], length of the growing cycle, crop tolerance to salinity and *LF* [6,40,41], irrigation time and weather forecasting. The use of mulching or not indicates whether *E* will be discarded or accounted for, respectively, when estimating irrigation amounts.

One of the main novelties of IA is that it can be used with past records or forecasted weather data as inputs. This fact provides more flexibility to the model to compute plant transpiration and soil evaporation, although the objective of using past or forecasted weather data does not change. The variables used include air temperature, relative humidity, solar radiation, wind speed and rainfall. The forecasted data were provided by the "Fundación para la Investigación del Clima" (FIC, https://www.ficlima.org) and allowed for predicting crop water requirements for 2–3 days ahead. The forecasting system combines numerical prediction, error feedback-correction, transfer functions and two-step downscaling methods from historical observations [43]. In brief, temperatures (minimum, maximum, mean, dewpoint) were estimated through the combination of lineal transfers of the probability distribution observed during the seven days before the estimation and a two-step downscaling approach [43,44]. Relative humidity, both minimum and maximum, were obtained using the Clausius–Clapeyron relation from temperature and dewpoint. Average and maximum wind speeds were corrected using the Weibull and Rayleigh distributions, whereas rainfall was re-distributed according to the probability models proposed by Monjo et al. [45]. These weather forecasts are given on an hourly basis; however, for their use in IA, the averages for 24 h were calculated, except for solar radiation in which only daylight values were considered. In addition, the estimations for daily rainfall were achieved by adding up the hourly values forecasted.

Moreover, crop growth (height and ground cover) must be monitored over the season in order to adjust the estimations of the model for the different developmental stages of the crop. In the current study, weekly measurements of crop height and coverage have been performed. However, to overcome this issue and avoid making repeated measures in the field, different alternatives exist, such as using empirical equations relating crop height and ground cover [46]; or incorporating remote sensing technologies for deriving these parameters from vegetation indices calculated from satellite or drone

imagery [47,48]. In the current study, a previously published monomolecular function was used for estimating crop growth [46] for lettuce and endive, while crop growth for muskmelon and potato was estimated from the weekly crop height and coverage measurements. Furthermore, LAI was estimated from the ground cover data using the expressions for lettuce and potato found in the literature [49,50].

2.3. Field Experiments for Model Testing

Three open-field sites (Figure 1) were used for testing the model under different agricultural situations involving four crop species and six growing cycles. These plots were located in Murcia (SE Spain): (i) Plot 1, Los Alcáceres (1.32 ha, 37°46'7"N, 0°50'13"W; Figure 1A); (ii) Plot 2, Los Alcáceres (0.80 ha, 37°45'32.6"N, 0°52'14.78"W; Figure 1B); and (iii) Plot 3, Torre Pacheco (0.68 ha, 37°45'36"N, 0°54'28"W; Figure 1C). Soil is clay-loamy textured in all fields, which will be referred to hereafter by their respective plot numbers.
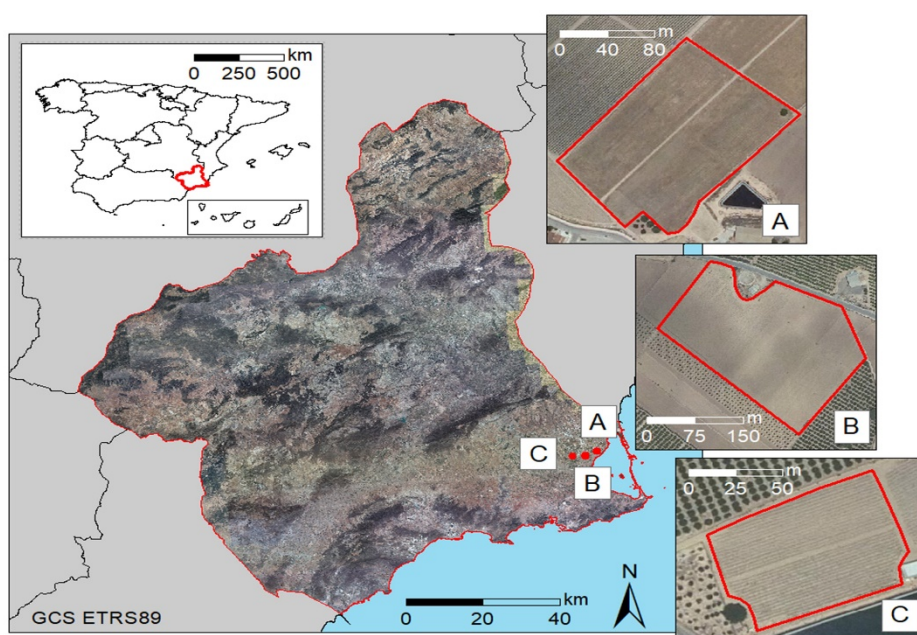

Figure 1. Location of the study sites in Southeast Spain: (**A**) Plot 1, Los Alcáceres; (**B**) Plot 2, Los Alcáceres; (**C**) Plot 3, Torre Pacheco.

The climate of the study area is semiarid Mediterranean, with an annual mean temperature and relative humidity of 18 °C and 69%, respectively; and an annual rainfall and ET_o of 300 and 1275 mm, respectively. Weather data were obtained from the nearest meteorological stations (Sistema de Información Agrario de Murcia, https://siam.imida.es, station codes TP22 for Plots 1 and 2, and TP42 for Plot 3). Data on air temperature, relative humidity, rainfall and ET_o for the growing seasons of the crops considered in the current study are displayed in Table 1.

In Plot 1, an experiment was performed on potato (*Solanum tuberosum* L. cv. 'Rudolph'). In Plot 2, the experiment dealt with lettuce (*Lactuca sativa* L. cv. 'Romana'). In Plot 3, four experiments were performed, one with muskmelon (*Cucumis melo* L. cv. 'Piel de sapo') and three with endive (*Cichorium endivia* L. cv. 'Cuartana'). The experiments were carried out from November 2016 to February 2019. Planting and harvest dates, plant densities, as well as the length of the growing cycle for each crop are reported in Table 1.

Table 1. Planting and harvest dates, length of the growing cycle and plantation characteristics for the different experiments and main weather data values for each growing season (mean air temperature, T_{air}; mean relative humidity, RH; total precipitation, P; and total reference evapotranspiration, ET_o).

Crop Species	Dates		Length of the Growing Cycle	Plantation Characteristics				Weather Variables over the Growing Season			
	Planting	Harvest		Plant Density (plants m^{-2})	Density of Emitters (drippers m^{-2})	Flow (L h^{-1})	Electrical Conductivity of Irrigation Water(dS m^{-1})	T_{air} (°C)	RH (%)	P (mm)	ETo (mm)
Plot 1											
Potato	14 January 2017	22 June 2017	160	-	3.3	1.7	3.15	16.2	66.0	124.3	565.2
Plot 2											
Lettuce	14 October 2017	09 January 2018	88	5.0	3.3	1.7	3.02	13.8	65.1	17.5	145.4
Plot 3											
Endive	07 November 2016	25 February 2017	111	5.0	5.0	1.7	2.74	12.1	73.9	385.8	145.4
Muskmelon	30 March 2017	01 July 2017	94	0.4	1.2	2.5	3.48	20.5	64.2	5.3	457.0
Endive	07 November 2017	17 February 2018	103	5.0	5.0	1.0	4.48	11.6	65.6	57.6	162.0
Endive	31 October 2018	04 February 2019	97	5.0	2.5	2.5	2.79	12.4	70.5	90.0	147.4

In all experiments, the irrigation amounts recommended by IA were compared with those applied by the farmer (F). Additionally, in the case of endives, two additional treatments were considered: a supplementary irrigation consisting of applying 125% of the IA recommendation (IA_s) and a deficit irrigation consisting of applying 75% of the IA recommendation (IA_d). Over-watering or inducing a water deficit in vegetable crops is not a usual practice in southeastern Spain. In fact, vegetables are sensitive to water deficit and availability of water can influence crop yield and quality considerably [51]. However, these two treatments were selected to validate previous research conducted on lettuce and broccoli that reported that applying 25% of excess or deficit irrigation did not have any effect on yield and increased crop water use efficiency [52–54]. In the first growing cycle of endive, only the F, IA and IA_s treatments were applied.

The experimental design was adapted to the characteristics of the irrigation systems in each plot and to the growing conditions for each species. Plots 1 and 2 were very homogeneous in soil characteristics and therefore, one-half of the field received the F treatment whereas the other half was subjected to the IA treatment. Within each treatment, ten randomly selected locations were used for sample collection. In Plot 3, a randomized-block design with three replications (three rows each for muskmelon and five rows each for endive) per treatment was used. Samplings were carried out separately in each replication.

A drip irrigation system was used, although the flow and density of drippers differed depending on the crop studied (Table 1). Irrigation amounts were measured with one water meter per treatment. Fertilization regimes (applied through the irrigation system) and irrigation frequency were the same for all treatments within a given field and growing season, ensuring that the irrigation volume applied would be the only cause of differences among treatments. Depending on the growing cycle considered, the average electrical conductivity of irrigation water ranged from 2.7 to 4.5 dS m^{-1} (Table 1).

In order to assess whether irrigation was correctly managed, soil water content was monitored at 20 cm depth using two frequency domain reflectometry (FDR) probes (EC-10 model, Decagon Devices Inc., Pullman, WA, USA) per treatment (F and IA). Data were collected at 30-min intervals. Probes were not calibrated for the specific soils of the studied plots; however, they are useful for assessing the deviation between F and IA treatments over the measurement period in a qualitative way [55,56].

An additional testing of the model performance was carried out by agronomic observations of crop performance. At harvest, a representative number of samples (15 linear meters per treatment for potato, 30 plants per treatment for lettuce, 20 plants per replication for endive, 15 plants per replication for muskmelon) was collected for determining aboveground biomass (for lettuce and endive) and crop yield (for potato and muskmelon) directly in the field. In all cases, water productivity (WP) was calculated for each treatment by dividing aboveground biomass or crop yield by the irrigation water amount applied over the growing season.

2.4. Model Evaluation and Statistical Analysis

From ET_o data recorded in the weather stations closest to the studied sites (calculated using the FAO-56 methodology [6]) and the K_c recommended by the Agricultural Service of the Murcia Regional Government (https://siam.imida.es) for each stage of the growing cycle of each species, the daily ET_c was computed. This extension service gathered information from several studies carried out in the region to obtain tailored K_c for a number of crops; they provide irrigation recommendations through their website and advise farmers about the optimal irrigation scheduling based on the FAO-56 approach, using the adapted K_c. These values were considered as reference and used to evaluate the performance of IA following two approaches: (i) daily values of evaporation plus transpiration estimated by IA were compared to the ET_c calculated using records from the closest weather station for the corresponding dates; and (ii) IA daily values were compared with ET_c calculated using weather forecasts.

Model performance was assessed using five statistical indicators: mean bias error (ME), root-mean-squared error (RMSE), normalized RMSE (NRMSE), modeling efficiency (EF) and index of agreement. These indices have been calculated as described by Yang et al. [57].

The ME shows positive or negative deviations of the simulations from the observed values, whereas RMSE indicates the mean difference between observed and predicted values. The NRMSE represents the relative size of the mean differences as an unbounded percentage. The EF is a dimensionless indicator that varies between $-\infty$ and 1, which corresponds to a perfect match between model outputs and measured observations [57]. The index of agreement varies between 0 and 1 and the closer it is to 1, the better the model performance is.

For the field experiments, differences among treatments were assessed through analysis of variance (ANOVA) and, when needed, comparison of means was performed using the Tukey's test at the 0.05 level of significance. Statistical analyses were carried out using R v3.4.1 software [58].

3. Results

3.1. Model Evaluation

When plotted against the ET_c obtained from the records of the weather stations closer to the experimental fields and the K_c values recommended by the agricultural extension service of the region for a given crop (ET_c, WS; Figure 2), IA tended to overestimate crop water needs at the beginning and to underestimate them by the end of the season, except for potato (Figure 2a).
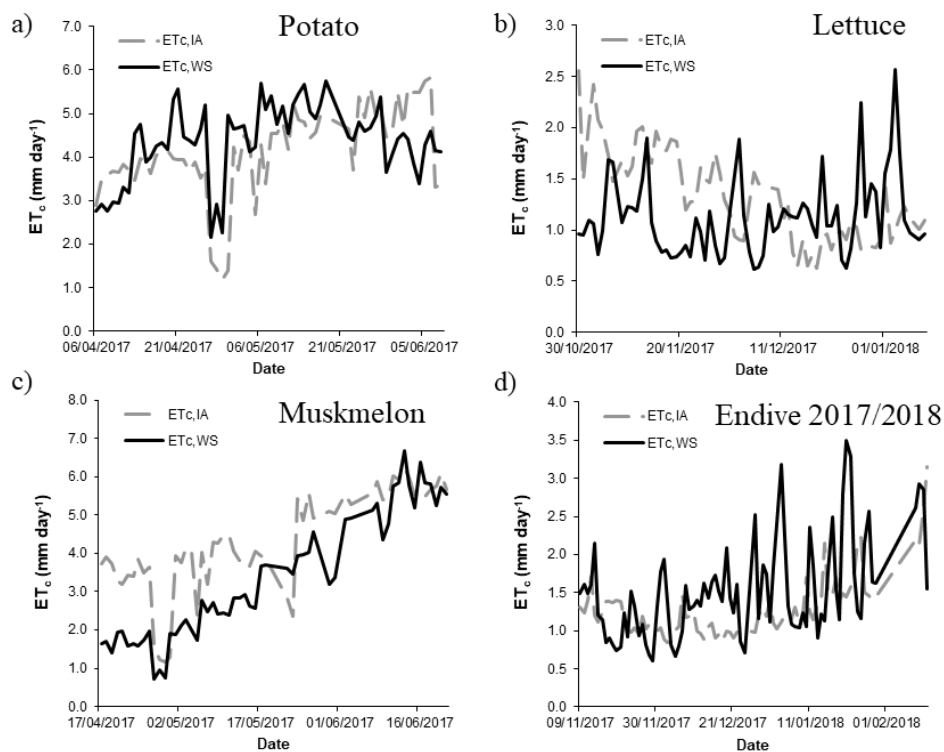

Figure 2. Evolution of crop evapotranspiration (ET_c) calculated using the weather records from the closest weather station and the crop coefficients provided by the Murcia agricultural extension service (ET_c, WS) and using Irrigation-Advisor (ET_c, IA): (**a**) Potato; (**b**) Lettuce; (**c**) Muskmelon; (**d**) Endive 2017/2018.

The statistical indicators showed that estimations of E and T provided by IA resulted in moderate agreements when compared to the ET_c obtained from the records of the closest weather stations and the K_c recommended by the agricultural extension service of the region (Table 2). However, the performance of IA differed depending on the crop species (Table 2). In summary, Irrigation-Advisor underestimated ET_c for potato, lettuce and endive, while it overestimated crop water needs for muskmelon. The same trend was observed when IA estimations were compared with ET_c calculated from weather forecasts (Table 2).

Table 2. Statistical indicators of model performance for the crop species studied. Abbreviations: ME = mean bias error; RMSE = root-mean-squared error; NRMSE = normalized root-mean-squared error; EF = modeling efficiency.

Crop Species	Statistical Indicators				
	ME (mm Day^{-1})	RMSE (mm Day^{-1})	NRMSE (%)	EF	Index of Agreement
Comparison against ET$_c$ from weather station					
Potato 2017	−0.85	1.22	27.89	−1.03	0.75
Muskmelon 2017	0.19	0.95	28.20	0.66	0.87
Lettuce 2017–2018	−0.20	0.58	51.36	0.76	0.79
Endive 2017–2018	−0.69	0.94	61.04	−1.11	0.56
Comparison against ET$_c$ from weather forecasts					
Potato 2017	−1.04	1.32	28.99	−0.50	0.79
Muskmelon 2017	0.44	1.14	36.66	0.62	0.89
Lettuce 2017–2018	−1.12	1.53	74.53	−2.25	0.69
Endive 2017–2018	−1.17	1.53	76.29	−1.32	0.72

3.2. Field Experiments

Figure 3 shows the distribution of irrigation amounts over the growing season for the different treatments and crops considered in this study. The irrigation volume curves showed that IA applications followed those of the farmer (F) at the beginning of the season until a certain moment when they became lower (potato, muskmelon and endive) or higher (lettuce).

The high irrigation volume for all treatments during the first weeks after plantation is noticeable (Figure 3). At this time, the differential application of the irrigation scheduling had not started in order to avoid initial differences in plant establishment and allow for promoting root growth. In the case of endive in 2016/2017, the differentiation of treatments began late (Figure 3d), due to a huge rainfall event (200 mm) that occurred during the middle of the growing season and caused modifications in the irrigation scheduling.

Moreover, the dynamics of soil water content were similar between treatments (Figure 4). In muskmelon, a higher soil water content was observed for IA by the end of the growing season when compared to the F treatment (Figure 4b) because the farmer stopped irrigation to increase fruit sugar concentration.

In general, irrigation scheduling according to IA allowed for saving water, except for lettuce in Plot 2, when 31% more water was applied in IA than in F (Table 3).
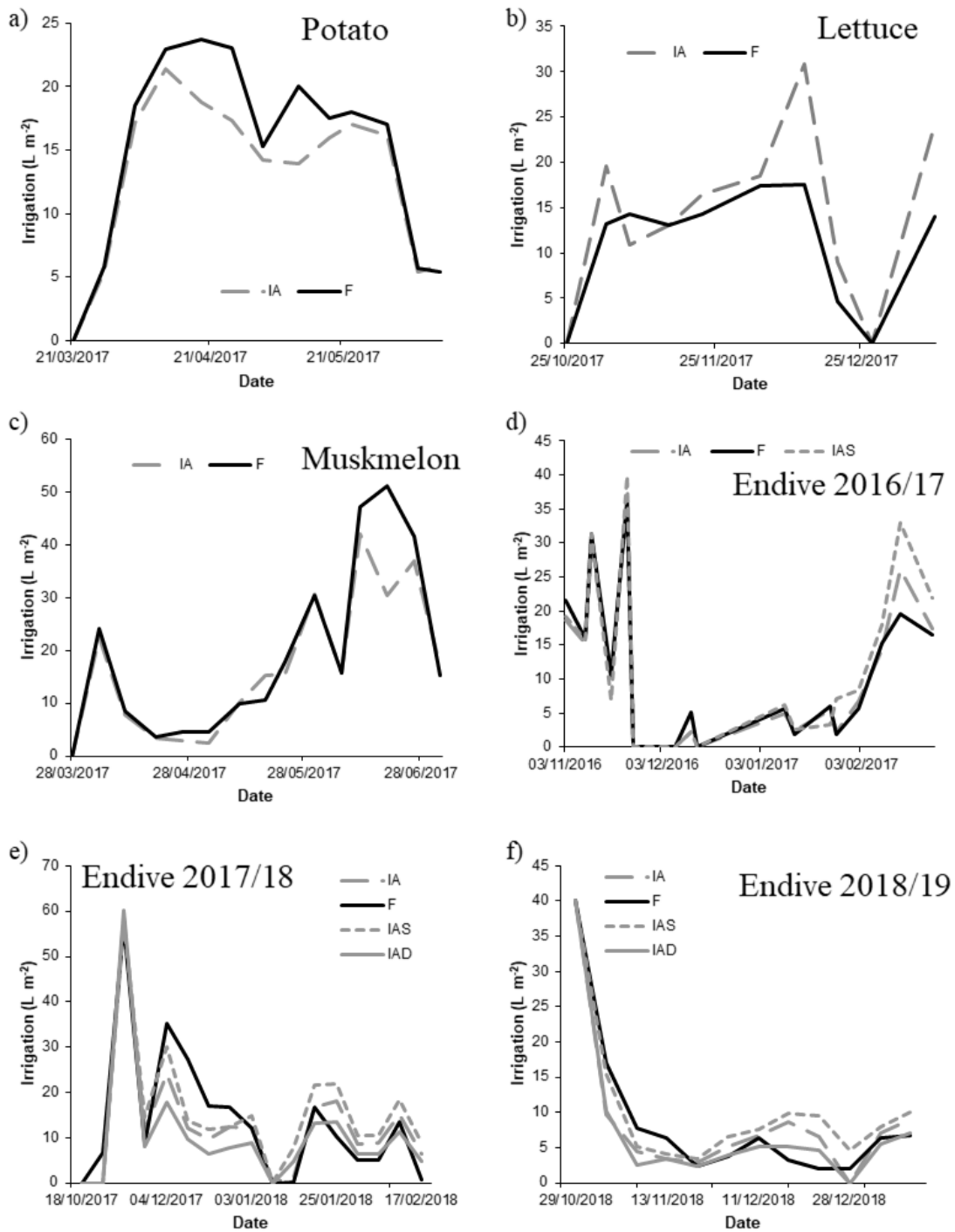
Figure 3. Irrigation patterns in each treatment over the growing seasons for the six crop cycles studied. F = Irrigation according to farmer's practices; IA = irrigation according to Irrigation-Advisor recommendations; IAS = irrigation according to Irrigation-Advisor recommendations with a 25% surplus; IAD = irrigation according to Irrigation-Advisor recommendations with a 25% deficit: (**a**) Potato; (**b**) Lettuce; (**c**) Muskmelon; (**d**) Endive 2016/17; (**e**) Endive 2017/18; (**f**) Endive 2018/19.
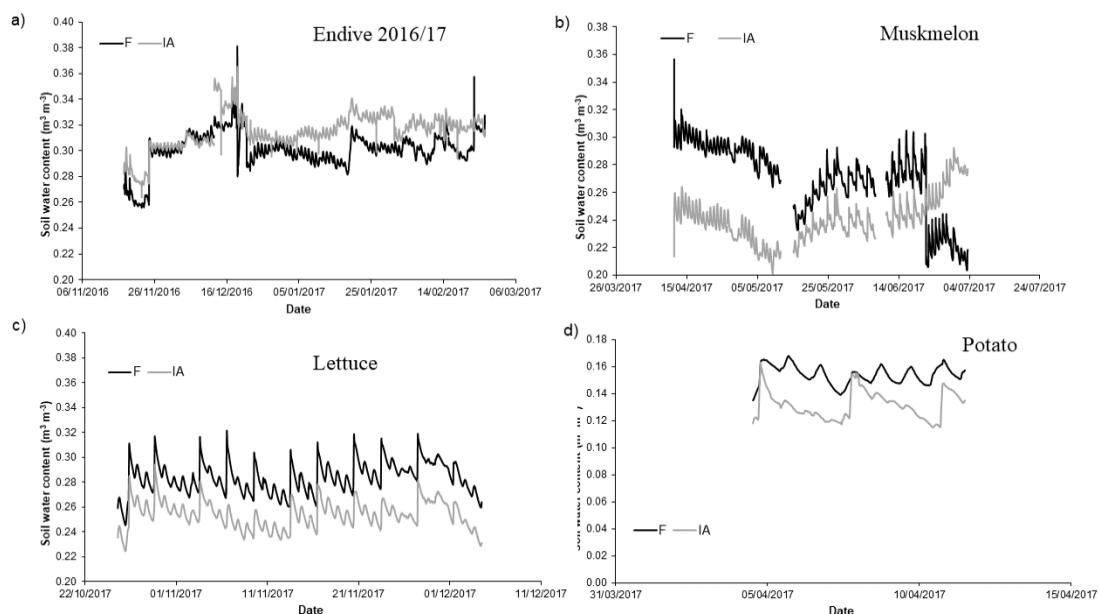
Figure 4. Evolution of soil water content at 20 cm depth in each treatment. F = Irrigation according to farmer's practices; IA = irrigation according to Irrigation-Advisor recommendations: (**a**) Endive 2016/17; (**b**) Muskmelon; (**c**) Lettuce; (**d**) Potato.

Table 3. Percentage of difference between treatments when compared to the farmer treatment: irrigation water amounts applied, yield and water productivity for the different crop species considered in the current study. F = Irrigation according to farmer's practices; IA = irrigation according to Irrigation-Advisor recommendations; IA_s = Irrigation-Advisor recommendations +25%; IA_d = Irrigation-Advisor recommendations −25%.

Crop Species	Treatment	Irrigation Water Applied	Average Fruit/Plant Weight	Yield	Water Productivity
		Plot 1			
Potato 2017	F vs. IA	87.3	93.0 *	93.5 *	106.6 *
		Plot 2			
Lettuce 2017/2018	F vs. IA	131.2	118.2 *	118.1 *	90.1 *
		Plot 3			
Muskmelon 2017	F vs. IA	88.7	94.5	93.0 *	104.9 *
Endive 2016/2017	F vs. IA	99.5	104.5	104.5	105.2
	F vs. IAs	111.9	101.7	101.7	92.2 *
Endive 2017/2018	F vs. IA	92.5	100.8	1007	100.8
	F vs. IA_s	109.7	98.1	98.1	98.3
	F vs. IA_d	76.9	101.9	101.9	102.0
Endive 2018/2019	F vs. IA	99.2	91.2	91.3	92.0
	F vs. IA_s	119.4	92.5	92.5	77.5 *
	F vs. IA_d	86.4	93.8	93.9	108.5

Asterisk indicate significant differences among the treatments compared in the row at $p < 0.05$.

In potato, muskmelon and endive, IA resulted in water savings ranging from 0.5% to 13% when compared with the F treatment (Table 3). These differences in irrigation volumes resulted in significant variations in aboveground biomass or crop yield in some of the experiments (Table 3). For instance, individual potatoes and muskmelons were heavier for the F treatment than for IA (by 7% and 5.5%, respectively), while the contrary occurred for lettuces (18.2%), leading to significant differences in yield (Table 3). Moreover, in the case of the three seasons of endive, applying 25% more water than IA induced greater irrigation amounts, ranging from 9% to 19%, when compared with F. In contrast,

reducing IA irrigation volumes by 25% caused greater water savings with respect to F, from 13% to 23% (Table 3). However, despite the irrigation amounts applied, no differences among treatments were detected for endive weight in any of the growing seasons considered. Finally, water productivity was higher in those treatments receiving lower irrigation volumes, independently of the crop species (Table 3).

4. Discussion

4.1. Model Evaluation: Advantages, Main Sources of Error and Limitations

The approach described in the current study, IA, aims to be an inexpensive and easy-to-use tool with few input data for supporting decision in irrigation scheduling of vegetable crops. Nowadays, models in agriculture provide accurate estimations of many processes but they need a large number of inputs [59]. Consequently, their application to solve problems for the agricultural sector is reduced. In this context, IA is intended to be an operational tool that overcomes these limitations and those detected for the widely used FAO-56 method [6,39]. In this sense, IA employs a method for calculating canopy resistance that accounts for the dynamic nature of this parameter [37] and allows for a separate computation of evaporation and transpiration. This approach avoids the employment of empiric K_c [6], is more flexible and allows for considering certain agricultural practices, such as mulching or the use of anti-frost meshes, providing that some adjustments in the input data are made. In the current study, IA was able to mimic the irrigation practice used by farmers in the study area, as proven by similar soil water dynamics over the growing season (Figures 2 and 4).

Another advantage of IA over FAO-56 is that it can be adapted to any type of climate, while several studies pointed out underestimations in the ET_c calculated by the FAO-56 approach in Mediterranean climates [39,60]. This is caused by the consideration of a single value of canopy conductance over the growing season and for the use of crop coefficients that have been determined under sub-humid conditions [6], although, in many cases, these crop coefficients have been adapted to local conditions [7,8,14].

The statistical indicators showed moderate to poor agreements when comparing IA estimations to the ET_c calculated either with weather records or with forecasts. These discrepancies might have been caused by different factors. First, an accurate determination of crop growth (height and surface coverage) is needed for obtaining suitable estimations of plant transpiration and evaporation from the soil. Results indicated poorer agreements between IA estimations and the observed ET_c when using empirical equations for estimating crop growth, as in the case of lettuce and endive. This disagreement might be caused by the specificity of the model used for crop growth [46], which referred to a cultivar smaller than those considered in the current experiments. It is also important to point out that weekly measurements of crop growth proved to be fairly sufficient for obtaining reliable estimates of crop transpiration using IA, as pointed out by the results observed for muskmelon and potato. Nevertheless, this is a limitation of the current version of the model, since its final aim is to avoid any reliance on field measurements.

Another source of discrepancies between IA and the FAO-56 method is the weather forecast, whose accuracy decreases when increasing the horizon of prediction, despite the considered corrections [43,45]. Previous reports showed that the daily ET_o measured and that predicted by several approaches differed in a range between 0.65 and 0.76 mm day^{-1} [61], depending on the horizon of the forecast. These discrepancies led to differences in irrigation depth close to 10% [61], which amounted up to 31% in the current study. The difficulty in the estimation of some weather variables, especially rainfall and wind speed [45], might be the cause of these disagreements. Moreover, RMSE between measured and predictions of ET_o were larger in regions with semi-arid than with sub-humid climates [62], the former being similar to those observed in the current study (RMSE ranged from 0.6 to 1.5 mm day^{-1}). In any case, the use of weather forecasts is an asset for RA due to three main advantages: (i) overcoming the low density and uneven distribution of well-managed weather

stations [63]; (ii) the complexity of accessing remote sensing data [61]; and (iii) to better predict sudden extreme events (heatwaves or warm winds).

Another issue to consider when using IA is the fact that salinity (or electrical conductivity) of irrigation water must be evaluated periodically for an adequate LF determination. This is particularly relevant in regions such as Southeast Spain where irrigation water comes from different sources (wells, desalination plants, treated wastewater, irrigator communities) and, consequently, presents contrasting qualities [64,65], which might be reduced if water from different sources is mixed prior to be used for irrigation.

4.2. Effects of Using the Current Irrigation-Advisor Version on Crop Yield

In all the cases considered in the field experiments, irrigation doses were high at the beginning of the growing cycle (the day before and immediately after planting), followed by a period (5–7 days) without irrigation. This is a common agricultural practice for helping seedling establishment and promoting root growth and development [32], so roots colonize a great volume of soil and make more efficient use of water and nutrients over the growing season. Additionally, in the study area, this practice also aims at washing salts accumulated in the upper centimeters of the soil [66], bringing soil to field capacity. The current version of IA does not consider this practice but uses it as a starting point for beginning the recommendations. From that moment, IA was able to provide fair recommendations for irrigating several crop species (endive, lettuce, muskmelon and potato) and the water amounts irrigated over the growing season were similar to those commonly applied by farmers in the study area, as reinforced by the soil water content measurements.

Therefore, water savings were limited since the farmers' irrigation doses were well adjusted to the crop water requirements and because of the need for applying an LF due to the high salinity level of the irrigation water, leading to small differences in yield between treatments. It is interesting to notice the case of endive, since its response to the treatments differed among years, although not significantly in any case even though 25% more or less water was applied. This suggests that IA provides fair recommendations (applying 25% more water did not modify yield) but still there is room for improvements since reducing irrigation by 25% did not modify crop response. In the current scenario of water scarcity and expected climate change, irrigation tools that allow for maximizing the production per unit of water consumed, i.e., the water productivity [67], are needed. In this context, IA fills this gap even in its current version, as proven by the results for water productivity observed in the four crop species studied, including a staple such as potato. In the current study, the EC of irrigation water ranged from 2.74 to 4.48 dS m^{-1}, which are values within the interval of tolerance of the crops used in the experiments (endive, lettuce, muskmelon and potato). Under these conditions, IA provided recommendations for irrigating crops in line with the scheduling commonly performed by farmers from the region.

The main advantages of IA over these existent DSS tools [16,22–25] are that IA requires the estimation of a lower number of parameters, while it needs a similar amount of inputs. Additionally, IA is easy to use, which might broaden its utilization among less specialized users. Moreover, IA is not restricted to herbaceous crops since it can be easily adapted to a wide range of species. Remotely sensed data can be easily incorporated into IA by calculating inputs from satellite or drone acquired imagery, such as the vegetated fraction cover [31]. In this way, IA could provide a spatial representation of the variability on crop water demands over a given plot or orchard.

4.3. Future Improvements of the Model

Since the challenge for agriculture in the near future is increasing yield per surface unit while reducing water consumption [68], future improvements of IA must focus on several aspects.

First, irrigation management for yield-increasing purposes should be aimed to meet market demands and not only to increase biomass. For instance, when plants (such as lettuce and endive) achieved a marketable size (or other requirements), the farmer was not interested in replacing all the

water consumed by the crop (as IA does) but in exploiting the available water remaining in the soil. Therefore, the system could be programmed to exhaust the available water at harvest in the case of certain species. In its current version, the model maximizes crop growth by restoring soil water to field capacity, which sometimes is detrimental for food quality. In this sense, regulated deficit irrigation strategies [67] should be introduced in the model.

Second, in order to reduce the dependency on field measurements or empirical models for estimating crop coverage, remote sensing technologies could be incorporated in IA for obtaining an accurate description of the surface of the field covered by crops at several times over the growing season, as recently reported for other tools [16].

Third, IA must consider rapid changes in climatic conditions better; future improvement in weather forecasts, downscaling approaches and corrections of the probability distributions of rainfall, temperature and other variables will lead to precise estimations of crop irrigation requirements allowing to adapt IA for facing the challenges posed by climate change to agricultural water management [44,45,69].

Fourth, our findings showed that IA needs adjustments and fine-tuning for adapting to different situations and agronomic practices such as diverse water qualities (accounting for the water sources), different crop covers, different types of mulching and different irrigation frequencies. In the case of vegetables, these enhancements should deal with low water quality, i.e., salinity or specific ions in the irrigation water, as well as with nutrient management [66].

5. Conclusions

A tool, IA, for providing irrigation recommendations in vegetable crops has been developed and tested. This approach has the main advantages of avoiding the reliance on sensors deployed on-site, using weather forecasts for anticipating near-future conditions and optimizing water applications, as well as a low number of inputs, making it easy to implement into decision support systems. The six field experiments performed in the current study demonstrated that IA is able to successfully mimic the actual irrigation management performed by the farmer. The main discrepancies observed between both strategies were caused by the fact that IA does not consider cultural management practices during specific moments of the growing season. Nevertheless, when the farmer adopted no specific actions, IA tended to estimate lower irrigation volumes, resulting in water savings without compromising yield. However, further improvements are required to adapt IA to different agricultural situations and reduce its uncertainties.

6. Patents

The algorithms for determining soil evaporation and plant transpiration used in Riego-Asesor have been notarized "AN4020-2017 Algoritmo para el cálculo de dosis de riego en cultivos hortícolas". The commercial exploitation of the routines has been licensed by CSIC and UPCT to Grupo Hispatec informática empresarial S.A.

Author Contributions: Conceptualization, J.F.M.-V. and D.S.I.; methodology, J.M.M.-A., J.M.R.-C. and J.S.R.-A.; modeling, J.M.M.-A.; validation, J.M.M.-A., J.M.R.-C. and J.S.R.-A.; formal analysis, J.M.M.-A.; investigation, J.M.M.-A., J.M.R.-C., J.S.R.-A. and D.S.I.; funding acquisition, J.F.M.-V. and D.S.I.; writing—draft preparation, all authors; writing—review and editing, all authors; supervision and project management, D.S.I.

References

1. FAO. *Water for Sustainable Food and Agriculture. A Report for the G20 Presidency of Germany*; Food and Agriculture Organization of the United Nations (FAO): Rome, Italy, 2017; p. 33.
2. AQUASTAT. FAO's Global Water Information System. Available online: http://www.fao.org/nr/aquastat (accessed on 25 February 2019).
3. Turral, H.; Burke, J.; Faurès, J.M. *Climate Change, Water and Food Security*; Water Reports N° 36; Food and Agriculture Organization of the United Nations (FAO): Rome, Italy, 2011; p. 200.
4. Ventura, F.; Faber, B.A.; Bali, K.M.; Snyder, R.L.; Spano, D.; Duce, P.; Schulbach, K.F. Model for estimating evaporation and transpiration from row crops. *J. Irrig. Drain. Engin.* **2001**, *127*, 339–345. [CrossRef]
5. Payero, J.O.; Irmak, S. Daily energy fluxes, evapotranspiration and crop coefficient of soybean. *Agric. Water Manage.* **2013**, *129*, 31–43. [CrossRef]
6. Allen, R.G.; Pereira, L.S.; Raes, D.; Smith, M. *Crop. Evapotranspiration–Guidelines for Computing Crop Water Requirements*; Irrigation and Drainage N° 56; FAO: Rome, Italy, 1998; p. 300.
7. Giménez, L.; Paredes, P.; Pereira, L.S. Water use and yield of soybean under various irrigation regimes and severe water stress. Application of AquaCrop and SIMDualKc models. *Water* **2017**, *9*, 393. [CrossRef]
8. Hong, M.; Zeng, W.; Ma, T.; Lei, G.; Zha, Y.; Fang, Y.; Wu, J.; Huang, J. Determination of growth stage-specific crop coefficients (K_c) of sunflowers (*Helianthus anuus* L.) under salt stress. *Water* **2017**, *9*, 2154. [CrossRef]
9. Paredes, P.; D'agostino, D.; Assif, M.; Todorovic, M.; Pereira, L.S. Assessing potato transpiration, yield and water productivity under various water regimes and planting dates using the FAO dual K_c approach. *Agric. Water Manag.* **2018**, *195*, 11–22. [CrossRef]
10. Dzikiti, S.; Volschenk, T.; Midgley, S.J.E.; Lötze, E.; Taylor, N.J.; Gush, M.B.; Ntshidi, Z.; Zirebwa, S.F.; Doko, Q.; Schmeisser, M.; et al. Estimating the water requirements of high yielding and young apple orchards in the winter rainfall areas of South Africa using a dual source evapotranspiration model. *Agric. Water Manag.* **2018**, *20*, 152–162. [CrossRef]
11. Gharsallah, O.; Facchi, A.; Gandolfi, C. Comparison of six evapotranspiration models for a surface irrigated maize agro-ecosystem in Northern Italy. *Agric. Water Manag.* **2013**, *130*, 119–130. [CrossRef]
12. Cammalleri, C.; Ciraolo, G.; Minacapilli, M.; Rallo, G. Evapotranspiration from an olive orchard using remote sensing-based dual crop coefficient approach. *Water Resour. Manag.* **2013**, *27*, 4877–4895. [CrossRef]
13. Villalobos, F.J.; Testi, L.; Moreno-Pérez, M.F. Evaporation and canopy conductance of citrus orchards. *Agric. Water Manag.* **2009**, *96*, 565–573. [CrossRef]
14. Abrisqueta, I.; Abrisqueta, J.M.; Tapia, L.M.; Munguía, J.P.; Conejero, W.; Vera, J.; Ruiz-Sánchez, M.C. Basal crop coefficients for early-season peach trees. *Agric. Water Manag.* **2013**, *121*, 158–163. [CrossRef]
15. López-Urrea, R.; Montoro, A.; Trout, T.J. Consumptive water use and crop coefficients of irrigated sunflower. *Irrig. Sci.* **2014**, *32*, 99–109. [CrossRef]
16. Ramírez-Cuesta, J.M.; Mirás-Avalos, J.M.; Rubio-Asensio, J.S.; Intrigliolo, D.S. A novel ArcGIS toolbox for estimating crop wate demands by integrating the dual crop coefficient approach with multi-satellite imagery. *Water* **2019**, *11*, 38. [CrossRef]
17. Rallo, G.; González-Altozano, P.; Manzano-Juarez, J.; Provenzano, G. Using field measurements and FAO-56 model to assess the eco-physiological response of citrus orchards under regulated déficit irrigation. *Agric. Water Manag.* **2017**, *180*, 136–147. [CrossRef]
18. Rana, G.; Katerji, N. Measurement and estimation of actual evapotranspiration in the field under Mediterranean climate: A review. *Eur. J. Agron.* **2000**, *13*, 125–153. [CrossRef]
19. Soulis, K.X.; Elmaloglou, S. Optimum soil water content sensors placement for surface drip irrigation scheduling in layered soils. *Comput. Electron. Agric.* **2018**, *152*, 1–8. [CrossRef]
20. Rana, G.; Katerji, N.; de Lorenz, F. Measurement and modelling of evapotranspiration of irrigated citrus orchard under Mediterranean conditions. *Agric. For. Meteorol.* **2005**, *128*, 199–209. [CrossRef]
21. Moreno-Rivera, J.M.; Calera, A.; Osann, A. SPIDER–An Open GIS Application Use Case. In Proceedings of the Open GIS UK Conference, Nottingham, UK, 22 June 2009.
22. Steduto, P.; Hsiao, T.C.; Raes, D.; Fereres, E. AquaCrop: The FAO crop model to simulate yield response to water. I. Concepts and underlying principles. *Agron. J.* **2009**, *101*, 426–437. [CrossRef]
23. Verrelst, J.; Romjin, E.; Kooistra, L. Mapping vegetation density in heterogeneous river foodplain ecosystem using pointable CHRIS/PROBA data. *Remote Sens.* **2012**, *4*, 2866–2889. [CrossRef]

24. Lorite, I.J.; García-Vila, M.; Santos, C.; Ruiz-Ramos, M.; Fereres, E. AquaData and AquaGIS: Two computer utilities for temporal and spatial simulations of water-limited yield with AquaCrop. *Comp. Electron. Agric.* **2013**, *96*, 227–237. [CrossRef]

25. Gallardo, M.; Thompson, R.B.; Giménez, C.; Padilla, F.M.; Stöckle, C.O. Prototype decision support system based on the VegSyst simulation model to calculate crop N and water requirements for tomato under plastic cover. *Irrig. Sci.* **2014**, *32*, 237–253. [CrossRef]

26. Giménez, C.; Thompson, R.B.; Prieto, M.H.; Suárez-Rey, E.; Padilla, F.M.; Gallardo, M. Adaptation of the VegSyst model to outdoor conditions for leafy vegetables and processing tomato. *Agric. Syst.* **2019**, *171*, 51–64. [CrossRef]

27. Thysen, I.; Detlefsen, N.K. Online decision support for irrigation for farmers. *Agric. Water Manag.* **2006**, *86*, 269–276. [CrossRef]

28. Navarro-Hellín, H.; Martínez-del-Rincón, J.; Domingo-Miguel, R.; Soto-Valles, F.; Torres-Sánchez, R. A decision support system for managing irrigation in agriculture. *Comput. Electron. Agric.* **2016**, *124*, 121–131. [CrossRef]

29. Yang, G.; Liu, L.; Guo, P.; Li, M. A flexible decision support system for irrigation scheduling in an irrigation district in China. *Agric. Water Manag.* **2017**, *179*, 378–389. [CrossRef]

30. Li, H.; Li, J.; Shen, Y.; Zhang, X.; Lei, Y. Web-based irrigation decision support system with limited inputs for farmers. *Agric. Water Manag.* **2018**, *210*, 279–285. [CrossRef]

31. Ormsby, J.P.; Choudhury, B.J.; Owe, M. Vegetation spatial variability and its effect on vegetation indices. *Int. J. Remote Sens.* **1987**, *8*, 1301–1306. [CrossRef]

32. Soundy, P.; Cantiffle, D.J.; Hochmuth, G.J.; Stoffella, P.J. Management of nitrogen and irrigation in lettuce transplant production affects transplant root and shoot development and subsequent crop yields. *HortScience* **2005**, *40*, 607–610. [CrossRef]

33. USDA-SCS. *Urban. Hydrology for Small Watersheds. Technical Release 55*, 2nd ed.; United States Department of Agriculture, Soil Conservation Service: Washington, DC, USA, 1986; p. 164.

34. Ritchie, J.T. Model for predicting evaporation from a row crop with incomplete cove. *Water Resour. Res.* **1972**, *8*, 1204–1213. [CrossRef]

35. McEvoy, A.; Markvart, T.; Castaner, L. *Practical Handbook of Photovoltaics: Fundamentals and Applications*; Academic Press: Cambridge, MA, USA, 2012; p. 1268. [CrossRef]

36. Zhang, L.; Hu, Z.; Fan, J.; Zhou, D.; Tang, F. A meta-analysis of the canopy light extinction coefficient in terrestrial ecosystems. *Front. Earth Sci.* **2014**, *8*, 599–609. [CrossRef]

37. Rana, G.; Katerji, N. Operational model for direct determination of evapotranspiration for well watered crops in Mediterranean region. *Theor. Appl. Climatol.* **2009**, *97*, 243–253. [CrossRef]

38. Arya, S.P. *Introduction to Micrometeorology*, 2nd ed.; Academic Press: London, UK, 2001; p. 420. [CrossRef]

39. Katerji, N.; Rana, G. FAO-56 methodology for determining water requirement of irrigated crops: Critical examination of the concepts, alternative proposals and validation in Mediterranean region. *Theor. Appl. Climatol.* **2014**, *116*, 515–536. [CrossRef]

40. Ayers, R.S.; Westcot, D.W. *Water Quality for Agriculture*; Irrigation and Drainage N° 29; FAO: Rome, Italy, 1985.

41. Monge-Redondo, M.A. *Diseño Agronómico e Hidráulico de Riegos Agrícolas a Presión*; Agrícola: Madrid, Spain, 2018; p. 632.

42. Saxton, K.E.; Rawls, W.J. Soil water characteristic estimates by texture and organic matter for hydrologic solutions. *Soil Sci. Soc. Am. J.* **2006**, *70*, 1569–1578. [CrossRef]

43. Ribalaygua, J.; Torres, L.; Pórtoles, J.; Monjo, R.; Gaitán, E.; Pino, M.R. Description and validation of a two-step analogue/regression downscaling method. *Theor. Appl. Climatol.* **2013**, *114*, 253–269. [CrossRef]

44. Gaitán, E.; Monjo, R.; Pórtoles, J.; Pino-Otín, M.R. Projection of temperatures and heat and cold waves for Aragón (Spain) using a two-step statistical downscaling of CMIP5 model outputs. *Sci. Tot. Environ.* **2019**, *650*, 2778–2795. [CrossRef]

45. Monjo, R.; Caselles, V.; Chust, G. Probabilistic correction of RCM precipitation in the Basque Country (Northern Spain). *Theor. Appl. Climatol.* **2014**, *117*, 317–329. [CrossRef]

46. Escarabajal-Henajeros, D.; Molina-Martínez, J.M.; Fernández-Pacheco, D.G.; Cavas-Martínez, F.; García-Mateos, G. Digital photography applied to irrigation management of Little Gem lettuce. *Agric. Water Manag.* **2015**, *151*, 148–157. [CrossRef]

47. Mousivand, A.; Menenti, M.; Gorte, B.; Verhoef, W. Multi-temporal, multi-sensor retrieval of terrestrial properties from spectral-directional radiometric data. *Remote Sens. Environ.* **2015**, *158*, 311–330. [CrossRef]

48. González-Esquiva, J.M.; García-Mateos, G.; Escarabajal-Henajeros, D.; Hernández-Hernández, J.L.; Ruiz-Canales, A.; Molina-Martínez, J.M. A new model for water balance estimation on lettuce crops using effective diameter obtained with image analysis. *Agric. Water Manag.* **2017**, *183*, 116–122. [CrossRef]

49. Tei, F.; Scaife, A.; Aikman, D.P. Growth of lettuce, onion, and red beet. 1. Growth analysis, light interception, and radiation use efficiency. *Ann. Bot.* **1996**, *78*, 633–643. [CrossRef]

50. van Delden, A.; Pecio, A.; Haverkort, A.J. Temperature response of early foliar expansion of potato and wheat. *Ann. Bot.* **2000**, *86*, 355–369. [CrossRef]

51. Harmanto Salokhe, V.M.; Babel, M.S.; Tantau, H.J. Water requirement of drip irrigated tomatoes grown in greenhouse in tropical environment. *Agric. Water Environ.* **2005**, *71*, 225–242. [CrossRef]

52. Kuslu, Y.; Dursun, A.; Sahin, U.; Kiziloglu, F.M.; Turan, M. Short communication. Effect of deficit irrigation on curly lettuce grown under semiarid conditions. *Span. J. Agric. Res.* **2008**, *6*, 714–719. [CrossRef]

53. Capra, A.; Consoli, S.; Russo, A.; Scicolone, B. Integrated agro-economic approach to deficit irrigation on lettuce crops in Sicily, Italy. *J. Irrig. Drain. Eng.* **2008**, *134*, 437–445. [CrossRef]

54. Kirnak, H.; Taş, I.; Gökalp, Z.; Karaman, S. Effects of different irrigation levels on yield of lettuce grown in an unheated greenhouse. *Curr. Trends Nat. Sci.* **2016**, *5*, 145–151.

55. Kargas, G.; Soulis, K.X. Performance analysis and calibration of a new low-cost capacitance soil moisture sensor. *J. Irrig. Drain. Eng.* **2012**, *138*, 632–641. [CrossRef]

56. Visconti, F.; de Paz, J.M.; Martínez, D.; Molina, M.J. Laboratory and field assessment of the capacitance sensors Decagon 10HS and 5TE for estimating the water content of irrigated soils. *Agric. Water Manag.* **2014**, *132*, 111–119. [CrossRef]

57. Yang, J.M.; Yang, J.Y.; Liu, S.; Hoogenboom, G. An evaluation of the statistical methods for testing the performance of crop models with observed data. *Agric. Syst.* **2014**, *127*, 81–89. [CrossRef]

58. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2017.

59. Antle, J.M.; Jones, J.W.; Rosenzweig, R. Next generation agricultural system models and knowledge products: Synthesis and strategy. *Agric. Syst.* **2017**, *155*, 179–185. [CrossRef]

60. Azhar, A.H.; Perera, B.J.C. Evaluation of reference evapotranspiration estimation methods under southeast Australian conditions. *J. Irrig. Drain. Eng.* **2011**, *137*, 268–279. [CrossRef]

61. Lorite, I.J.; Ramírez-Cuesta, J.M.; Cruz-Blanco, M.; Santos, C. Using weather forecast data for irrigation scheduling under semi-arid conditions. *Irrig. Sci.* **2015**, *33*, 411–427. [CrossRef]

62. Er-Raki, S.; Chehbouni, A.; Khabba, S.; Simmoneaux, V.; Jarlan, L.; Ouldbba, A.; Rodríguez, J.C.; Allen, R. Assessment of reference evapotranspiration methods in semiarid regions: Can weather forecast data be used as alternate of ground meteorological parameters? *J. Arid Environ.* **2010**, *74*, 1587–1596. [CrossRef]

63. Collins, J.M. Temperature variability over Africa. *J. Clim.* **2011**, *24*, 3649–3666. [CrossRef]

64. Pedrero, F.; Kalavrouziotis, I.; Alarcón, J.J.; Koukoulakis, P.; Asano, T. Use of treated municipal wastewater in irrigated agriculture–Review of some practices in Spain and Greece. *Agric. Water Manag.* **2010**, *97*, 1233–1241. [CrossRef]

65. Nicolás, E.; Alarcón, J.J.; Mounzer, O.; Pedrero, F.; Nortes, P.A.; Alcobendas, R.; Romero-Trigueros, C.; Bayona, J.M.; Maestre-Valero, J.F. Long-term physiological and agronomic responses of mandarin trees to irrigation with saline reclaimed water. *Agric. Water Manag.* **2016**, *166*, 1–8. [CrossRef]

66. Cameira, M.R.; Mota, M. Nitrogen related diffuse pollution from horticulture production–Mitigation practices and assessment strategies. *Horticulturae* **2017**, *3*, 25. [CrossRef]

67. Fereres, E.; Soriano, M.A. Deficit irrigation for reducing agricultural water use. *J. Exp. Bot.* **2007**, *58*, 147–159. [CrossRef]

68. Fereres, E.; Orgaz, F.; González-Dugo, M.V. Reflections on food security under water scarcity. *J. Exp. Bot.* **2011**, *62*, 4079–4086. [CrossRef]

69. Iglesias, A.; Garrote, L. Adaptation strategies for agricultural water management under climate change in Europe. *Agric. Water Manag.* **2015**, *155*, 113–124. [CrossRef]