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Remote sensing–based soil water balance for irrigation water accounting at plot and water user association management scale

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ABSTRACT

Irrigation water accounting (IWA) plays a key role in irrigation management in arid or semi-arid environments. Currently, water managers perform IWA through indirect or direct measurements such as statistical methods or flow meters. However, they have a high maintenance cost and great efforts must be done when large irrigated areas must be covered. The presented framework based on the dual crop coefficient FAO56 methodology introduces an operative application of a Remote Sensing-based Soil Water Balance (RS-SWB) to obtain a Remote Sensing-based Irrigation Water Accounting (RS-IWA). A basic input of the model is the time series of basal crop coefficient and fractional vegetation cover. It has been implemented in a large water user association (100,000 ha) along three years (2010 – 2012). The results are analysed from the perspective of two water management scales: the plot and the water user association. At plot scale, the RS-IWA of maize and wheat, as primary crops irrigated on demand, show a root square mean error (RMSE) of about 12 % compared with the records from local farmers. At water user association management scale, the results from RS-IWA show an RMSE of about 15 % for a comprehensive range of irrigated crops group such as spring crops, summer crops, double harvest, alfalfa, and vineyards. Hence, RS-IWA based on RS-SWB offers reproducible and reliable mapped estimations that can be used for different water managers, as they are being required from actual agro-environmental laws that are pushing these actors to better knowledge in time and space of those water resources applied.

1. Introduction

Latest figures on global water resources from the FAO's global water information system (FAO, 2016) accounts for 260 Mha of the total irrigated area, that implies around 70 % (2700 Km^3) of global withdrawal water, with an important range of variations depending on the continent, country or region (ranging from 25 % in Europe to 85 % in Asia or Africa). Irrigated agriculture is the main water consumer in Southern Europe, where it uses up to 80 % of water resources (EEA, 2009). Besides, the continuous increase in irrigated surface areas, parallel to the world population, will impact on more pressure on water withdrawals (FAO, 2011). In such a context, world leaders are facing up the forthcoming situation by promoting legal instruments that provide precise control frameworks on water allocation and use. Nowadays, the third implementation review of the Water Framework Directive (WFD) on European Union, emphasizes water accounting as a key instrument for sustainable water use (European Commission, 2012). Furthermore, public or private water authorities are responsible for the application of those regulations.

So far, water authorities are commonly using indirect or direct measurements such as statistical methods or flow meters respectively, to account and allocate water resources when they elaborate the River Basin Management Plans. However, the same authorities recognize limitations in actual irrigation water accounting approaches. As an example, some Spanish River basin water managers have been expressing their concern about abstraction monitoring networks that are only based on flow meters. They generally emphasize the complexity of installation and maintenance due to lack of awareness on the users'

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side, and quite specifically, describe evidence of incorrect hydraulic settings, high cost, deterioration and incorrect management (Bayó Dalmau and Loaso Vierbücher, 1999; Díaz Mora, 1999), which all lead to deviations between authorized and actual abstractions. The same evidence is listed by FAO Water Report Nº 28 (Cornish et al., 2004), a complete report that brings actual knowledge on existing approaches to account for the resource, and then price water, regarding their advantages or disadvantages. In that sense, a comprehensive study conducted by the Spanish National Centre of Irrigation Technology shows that each flow meter requires a specific installation to provide reliable results, and it also concludes that the functioning of any flow meter deteriorates with time due to residues in the water. On the other hand, statistical approaches bring the opportunity to account for water demand over large territories using tabulated thresholds of annual crop water demand assigned to estimated irrigated surface areas. However, and regarding water manager's knowledge, there is a lack of distributed spatio-temporal information at field plot scale that ranges from irrigation schemes to river basin districts.

Nevertheless, the FAO56 approach has been largely applied for crop water requirements estimation at field plot spatial scale (Allen et al., 1998). To that end, no matter which crop coefficient approach the user is applying (single or dual), FAO56 offers both equations or tabulates values for crop coefficient (K_c), basal crop coefficient (K_{cb}) and even the fraction of soil surface covered by vegetation (f_c), at different crop stages (initial, development, middle season and late season). However, the same authors strongly recommend implementing local adaptations. Consequently in many countries, scientific community or Irrigation Advisory Services adapted the original tabulate values at their local crop varieties under particular climatic conditions, and even added new K_c or K_{cb} values for crops that were not originally covered (Pereira et al., 2015). However, when big and diverse irrigated surface areas are fully monitored, huge and continuous efforts to achieve correct local adaptations must be taken into consideration. Different crop species cultivated, their sowing dates, or even their crop architectural developments across time among many other parameters, are necessarily achieved to obtain the whole and complete geodatabase that allows applying tabulated values over such areas. Notwithstanding, the use of Remote Sensing (RS) data has become a powerful link to apply the FAO56 approach in the last decades, showing that RS products offer the capacity to monitor crop growth over large areas (Tasumi and Allen, 2007), and providing time series of information that allows for near-real-time decision support (Moran et al., 1997).

Regarding FAO56 approach, estimations of crop evapotranspiration (ET_c) can be achieved by using the optical or thermal spectrum data from satellite sensors, or even a combination thereof (Gilabert et al., 2010; Glenn et al., 2011), generally classified into surface energy balances (SEB) and soil water balances (SWB). Both categories differ in the nature of the input data, the physics of the processes analysed and the models' ability to reproduce the different processes. The SEB approach is based on the capability to obtain the surface latent heat flux even under water stress conditions by using as primary input the surface temperature supplied by the RS methodologies (Allen et al., 2007). In parallel, the SWB approach takes advantage of the demonstrated capability of spectral vegetation indices (Jackson and Huete, 1991) to provide a precise estimation of the canopy potential transpiration (Gonzalez-Dugo et al., 2009). Then, it balances the other water budget components to achieve the net irrigation requirements (NIR), to maintain the crop under the desired water conditions. Methodologies to obtain crop coefficients from vegetation indices has been demonstrated and validated for a wide range of herbaceous crops (Bausch and Neale, 1987; Choudhury et al., 1994; D'Urso and Calera Belmonte, 2006; Duchemin et al., 2006; Er-Raki et al., 2007; González-Dugo and Mateos, 2008; González-Piqueras, 2006; Hunsaker et al., 2003; Jayanthi et al., 2007) and several important perennials (Campos et al., 2010b; Odi-Lara et al., 2016; Samani et al., 2009).

In consequence, RS operative applications are being offered to different water managers as it introduces the advantage of monitoring large areas at plot spatial scale. Different studies have been published showing the operational use of the methodology, e.g., the monitoring of crops reporting maps to users accounting water withdrawal at different spatial scales that are based on thermal data (Anderson et al., 2011; Karimi et al., 2013; Ramírez-Cuesta et al., 2017), or in optical spectrum (Cherif et al., 2012; González-Dugo et al., 2013; Hornbuckle et al., 2009; Le Page et al., 2009; Melton et al., 2012; Pereira et al., 2003; Vuolo et al., 2015). Therefore, RS techniques are sufficiently mature to be used as required and requested by the water managers (Calera et al., 2017; Gowda et al., 2008), and even, through global free platforms that allow public access to satellite data products and algorithms (Gorelick et al., 2017).

The purpose of this paper is to demonstrate and validate an operational approach to obtain Remote Sensing-based Irrigation Water Accounting (RS-IWA), across large and diverse irrigation surface areas, after computing a Remote Sensing-based Soil Water Balance (RS-SWB). To that goal, the methodology applied is the well-known FAO56 model (Allen et al., 1998), but assisted by vegetation indices (VI) derived from remote sensing time series, to monitor crop development in a pixel-based scale (Pôças et al., 2020, this Special Issue). The combination across time of such vegetation information, daily agrometeorological variables and soil properties plus the water available for crops at their root depth by means of a soil water balance, allows computing daily estimations of crop transpiration and soil evaporation. These parameters configure the adjusted crop evapotranspiration ($ET_{c\ adj}$), which is the most detailed and main component that extracts water at roots soil depth. Therefore, to maintain crops under commercially beneficial conditions over irrigated surface areas, irrigation practices are necessary to replenish the soil water depletion. After all, the estimated NIR computed at pixel-based scale by means of RS-SWB, is the key parameter that allows computing the RS-IWA, after spatial and temporal aggregation to the adequate scale.

The software that allows spatial and temporal distribution of the RS-SWB following FAO56 approach, with the goal to obtain a RS-IWA, is called HidroMORE. Lately, this model has been demonstrated over irrigation surface areas at larger and different spatial and water resource scales, like the aquifer (Garrido-Rubio et al., 2019) and in the Spanish mainland river basins (Garrido-Rubio et al., 2018). However, in the following paper, we afford the opportunity to demonstrate its reliability regarding a ground-truth data set infrequently found in the literature, irrigation volumes at two water and agricultural management scales: the plot and the water user association (WUA). Hence, this paper focused on the operational application of the RS-SWB, based on FAO56 methodology to fully monitor large and diverse irrigation surface areas.

2. Methodology

This section describes the methodology for obtaining and validating indirect measurements of Remote Sensing-based Irrigation Water Accounting (RS-IWA) over big and diverse irrigation surface areas, by means of an operative tool called HidroMORE, that performs a Remote Sensing-based Soil Water Balance (RS-SWB) applying the dual crop coefficient FAO56 approach (Fig. 1). The details of methodological steps and data sources are given in the sections below. The starting point is a time series of Normalized Difference Vegetation Index (NDVI, Rouse et al., 1973) derived from satellite images, which serves for two purposes. On the one hand, a map of irrigated crops is produced by supervised multi-temporal classification. On the other hand, the biophysical components such as the basal crop coefficient (K_{cb}) and the fraction of soil surface covered by vegetation (f_c), are obtained applying linear relationships from NDVI. In parallel, local data (meteorology, soil hydrology, and crop characteristics) are gathered from direct observations and geodatabases. The workflows continue by feeding the HidroMORE model with the geodatabases and the NDVI time series to

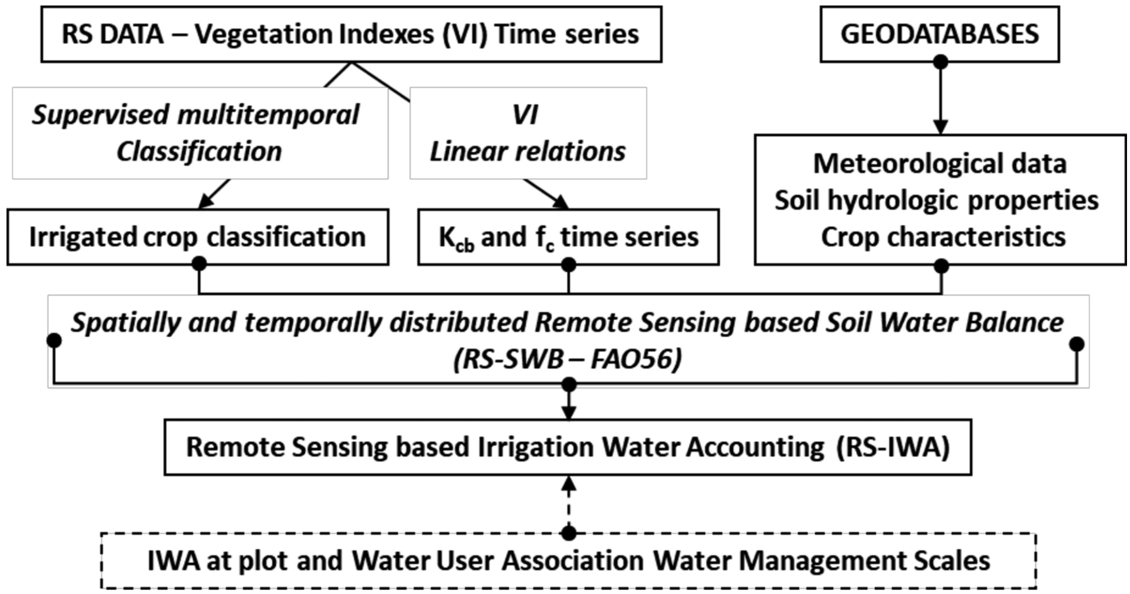

Fig. 1. Schematic overview framework of the methodology presented for a Remote Sensing-based Irrigation Water Accounting (RS-IWA).

obtain temporal and spatially distributed pixel-based maps of NIR at daily and pixel-based scale. Managed at different spatial water management scales (plot and Water User Association), the RS-IWA is then validated through the irrigation volumes obtained from in-situ data gathered at those same scales. For this study case, the validation has been carried out along three consecutive irrigation campaigns (2010 – 2012), covering dry and humid years, consisting of a comprehensive comparison of the NIR computed through the RS-SWB model and ground truth data provided at plot and water user association scale for seasonal herbaceous (wheat, maize, and barley) and permanent crops (mainly vineyards).

2.1. Study area and climatic context

The test site is located at the Mancha Oriental Central Irrigation Water Board (JCRMO, Junta Central de Regantes de la Mancha Oriental), located in the Júcar river basin, Southeast of Spain (Fig. 2). The JCRMO is a large Irrigation Water Users Association (WUA), mainly dependent on groundwater resources and involved in the use of remote sensing techniques for water management. Around 92 % of the water resources used are withdrawal from the groundwater Mancha Oriental system (Sanz et al., 2009). The WUA is the authority in charge of the 900 water management units (plots, farms, or groups of farms served by the same resource, e.g. pumping station or pond) covering a total of 100,000 ha of irrigated land. It has become known for its singular model of collective self-regulating water management, having sustained stable aquifer levels for the past 20 years (Esteban and Albiac, 2012). On the finest management scale, there are individual farm holdings (members of the WUA). The most common irrigation systems in cereals are sprinkler (41 %) and centre pivot (39 %), with drip irrigation (15 %) being mostly used in perennials. The average plot size is 5 ha.

The study area is characterized by the Mediterranean and semi-arid climate (UNEP, 1997), with an aridity index of 0.26 between 2000 and 2013. The mean annual rainfall for the reference period of 1981 – 2010 is 353 mm, regarding the Spanish Meteorological Agency (AEMET). Precipitation (*P*) is highly variable with seasonal peaks in spring and fall. Daily climatic conditions and seasonal variations of ET_o and *P* have a significant impact on crop water requirements. The bottom panel on Fig. 2 shows similar behaviour of ET_o in the three years of study, but different *P* patterns and cumulative values (Table 1).

Regarding the Spanish Meteorological Agency (AEMET), Table 1 indicates the year 2010 as very humid, 2011 as dry, and 2012 as humid compared to the period 1981 – 2010. This would a priori mean that crop water requirements would be highest in 2011. However, only the seasonal and monthly data can show the true situation. The most crucial influencing factor is mean spring rain, followed by mean summer precipitation. The high value of mean summer precipitation in 2012 is misleading since most of the rain (63 out of 65 mm) was falling in September, i.e., beyond the main irrigation season period.

2.2. Field data for irrigation water accounting at two water management scales

On one hand, the WUA provided the following data: irrigated surface areas and annual net irrigation requirements, for both spring and summer crops, double-harvest group crops, alfalfa, and vine crop types. Data on irrigated surface areas are taken from the annual cultivation plan that each water management unit must submit at the beginning of each irrigation season. In parallel, annual net irrigation requirements have been calculated by WUA based on average values of the past five years, provided to the WUA by the local Irrigation Advisory Service.

On the other hand, data for the plot scale analysis provided by the individual farm holdings include records of irrigated surface areas per crop and the annual irrigation water applied (as measured by flow meters). Regarding annual applied irrigation water, a total of 49 records has been provided, while regarding irrigated surface areas a total of 47 records. Besides, among these farm holdings, a smaller but quite similar group of farm holdings also provided their irrigation calendar, with a total of 41 records. Table 2 shows these data disaggregated by year, crop and type of data.

2.3. Methodology to obtain Remote Sensing-based Soil Water Balance (RS-SWB)

The well-known FAO56 root zone depletion model (Allen et al., 1998, Eq. 85) was used. For that reason, the following methodological description avoids redundant explanations on such balance and focuses on how RS data is used to assist the model.

Eq. (1) describes the soil water balance at root depth. On one hand, water inputs into the balance (do not confuse with input model parameters) are precipitation (*P*), net irrigation depth (*I*), and capillary rise (*CR*). In our approach, the latter is negligible in the study area due to the depth of its vadose zone (Torres, 2010). On the other hand, the water outputs from the balance (do not confuse with output model

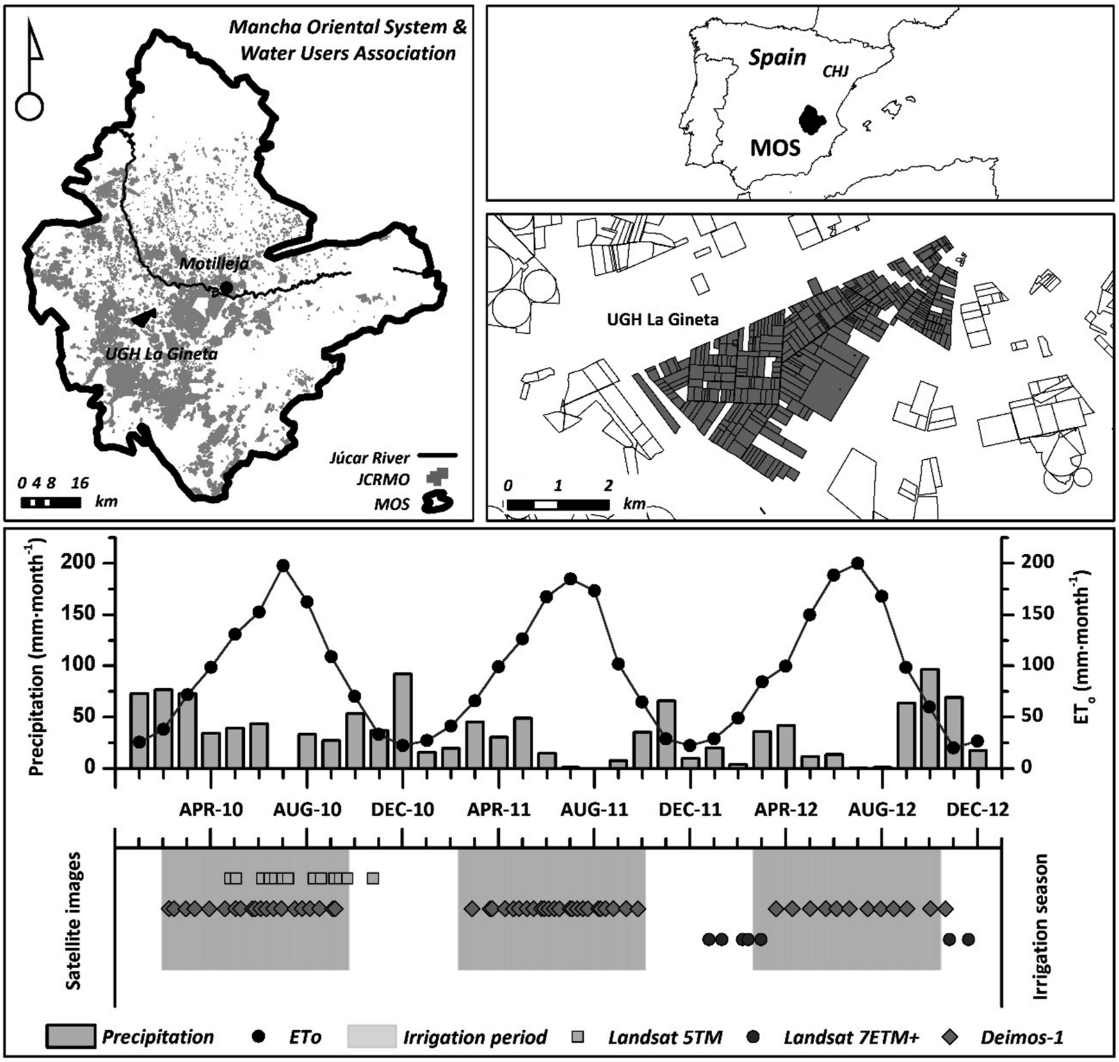

Fig. 2. The study area and core data. Upper panel: Mancha Oriental System (MOS) location in Spain (upper right corner) and the two management scales studied (Water Users Association in the upper left corner and example of plots located at La Gineta water management unit). Lower panel: Monthly distribution of P and ET_o for the study period (2010 – 2012) at La Motilleja agrometeorological station, and timing of RS satellite images and irrigation season.

Table 1
Climatic reference of mean annual and seasonal precipitation in the study area compared to actual values for the three years of study.

Climatic mean values of precipitation (mm) for the reference period 1981 – 2010[a]			Actual mean precipitation (mm) for the study period, 2010 – 2012[b]				ET_o (mm)[b]
Annual	Spring	Summer	Year	Annual	Spring	Summer	Annual
353	118	54	2010	583	117	60	1113
			2011	295	94	8	1102
			2012	374	66	65	1173

[a] Spanish Meteorological Agency (http://www.aemet.es/es/serviciosclimaticos/datosclimatologicos/valoresclimatologicos).
[b] SIAR, the Spanish network of agrometeorological stations in irrigated areas (www.siar.es).

Table 2
Number of data records provided by farm holdings regarding the type, year and crop.

		Number of records provided by farm holdings		
Year	Crop	Irrigated surface area	Annual irrigation	Irrigation calendar
2010	**Wheat**	3	4	3
2011	**Wheat**	11	12	9
	Maize	5	5	3
2012	**Wheat**	15	15	15
	Maize	6	6	4
	Barley	7	7	7
Total		47	49	41

products) are crop evapotranspiration (ET_c), root zone deep percolation (DP), and surface runoff (RO). In the present study, the model starts simulation on 1 January 2010, with a soil profile considered fully watered (initial $D_{r,i\text{-}1} = 0$ mm), according to a normal to the humid previous year 2009 regarding the Spanish Meteorological Agency. Then, the soil water content is calculated at pixel-based scale in a daily iteration as the root zone depletion (D_r) at the end of the day i (from 1 to 365).

$$D_{r,i} = D_{r,i-1} - (P - RO)i - I_i - CR_i + ET_{c,i} + DP_i \quad (1)$$

In the case of ET_c, the methodology follows the dual crop coefficient approach, Eq. 2 (Wright, 1982), recommended also for crops with partial ground cover (like perennial crops or herbaceous at its first stages present in the study zone), or under frequent irrigation (like onion or garlic, quite present in the study zone, as well) (Allen et al., 2005, 1998). Such approach splits the crop coefficient (K_c) into the soil evaporation coefficient (K_e), which describes soil evaporation (E), and the basal crop coefficient (K_{cb}), which describes potential crop transpiration (T). The model also includes the water stress coefficient (K_s), which accounts for crop transpiration decreasing with water availability. Hence, the approach estimates crop adjusted evapotranspiration $ET_{c\ adj}$.

$$ET_{c\,adj} = ET_o(K_{cb}K_s + K_e) = E + T \tag{2}$$

In that equation, the development of crops determines T and E components. While K_{cb} allows estimating T, the fraction of soil surface covered by vegetation (f_c) allows estimating the fraction of the soil that is both exposed to solar radiation and is wetted (f_{ew}), after a precipitation or irrigation event, and hence E through the K_e. Despite the use of tabulated values proposed in the literature, the soil water balance uses remote sensing data, particularly VI, so it turns into a RS-SWB. VI are one of the basic RS products (Huete, 1988; Jackson and Huete, 1991). The most commonly used VI is NDVI, which is also used here for vegetation monitoring. NDVI is the key to obtaining linear relations that allows for K_{cb} and f_c estimations (Pôças et al., 2020, this Special Issue). Since these parameters, derived by RS data, show the actual vegetation cover conditions they should be referred to as $K_{cb\ act}$ and $f_{c\ act}$ to differentiate them from FAO56 nomenclature (K_{cb} and f_c), which refers to standard vegetation (Pereira et al., 2015). Eqs. (3) and (4) provide the linear relations used here and obtained in the study area for NDVI-$K_{cb\ act}$ (Campos et al., 2010a) and NDVI-$f_{c\ act}$ (González-Piqueras, 2006), respectively.

$$K_{cb\,act} = 1.44 \cdot NDVI - 0.1 \tag{3}$$

$$f_{c\,act} = 1.19 \cdot NDVI - 0.16 \tag{4}$$

Both equations were conceived after field experiments and ground-truth data and showed strong relationships. The first one (Eq. 3), originally developed for irrigated vineyard crops, does not differ from other NDVI-$K_{cb\ act}$ linear relationship specifically developed for herbaceous crops like maize (Bausch and Neale, 1987; Gonzalez-Piqueras et al., 2004), or sorghum (López-Urrea et al., 2016). Besides, that relationship has been positively evaluated for other authors under different climatic areas, like the case of wine-grapes in Australia (Hornbuckle et al. 2014), or it has been compared in a case of apple trees in the south of Chile, where authors did not find strong differences in the $K_{cb\ act}$ behaviour when the linear relationship is based in a different VI like the SAVI (Odi-Lara et al., 2016). Finally, it has been validated for other uses different than irrigated crops like savahan dehesa (Campos et al., 2013). On the other hand, the second relationship (Eq. 4) was originally developed for herbaceous crops, like maize and wheat, and has been positively evaluated against other linear relationships developed for vineyards (Campos et al., 2014). Furthermore, this relationship has been implemented into HidroMORE to run the RS-SWB to quantify the soil water content below fields of rain-fed cereals, summer irrigated crops and vineyards, in comparison with ground-truth data from the REMEDHUS network of 23 stations located in the central semi-arid zone of the Spanish Duero river basin, (Sánchez et al., 2010). Finally, we highlight the use of this NDVI-$f_{c\ act}$ relationship (among others) to obtain through remote sensing data a full vegetation development monitoring, including the critical *green-up* stage for maize, wheat and barley (González-Gómez et al., 2018). In parallel, today's discussion on the use or non-use of non-dependent VI linear relationships to estimate biophysical parameters has several authors that agree on its use when operational applications are run (Calera et al., 2017). Good examples of this include the application of the TOP-SIMS in California (Melton et al., 2012), and use in Australia for citrus crops and vineyards (Hornbuckle et al., 2009).

Besides the use of VI linear relationships to include in the RS-SWB, the model also follows a modification on how daily E is calculated in FAO56 approach. In that sense, the calculation of K_e uses a modified Eq. (5) to apply a correction coefficient (m) to the reduction coefficient (K_r), which has been shown necessary in areas with high atmospheric demand (Torres and Calera, 2010). K_r is obtained from Eq. (6) as the minimum of ratios involving the parameters Readily Evaporable Water (REW), ET_o, Total Evaporable Water (TEW), soil surface layer depletion (D_e), and the correction coefficient m:

$$K_e = K_r(K_{cmax} - K_{cb}) \le (1 - f_c)K_{cmax} \tag{5}$$

$$K_r = \min\{REW/ET_o,\ m((TEW - D_{e,i})/(TEW - REW))\} \tag{6}$$

Through the estimation of daily $ET_{c\ adj}$, Eq. 1 can be inverted (to Eq. 7) to estimate the temporal and spatially distributed pixel-based net irrigation requirements (NIR), defined as that needed to maintain the crop at potential transpiration rates (except for perennials). Therefore, in the case of herbaceous crops, the model maintains D_r values above Readily Available Water (RAW), i.e. keeping K_s around 1 value, by means of irrigation events as soon as the stress is shown up. The assumption of no-water stress conditions in herbaceous crops is reasonable based on: i) the 2012 Spanish National Annual Statistics Report accounts that average production for the irrigated crops in Albacete province (majority location of the study area) were higher to the national average in case of wheat, barley and maize (MAGRAMA, 2012); and ii) local irrigation practices and collective collaboration on sustainable groundwater management has been recognized as a successful case (Esteban and Albiac, 2012). In opposite, when the model deals with vineyards (perennials), an irrigation event is triggered when the K_s is reached.

$$NIR_i = (D_{r,i-1} - D_{r,i}) - (P - RO)_i + ET_{c\,adj,i} + DP_i \tag{7}$$

In accordance with the water use concept of Perry (Perry, 2011), the available individual plot data collected from flow meters, cover both the consumed and non-consumed fraction of the water applied. In parallel, the model-calculated NIR refer to the net irrigation depth placed at soil roots depth, and hence, does not account for non-beneficial consumed fraction or non-consumed fraction. Consequently, to achieve a consistent comparison between flow meters records and NIR, at least, the differences between gross and net irrigation volumes must be addressed. For this purpose, the model-calculated NIR have been increased by 15 % or 20 %, depending on the irrigation system in place (average system efficiencies obtained by the local irrigation Advisory Service for sprinkler and centre pivot, respectively).

2.4. The model HidroMORE, a tool for RS-SWB over large areas

The methodology to estimate RS-SWB described above has been implemented in the latest version of HidroMORE software (Moreno et al., 2017), which integrates RS derived products, and meteorological, edaphological, and crop data in the dual crop coefficient model of FAO56. Its innovative features are on the one hand the assimilation of multispectral RS data by means of the NDVI-$K_{cb\ act}$ and NDVI-$f_{c\ act}$ relations; on the other hand, the spatial distribution of the FAO56 model by means of a distributed hydrological model (Torres, 2010). The model runs at a daily time-step and pixel-based scale. The spatial coverage and resolution are defined by the footprint of the satellite images over the terrain and their pixel size, respectively.

The HidroMORE software and its different outputs have been validated at different scenarios. One commented before (Section 2.3), which used in situ soil moisture data from the REMEHDUS network for the application and validation of the RS-SWB (Sánchez et al., 2010; Sánchez et al., 2012). Moreover, groundwater withdrawals for irrigation purposes recorded by the Spanish official piezometers network were compared against NIR at the aquifer scale (Garrido-Rubio et al., 2019). Besides, in the same way to provide validations against the NIR, annual model estimations at river basin scale along 4 consecutive years (2014–2017) were compared against irrigation needs at 12 River Basin Management Plans (2nd cycle) over the Spanish mainland scale (Garrido-Rubio et al., 2018). Nowadays, previous data at monthly and annual scale is being collected by the Spanish Ministry for the Ecological Transition for further validations against in situ data with the purpose to include those results for management and planning of water resources (Ortega et al., 2019). Furthermore, 3 doctoral theses used the model for different purposes: i) the use of remote sensing data to assist the soil water balance model and achieve a distributed spatio-temporal data of percolation and NIR at the aquifer scale (Torres, 2010); ii) the validation of soil moisture output data from the RS-SWB model against in situ data (Sánchez, 2009; Sánchez et al., 2010); and iii) the spatio-temporal validation of NDVI-$K_{cb\ act}$ linear relationship at the aquifer scale for vineyards (Campos, 2012). Furthermore, two EU funded projects used HidroMORE for operative applications providing distributed spatio-temporal thematic cartography (ET_c, NIR…) at monthly time scale: i) to generate services on water management to water users at different levels (SIRIUS EU project, GA nº 262902, http://sirius-gmes.es/); and ii) to detect non-authorized irrigation water abstractions in comparison with the local water authorities data (DIANA EU project, GA nº 703109, https://diana-h2020.eu/en/). Besides, HidroMORE tool has been playing an important role in the Coquimbo region, south Chile, reporting among other parameters NIR spatio-temporal maps for irrigation management and information services to different water authorities and end-users (http://www.inia.cl/proyecto/502145/, CAPRA project).

In practical terms the input data for HidroMORE is a set of geospatial data like a) time series of NDVI images, b) maps of edaphological data for the calculation of soil hydrological parameters, c) annual maps of irrigated areas per crop type, and d) daily agrometeorological data from the national network of agrometeorological stations in irrigated areas, the Advisory service to the irrigator network (SIAR). Table 3 gives the list of input parameters and the corresponding data sources. Running HidroMORE at each pixel with a daily time-step requires interpolation of some input data. The daily RS-derived biophysical parameters are calculated interpolating between the time series of NDVI images, while the pixel values of climatic parameters were obtained from spatial interpolation (inverse distance squared) of point observations.

The daily outputs of HidroMORE are the spatially and temporally distributed terms of the soil water balance ($ET_{c\ adj}$, NIR, P, DP, D_r, RO) and maps of further parameters of interest (ET_o, $K_{cb\ act}$, K_s, K_c). In the first step, the output data have been temporally aggregated to monthly and annual accumulated values. Then, the spatial aggregation has been performed by extracting the vector layers statistics over the raster maps at the spatial scales of the plots and the WUA.

2.5. RS satellite data

A total of 76 images has been processed to obtain NDVI maps (bottom panel of Fig. 2). The images have been selected to monitor crop growth during the irrigation campaign. The time series consists of images from a constellation of sensors: Thematic Mapper (TM) on board of the Landsat 5 satellite (13 images in 2010); Enhanced Thematic Mapper Plus (ETM+) on board Landsat 7 (7 images in 2012), in either case using pathrows 199-033 and 200-033; and images from Deimos-1 satellite (20, 24, 12 images in 2010, 2011, 2012, respectively).

All Landsat images have been radiometrically corrected (Chander et al., 2009), while Deimos-1 images are delivered with completed correction. An absolute normalization procedure has been applied to each image to achieve atmospheric correction and inter-sensor cross-calibration. This method uses at least two invariant surfaces (Chen et al., 2005) to determine the regression line for NDVI values.

Any pixels contaminated with clouds have been eliminated. Given the different spatial resolution of the different satellite sensors (30 m for Landsat 5 and 7; 20 m for Deimos-1), pixels have been re-scaled through the nearest neighbour approach to 25 m for 2010 data and to 20 m for 2011 and 2012. The spatial accuracy of the NDVI time series when using different satellites in a virtual constellation is obtained by using a minimum 3×3 pixel spatial aggregation (Martínez-Beltrán et al., 2009). Therefore, this resolution obtained allowed for monitoring plots larger than 0.5 ha, enough for the study area where the average plot size is 5 ha.

2.6. Irrigated surfaces areas classification by remote sensing

Crop mapping of irrigated areas has been carried out using multi-temporal supervised classification of RS images. The classification maps belong as a core part of the ERMOT project, the more than 20 years-old project that monitors irrigated surface areas across the study area, through remote sensing techniques. Hence, the knowledge of the territory and its crop types cultivated allow recognising and using different temporal dynamics of vegetation development as expressed in a time series of NDVI maps. These profiles exhibit the characteristic vegetation periods, which are used to classify the crops. In consequence, threshold criteria are included in decision-tree methodologies based on the different growing and phenological development rates, which can be studied in the NDVI across the time series. This classification by vegetative periods yields crop classes with similar irrigation requirements and cover structure (Calera et al., 1999). For subsequent estimation of NIR, the main classes are defined as herbaceous (spring crops, summer crops, double harvest), and perennials (vineyards).

Classification accuracy was computed by an independent commission, supplying overall accuracy values after computing the error matrix and consequently, by dividing the total correct by the total number of pixels (Congalton, 1991). To that goal, maps of irrigated areas have been extensively validated through strategic field visits to 5% of the

Table 3
Input data for HidroMORE calculation of RS-SWB and corresponding data sources.

Input parameter	Data source
basal crop coefficient, $K_{cb\ act}$ (dimensionless)	time series of NDVI (from Landsat 5 T M, Landsat 7 ETM + y DEIMOS-1)
fraction of soil surface cover by vegetation, $f_{c\ act}$ (dimensionless)	
annual map of irrigated crops and areas	supervised multi-temporal classification
daily precipitation, P (mm/d)	SIAR, the Spanish network of agrometeorological stations in irrigated areas (www.siar.es)
daily ET_o (mm/d)	
field capacity, Θ_{FC} (m^3/m^3)	map of soil types, scale 1:1.000.000 (Guerra Delgado et al., 1968)
wilting point, Θ_{WP} (m^3/m^3)	
soil depth, Z_s (m)	
evapotranspiration depletion fraction, p (dimensionless)	FAO56, (Allen et al., 1998)
maximum root depth, Z_{rmax} (m)	
minimum root depth, Z_{rmin} (m)	
water stress coefficient, K_s (dimensionless)	
Allowed maximum net irrigation requirements per crop type, NIR_{max} (mm/d)	adapted to local practice
fraction of soil wetted by rain or irrigation, f_w (dimensionless)	adapted to local irrigation systems
irrigation period per crop type (days)	adapted to local practice

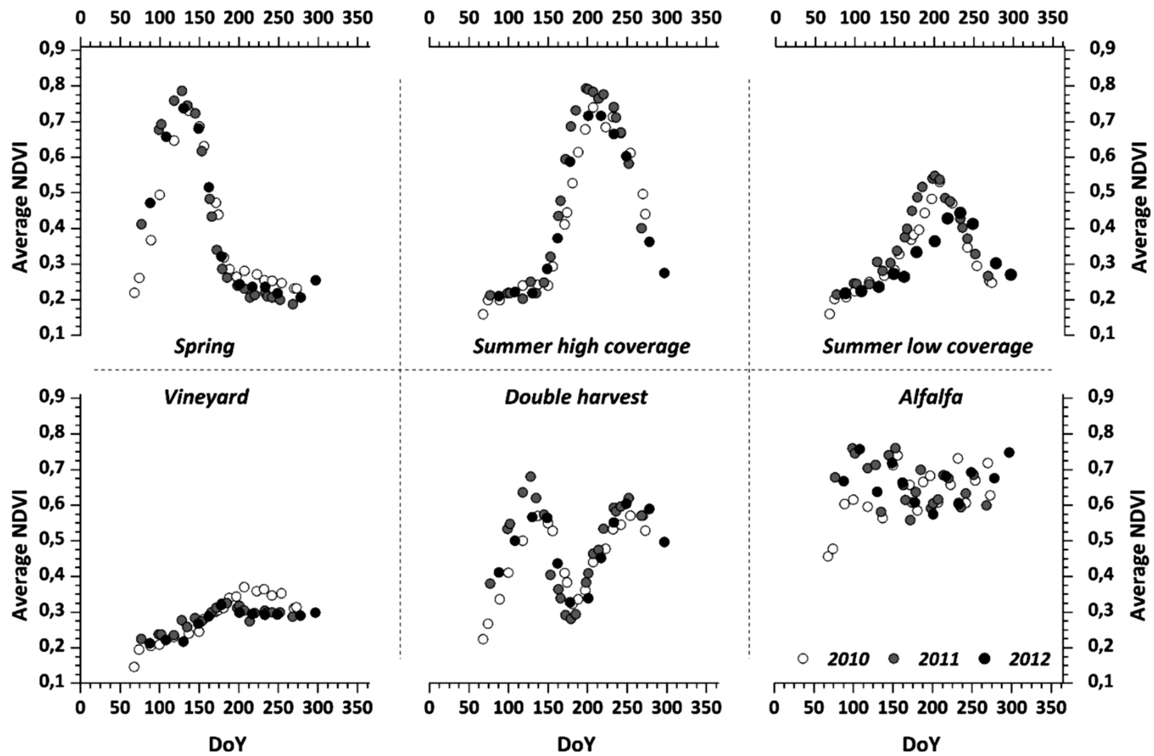

Fig. 3. NDVI profiles from Deimos-1 time series covering three years for different crop classes (from left to right and top to bottom: spring, high-coverage summer, low-coverage summer, double harvest, vineyard, and alfalfa).

total area. All plots selected for the study are larger than 0.5 ha, thus maintaining an inner core unaffected by potential effects of pixels on the border periphery. Annual overall accuracy classification for spring crops is 85 %, 96 % and 98 % in 2010, 2011 and 2012, respectively. In the case of summer crops and with similar chronological order, the accuracy values are 96 %, 97 % and 96 % respectively, while for the double harvest ones 83 %, 74 % and 63 %. Finally, in perennials crop group (vineyards), accuracy values range from 84 % in 2010 and 2011, to 90 % in 2012.

3. Results and discussion

3.1. Identification of irrigated areas

The crop inventory is based on a set of irrigated crop types with similar vegetative development, as evidenced in their NDVI profiles (Fig. 3): spring crops (e.g., wheat, barley), summer crops with high ground cover (e.g., maize), summer crops with low ground cover (e.g., onion), double harvest (e.g., annual rotation of wheat and maize), alfalfa, and vineyards.

The NDVI profiles for each crop class on Fig. 3 show slight differences between years. This is due to the influence of meteorological conditions on local agricultural practices, like sowing date or crop evolution (Tasumi and Allen, 2007). The alfalfa profiles play a special role here since the temporal frequency of the satellites used does not allow for determining the highly dynamic crop behaviour (very rapid growth and cut every 28 days approximately). However, the profiles are still quite characteristic and allow their discrimination from the other covers.

3.2. Irrigated surface area and RS-IWA at plot scale

Fig. 4 and Table 4 show the comparison of irrigated surface area (left panel) and annual RS-IWA (right panel) by individual plots and per crop type. The irrigated surface area results agree with the field values, with a root mean square error (RMSE) around 6% in 2010 and 2012, rising to 15 % in 2011. Detailed per-plot analysis of the 2011 data reveals a special situation, where 71 % of all plots were used for mixed cultivation (crop rotation and sub-plots, e.g. wheat, garlic, maize, onion in the same plot), in comparison with 2010 and 2012 years (25 % and 35 %, respectively). Hence, the irrigated surfaces areas classification for 2011 produced weakest results, so it is reflected in the increase in RMSE value for that year in contrast with RMSE values for 2010 and 2012 years.

The comparison of RS-IWA has been performed by crop type. The right panel of Fig. 4 shows the annual mean values and standard deviations per year for wheat, barley, and maize. RS-assisted values for wheat and maize are slightly lower than those declared by farmers, whereas those for barley are significantly higher. Fig. 4 shows that the model is able to respond to different climatic conditions. RS-IWA values in 2012 are higher than those in 2010 and 2011, in agreement with the records of the farmers.

The dispersion in the IWA values (right panel of Fig. 4) is consistently and significantly lower in the RS-assisted results (standard deviation ranges from 15, 22 and 43 mm/year for wheat in 2010, 2011 and 2012; 17–19 mm/year for maize in 2011 and 2012; and 20 mm/year in barley in 2012) than in those obtained from farmers (standard deviation ranges from 65, 26 and 104 mm/year for wheat in 2010, 2011 and 2012; 58–73 mm/year for maize in 2011 and 2012; and 72 mm/year for barley in 2012). This apparent lack of sensitivity of the RS-based approach is due to the resolution of the available soil map (1:1,100,000), which does not show much of the heterogeneities at a finer scale. The available soil water content depends among other factors on the maximum root depth (Z_{rmax}) and the limiting soil depth (Z_s). The latter is extracted from the soil map. It plays a key role in irrigation requirements, but it is difficult to obtain (Torres, 2010). The range of mean Z_s values in the study plots ranges on 0.3 – 0.6 m, thus limiting Z_{rmax}. Consequently, the model averages out the heterogeneities, as it is using the best soil map description available. However, regarding the standard deviation analysis previously described, it was expected that

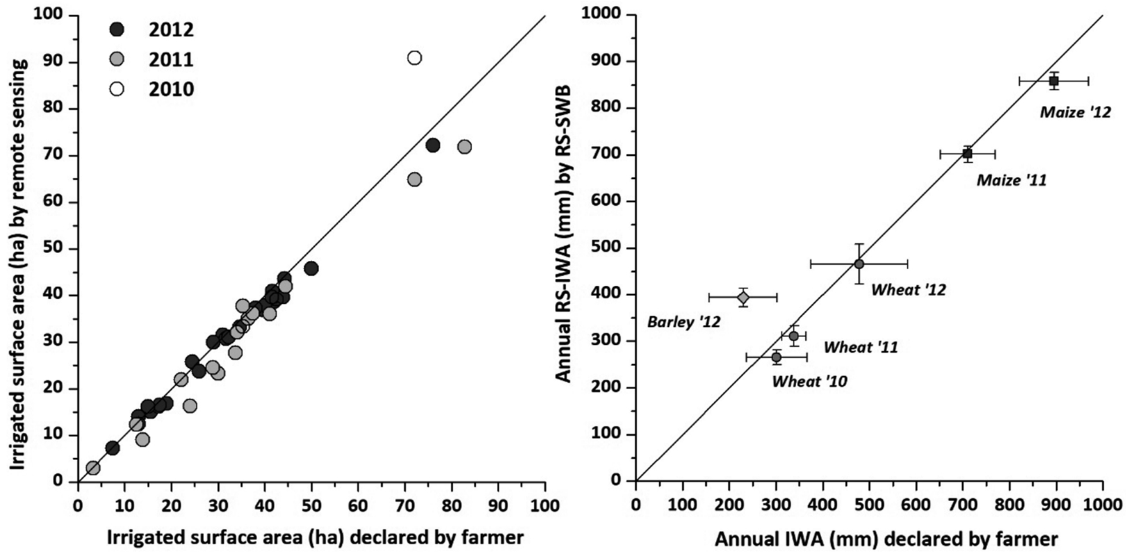

Fig. 4. Comparison at plot scale: Irrigated surface area (left panel) and the annual Irrigation Water Accounting (IWA) (right panel) from the RS-SWB versus those declared by farmers.

the modelled variability would not capture the full complexity of the soil profiles in the field plots.

At crop type level, the best agreement of values is found in maize (RSME around 7%), followed by wheat (15 %). In contrast, barley shows a remarkably high RMSE (76 %). Comparing the mean over all plots of the same crop yields RSMEs in maize of 3%, in wheat 6%, and in barley 72 %, respectively. The high RMSE shown for barley are discussed further below, mainly regarding agricultural practices and market prices at this area. Furthermore, a detailed comparison of per-crop mean values of cumulative NIR along with the irrigation campaign (Fig. 5) provides a first step towards explaining these differences. The time axis in Fig. 5 has been normalized with the total duration of the irrigation campaigns. The results for wheat and maize show a good agreement with a slight overestimation of the model at the end of the crop cycle. In contrast, farmer-applied irrigation in barley is lower than the calculated requirements during most of the campaign. The reasons for this are discussed in the following.

Two additional external information sources have been used to explore the achieved results: annual irrigation recommendations (that do not account for non-consumed water fraction) provided by the Local Irrigation Advisory Services, LIAS (Table 5), and literature values for the study area. LIAS issues weekly irrigation recommendations based on the single crop coefficient (Allen et al., 1998) from fieldwork. The available literature sources either use directly the same ET_c data provided by LIAS (Martín de Santa Olalla et al., 1999; Peña-Haro et al., 2010) or apply the same methodology to calculate ET_c (Ortega et al., 2004). However, none of the literature studies deals with the same period as this study, so they can be considered only as a rough approximation and therefore, not included in the following discussion.

In wheat, the differences between LIAS recommendation and RS-IWA are minor, with a maximum deviation of 15 mm in the dry year 2012. The 3-year mean values differ by as little as 4 mm. This indicates good agreement between the two approaches. The comparison for maize with LIAS recommendations shows the largest differences in 2011 (56 mm, 9%) and the smallest in 2012 (18 mm, 3%), which is a generally good agreement of the RS approach.

The case of barley, with only one year of available data, does not allow for an in-depth comparison, although results indicate strong differences between estimations and in-situ data resulting in higher estimated irrigation doses than farmer practices. In agreement with such findings, local research concluded that farmers usually irrigate barley below recommended rates as it is more resistant to drought than other spring crops (Martín de Santa Olalla et al., 1999), which is in concordance with drought effects on barley regarding stage crop period. Particularly, water stress during early crop development stages reduces grain number and filled grain number, while at the terminal crop stage the grain number is reduced to a lesser degree (Rajala et al., 2011). Furthermore, barley is the cereal over Mediterranean areas with better water use conservative strategies (Acevedo, 1987). This agrees with central plot data in Fig. 5, where irrigation application by farmers remains almost constant in the first half of the irrigation campaign, but it is reduced at the final stages. This would suggest that barley is water-stressed and ET_c is overestimated at least during such final period, and hence higher NIR were calculated. A further reason for reduced irrigation rates lies in the lower market value of barley as compared to wheat in the same area. Previous issues would explain why estimated NIR are significantly higher than actual irrigation from field records, and hence, why the resultant calculated RMSE are so high.

In summary, the worst value differences between recommendations and RS-IWA range from 15 mm (wheat, 5%) to 56 mm (maize, 9%),

Table 4
Root mean square error values of comparison at plot scale.

		Irrigation in single plot		Plot average irrigation		Plot area	
Year	Crop	RMSE (mm)	RMSE (%)	RMSE (mm)	RMSE (%)	RMSE (ha)	RMSE (%)
2010	**Wheat**	61	20	28	9	2	4
2011	**Wheat**	44	13	28	8	5	14
	Maize	45	6	10	1	6	15
2012	**Wheat**	70	15	12	3	2	6
	Maize	66	7	38	4	2	6
	Barley	176	77	164	72	2	7

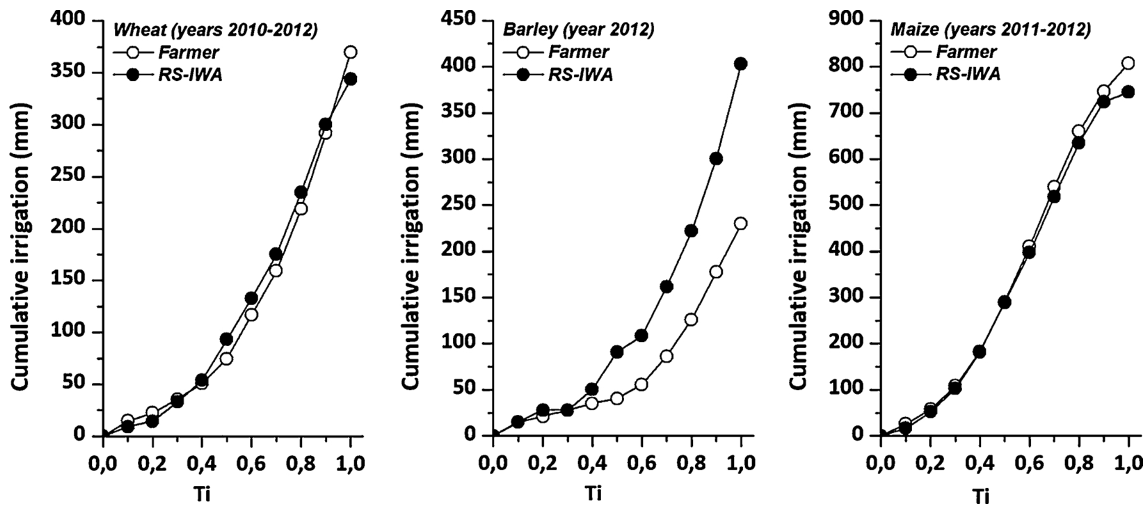

Fig. 5. Comparison of mean cumulative irrigation requirements per crop along: the three irrigation campaigns (2010-2012) for wheat (left plot), one irrigation campaign (2012) for barley (central plot), and the two irrigation campaigns (2011-2012) for maize (right plot). T_i is the normalized time between the beginning and end of the campaigns.

which means 1–3 irrigation events over the campaign period. The RMSE differences in the plot scale analysis are of similar magnitude. It is important taking into account that in contrast to RS-SWB, the FAO56 based recommendations were based on statistical general tables per crop type, not considering particular conditions of vegetation at plot level, in contrast to RS-derived biophysical variables. The one-year data for barley represent a special case as explained above. Considering only the data for wheat and maize, with a full three and two year period of available data, the analysis shows that RS-SWB is able to estimate properly the irrigation water management requirements (RS-IWA) for a range of special climatic conditions, with an overall 3-year RMSE of 12 %.

3.3. Irrigated surface and RS-IWA at Water User Association scale

Fig. 6 and Table 6 show the same comparison as in the previous section, but now at WUA scale. Like the plot-scale comparison, the mapping of irrigated areas shows results in better agreement than the net irrigation requirements. The RMSE for irrigated area mapping ranges from 10 % for summer crops to 17 % for vineyards. The RS-based multi-temporal classification slightly underestimates the irrigated areas of spring and summer crops while identifying at acceptable accuracy the alfalfa, double harvest, and vineyard. In this context, it is important to know that spring crops cover the largest area fraction (52 %), followed by summer crops (24 %), vineyard (13 %), alfalfa (5%), and double harvest (5%). These fractions remain constant from year to year, with only slight variations in the total irrigated area (largest in 2011 with 102,000 ha and smallest in 2010 with 95,000 ha). On the other hand, the dynamic in soil water balance and irrigation requirements are pronounced due to the annual variations in climatic conditions. The year 2010, with its abundant rainfall, shows the lowest irrigation requirements, while the dry year 2012 has the highest. Despite being even drier than 2012, the year 2011 exhibits similar irrigation requirements to 2010, due to the rainfall concentration in the critical spring months (Table 1).

The analysis by crop classes reveals the best agreement of net irrigation requirements for summer crops (RMSE 5%), closely followed by spring crops (9%). The major disagreement found for alfalfa (overestimation by 29 %) comes from the difficulty to determine the periodic multiple cuts (reducing net irrigation requirements) from the satellite images used. Double harvests also present difficulties, albeit to a lesser degree. Vineyard is a special case since the WUA defines a fixed irrigation requirement in its annual cultivation plan. Yet, RS-IWA provides quite similar values for the three years, with annual values varying according to climatic variations.

Further context for discussing these findings is again provided by two sources, the LIAS (Table 5) and literature values for the study area. Spring and summer crops show good agreement, with values 35 mm and 42 mm higher than LIAS recommendations in the year of largest deviations (2012). The overall mean value is 17 mm (spring) and 5 mm (summer) higher than LIAS values. The comparison looks quite different for the double harvest class, where RS-IWA values are 221 mm above the LIAS recommendation. The wide range of vegetative cycles involved in double harvest plots may play an important role here (see Fig. 3).

In summary, RS-IWA is in particularly good agreement with LIAS for

Table 5
Comparison between annual irrigation water recommendations (in mm) from the Local Irrigation Advisory Service (LIAS) and those estimated by the RS-SWB, for individual crop types and crop classes. Spr-Sum means double harvest, e.g. crops developed successively in spring and summer.

	Local irrigation Advisory Service				Estimated by the RS-SWB			
Single Crops								
	2010	**2011**	**2012**	**Mean**	**2010**	**2011**	**2012**	**Mean**
Wheat	237	242	364	281	226	250	379	285
Barley	161	180	275	205	–	–	335	–
Maize	521	617	675	604	–	561	693	627
Crop Groups								
	2010	**2011**	**2012**	**Mean**	**2010**	**2011**	**2012**	**Mean**
Spring	201	201	309	237	198	222	344	254
Summer	457	537	586	527	447	524	628	533
Spr-Sum.	–	–	631	–	647	782	853	761

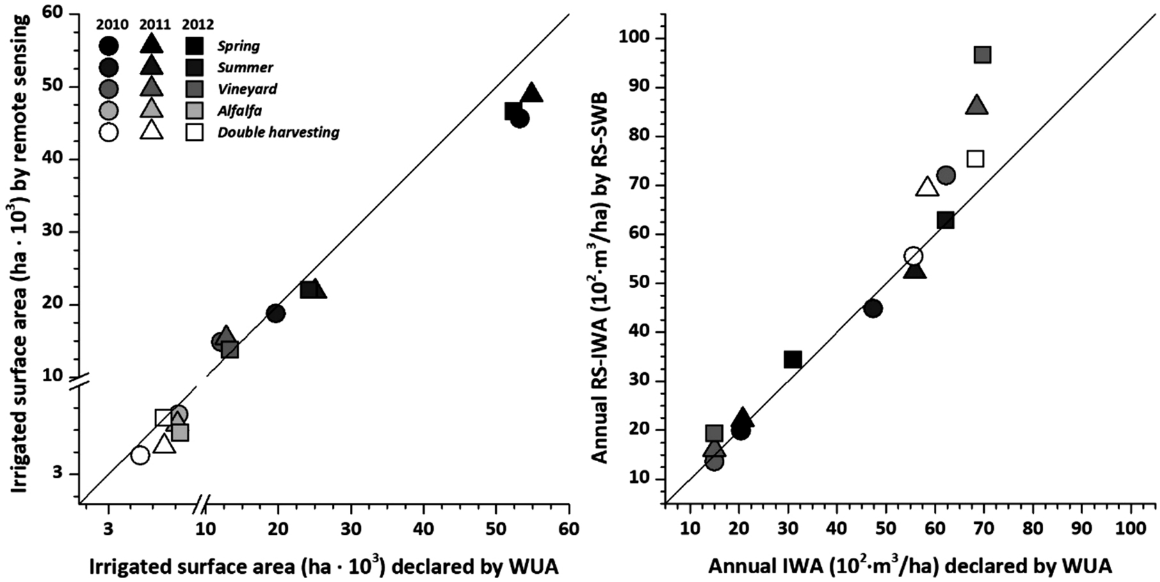

Fig. 6. Comparison at Water User Association scale: Irrigated surface area (left panel) and annual Irrigation Water Accounting (IWA) (right panel) RS-SWB versus the WUA records.

Table 6
Root mean square error values of comparison at Water User Association scale.

Irrigated crop classes/ types	Irrigated surface areas		Net Irrigation Requirements	
	RMSE (ha)	RMSE (%)	RMSE (m^3/ ha)	RMSE (%)
Spring	6510	12	210	9
Summer	2319	10	254	5
Alfalfa	717	13	1927	29
Double harvest	601	13	747	12
Vineyard	2192	17	295	18

spring and summer crops, with slight differences in annual recommendations. This again, as in the case of plot-scale analysis, translates into 1–3 additional irrigation doses per year. The largest differences are found for the year 2012 that is the driest of the studied period. The total three-year RMSE is 15 % considering that the alfalfa crop introduces the largest uncertainty due to the satellite overpass frequency does not show adequately the rapid growth and cut cycles. In the case of non-considering the alfalfa plots this uncertainty is reduced to 11 %.

4. Conclusions

The use of remote sensing time series data allows irrigation land monitoring. The combination of such data and ancillary data (agrometeorological, soil types and crop characteristics) into a Remote Sensing-based Soil Water Balance provides temporal and spatially distribution pixel-based maps of net irrigation requirements. Temporal and spatial aggregations into plot and water user association scale provide a Remote Sensing-based Irrigation Water Accounting (RS-IWA). The remote sensing driven FAO56 application presented in this article following the previous statements provides very useful information to water managers to monitoring and design of the River Basin Management Plans in the frame of the Water Framework Directive. Besides, the framework presented is not private water manager dependent, as it does not require data provided by them to run the model into the software HidroMORE used to obtain the results.

The presented methodology has been validated along with three successive irrigation campaigns (2010–2012) against different spatial and water management scales and implemented by end-users, the plot and the water user association. The RS-IWA results were compared with data provided by private water managers at different working scales show good agreement considering the different agrometeorological conditions of each year, achieving a RMSE about 12 % and 15 % for plot and water user association spatial scale respectively. Moreover, local agronomic practices like the shortage of water for barley shows the effect of additional criteria that determine irrigation water application decisions, such as stress resistance or economic considerations of market value. On the other hand, RS-IWA operates well in crops managed through established deficit irrigation practices, like vineyard.

These results confirm the reliability of the Remote Sensing-based Irrigation Water Accounting as a tool for transparent water management. It responds to requirements expressed by basin-scale water managers (derived from their own experiences with flow-meter-only networks). As such, it can be integrated into large-scale irrigation control networks providing independent indirect measurements over large areas and complementing a reference set of well calibrated and maintained flow meters. Finally, the actual European Satellite constellations, including the more recently introduced Sentinel-2A and Sentinel-2B, could further improve crop development monitoring at a much higher image frequency acquisition. Hence, such capabilities should also contribute to significantly improved the results.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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