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Estimating groundwater use patterns of perennial and seasonal crops in a Mediterranean irrigation scheme, using remote sensing

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ABSTRACT

This work explores the use of satellite-based vegetation indices (VI) to study groundwater use in a semi-arid agricultural irrigated area. The objective is to obtain insight in spatial and temporal patterns and differences in groundwater usage of perennial (mainly fruit trees) and seasonal crops (mainly row vegetable crops) under varying climatic conditions. Cropping intensities of seasonal crops are derived for each sector and irrigation water applied (IWA) is calculated using VI-based (NDVI from MODIS) actual evapotranspiration estimates and local efficiency factors. Groundwater use is then derived as the residual of total IWA and surface water supplies for each sector and crop type. The results of IWA following this methodology were compared with survey-based results for two crop types. Results correlated well, but deviate most during drought period, likely due to salt leaching practices. Monthly groundwater use patterns and spatial and temporal differences during normal water availability and drought conditions are reported. On average, about 50% of irrigation water is extracted from aquifers, but during droughts this percentage increases considerably. Perennial crops show sharper increases in groundwater use under such conditions than seasonal crops. Overall, seasonal crops put more pressure on the groundwater resource than perennial crops. Our results and methodology will be useful for water resource managers, and policy makers concerned with the role of groundwater resources on the sustainability of semiarid agricultural regions.

1. Introduction

Increasing demand on the limited source of water for irrigation is leading to over exploitation of groundwater resources in most Mediterranean basins (Daccache et al., 2014), which in turn threatens the sustainability of ecosystems and their economic services; including irrigated agriculture itself (Famiglietti, 2014). The pressure to use groundwater for irrigation is likely to increase over the next decades as a result of population growth, climate change and other factors (Green et al., 2011; Wada and Bierkens, 2014). Sustainable irrigation practices and adequate water allocation strategies at the right spatial scale are crucial to avoid overexploitation of various resources (Candela et al., 2012; Condon and Maxwell, 2014; Esnault et al., 2014).

Many studies have been done on groundwater abstractions on basin level. These studies were based on water table fluctuation methods (Cheng et al., 2009; Tsanis and Apostolaki, 2008), water balance methods (Castaño et al., 2009; Cheema et al., 2014; Ruud et al., 2004), or a combination of both (Jiménez-Martínez et al., 2009; Martínez-Santos and Martínez-Alfaro, 2010; Perrin et al., 2012). Water table fluctuation methods generally describe the groundwater balance and interactions at aquifer and basin level (Baudron et al., 2014a, 2013; Esnault et al., 2014; Jiménez-Martínez et al., 2010). However, at finer spatial scales, only water balance methods can provide the required level of detail but accurate information on evapotranspiration and irrigation efficiencies at the scale of interest is a prerequisite for their successful application (Alexandridis et al., 2014; Esnault et al., 2014; Taghvaeian and Neale, 2011).

It is important to understand irrigation practices and patterns at the spatial level of a particular irrigation scheme because it is at this level that sustainable water supply for agriculture can meaningfully be improved by active management (Alexandridis et al.,

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2014; Condon and Maxwell, 2014; Esnault et al., 2014). It is also at this level that different crop types can sensibly be included in water allocation and management decisions (Candela et al., 2012). Supplementing shortages in surface water supply with groundwater must be considered for conjunctive systems and be limited to what is physical and economic feasible.

Surface water demand for seasonal crops, to be considered by farmers, depends on a variety of short term factors, such as markets, water quality, weather forecasts and more (Tapsuwan et al., 2015; Lavee, 2010). The surface water demand of perennial crops on the other hand is less variable and farmers generally have a better grip on the shortfalls and usually supplement surface water supplies with groundwater. These differences in water management are reflected in the spatial and temporal patterns of groundwater usage within an irrigation scheme and they need to be addressed adequately to avoid over exploitation of groundwater in certain areas.

Estimating the water balance and especially the total amount of irrigation water applied through irrigation schemes is a complex task, particularly for schemes that utilise both surface and groundwater (Martínez-Santos and Martínez-Alfaro, 2010; Taghvaeian and Neale, 2011; Tsanis and Apostolaki, 2008). Metering is costly and often associated with practical and legal difficulties (Martínez-Santos and Martínez-Alfaro, 2010). Surveys of irrigation water use are likely to be biased and need to be repeated regularly to obtain temporal patterns. Data on surface water supplies are often readily available, but not so with groundwater data. Remote sensing methods can be of assistance in estimating groundwater usage in irrigated agricultural areas (Ahmad et al., 2004; Castaño et al., 2009; Contreras et al., 2011) and can in some cases be the only way to close the water budget (Contreras et al., 2014; Taghvaeian and Neale, 2011). Satellite-based vegetation indices have proven to be well correlated with evapotranspiration patterns (Glenn et al., 2011) and the study of their spatial anomalies and temporal dynamics have recently been proposed as indicators of the reliance of native ecosystems and agrosystems on groundwater (Barron et al., 2014; Contreras et al., 2013).

Several studies in the Mediterranean area and in parts of Spain, where this study was conducted, showed that groundwater is a critical resource and of concern to farmers (Baudron et al., 2014b, 2013; Contreras et al., 2014; IGME, 1994; Jiménez-Martínez et al., 2010); many aquifers are heavily over-exploited (Molina et al., 2009). It is not yet known which crop types are most dependant on groundwater. Results from a recent survey-based study (Martínez-Alvarez et al., 2014), which we also used in this study, showed that different crop types responded differently to droughts and depended to different degrees on groundwater. Alcon et al., (2011) reported similar phenomena based on earlier surveys carried out in the same area Affective management of the combined and interactive role of surface water and groundwater use by crops require a good understanding of (i) the spatial patterns of groundwater use by different irrigated crop types and (ii) the timing and amount of groundwater abstraction corresponding to each crop type (Condon and Maxwell, 2014; Esnault et al., 2014).

In this study a remote sensing-based water balance method was applied to quantify the relationship between cropping patterns and groundwater usage and the method was evaluated by comparing the results with survey-based values of irrigation water use. Spatial and temporal patterns of groundwater usage of perennial fruit orchards and seasonal horticultural row crops were determined for drought years and normal years by using monthly sector-level irrigation water applications.

2. Methodology

2.1. Study area

The study area is the Campo de Cartagena irrigation district located in south-east Spain (Fig. 1), which is representative of the intensive and export-oriented horticulture of the Murcia region. The climate is Mediterranean semiarid, with an average annual rainfall of 300 mm and a mean annual temperature of 18 °C. The total area under irrigation increased from 32,366 ha in 2011 to 41,065 ha currently, but it fluctuates based on annual water allocations. The total area comprises 23,498 plots which are managed by 2962 farmers. The theoretical annual water resources of the irrigation district amount to 141.6 hm^3, most of which comes from the Tagus–Segura Water Transfer (122 hm^3), and to a lesser degree

Fig. 1. Location of the Campo de Cartagena Irrigation District.

from other sources such as surface water, desalinated water and recycled sewage. As a consequence of the aforementioned water supply limitations, far smaller volumes of water have in practice been available (18–105 hm^3/year) (Soto-García et al., 2013). The major part of the irrigated area (96%) is equipped with drip irrigation.

The principal crop types cultivated in this irrigation district are: (i) seasonal herbaceous row crops (on average 19,607 ha) such as lettuce, artichoke, broccoli and melon; and (ii) perennial fruit tree crops (on average 10,963 ha) such as lemon trees, orange trees, mandarin trees. Farmers have a mix of both crop types on plots with an average size of 2 ha. The irrigation district is divided into 33 irrigated sectors. Greenhouse crops represent an important fraction of cropped area in some of the irrigation sectors. These sectors (7 in total) were excluded, resulting in a total of 26 sectors used in this analysis. The analysis is limited to the irrigable area within each sector, so pixels dominated by urban or other non-agricultural use were also excluded.

2.2. Modelling approach

Data on irrigation water use and sources are available at different management levels: the irrigation scheme-level, irrigation sectors-level (sub-scheme) and farm-level. For this analysis, the irrigation sector-level was considered most relevant. This is the level that corresponds to the principal water distribution infrastructure which is managed by the irrigators association. On the farm-level there is commonly not sufficient available information on water use to allow understanding of patterns at a higher spatial level. This motivated the exploration of a remote sensing-based approach to estimate irrigation applications and groundwater use at irrigation sector-level, for which data on surface water supplies and cropping patterns are available. The analysis was carried out on a monthly time step. The following water balance was used as the basis for the analysis:

$$\mathrm{IWA}^i + {P_{\mathrm{eff}}}^i = \mathrm{ET}_\mathrm{a}^i + F^i \tag{1}$$

where, IWA is the total irrigation water applied for each sector i and each month t, $\mathrm{ET_a}$: is VI-based monthly actual evapotranspiration, F refers to the on-farm losses from distribution, application and on-farm storage, further detailed in Section 2.5 on irrigation water applied, and P_{eff} is the effective precipitation defined as the fraction of the local precipitation that is consumed by crops (Allen et al., 1998; Brouwer and Heibloem, 1986). Differences in soil moisture content were excluded, as on the monthly timescale they are minimal in irrigated soils (Tanji and Kielen, 2002). This equation is considered valid for areas where drip irrigation is implemented and does not cater for more complex agro-hydrological fluxes under other irrigation practices.In the study area, IWA consists of a combination of surface water (SW) and groundwater (GW), thus:

$$\mathrm{IWA}^i = \mathrm{SW}^i + \mathrm{GW}^i \tag{2}$$

The irrigators association of the irrigation district measures continuously and automatically the amounts of water supplied to each irrigation sector by using flow-meters and energy-meters across the entire water distribution network (Soto-García et al., 2013). From these data, irrigation water supply to each sector and for each month over the study period (2002–2011) was derived. Groundwater abstractions happen on farm level and are not metered so no data on actual groundwater use exists on farm or sector-level. Therefore, we derived groundwater abstractions at the monthly level and at the sector level, from the residual of the previous equation (similar to Castaño et al. (2009); Gokmen et al. (2013); van Eekelen et al. (2015)).

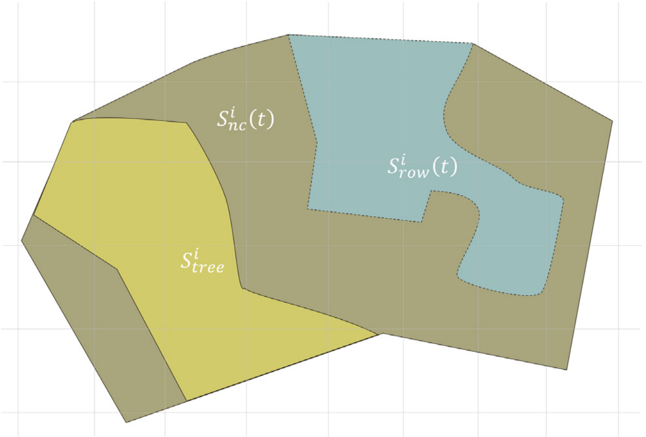

Fig. 2. Schematic representation of cropping areas in an irrigation sector, considering tree crops $\left(S^{\mathrm{i}}_{\mathrm{tree}}\right)$, constant in time, and seasonal row crops $\left(S^{\mathrm{i}}_{\mathrm{row}}(\mathrm{t})\right)$, variable in time. The grey lines represent a grid of MODIS pixels.

2.3. Cropping areas

Farmers report the type of crop they cultivate to the district irrigators' association. However, for the seasonal crops these data are subject to high uncertainty because there is no verification of these reported values. The data on perennial tree crops per district are more reliable as they hardly vary over time. Therefore, the tree cropping areas reported to the irrigators' association were used in this study as a direct input to our model.

Cropping patterns and cycles of seasonal crops are highly variable in this irrigation scheme. The decision to plant is not only a factor of climate, but also driven by drought periods in the Tagus Basin or political decisions on water transfers, markets and other economic factors. Therefore, no reasonable assumptions can be made on cropping intensities and timing of cropping cycles at the irrigation sector level. In this study remote sensing was used to quantify the temporal dynamics of both cropping systems for each sector.

The 16-day MODIS NDVI product was used (MOD13Q1), at 250 m spatial resolution, for the 10-year period 2002–2011. The NDVI maps were quality controlled, pre-processed using the software TIMESAT (Jönsson and Eklundh, 2004) and aggregated to monthly maps, similar to Contreras et al. (2014).

Each irrigated sector includes about 200 MODIS pixels of 250 × 250 m (6.25 ha). Agricultural plots in this area have on average and area of around 2 ha with either perennial or seasonal crops. So in general, most pixels in a sector are composed of a mixture of the main crop types. Also, the area of seasonal row crops under active irrigation, changes over time, while the coverage of tree crops remains relatively constant. Thus, for the irrigable area of each sector i and each t is:

$$S^i_{\mathrm{tree}} + S^i_{\mathrm{row}}(t) + S^i_{\mathrm{nc}}(t) = S^i_{\mathrm{ti}} \tag{3}$$

where S^i_{ti} is the total irrigable area in the sector i, S^i_{tree} is the cropping area of tree crops, both obtained as ancillary data from the irrigators association;$S^i_{\mathrm{row}}t$ is the cropping area of horticultural row crops and $S^i_{\mathrm{nc}}t$ non-cropped area; the latter two being variable in time. Fig. 2 represents schematically the MODIS pixel grid on top of a sector containing these three land use types.

Under the assumption of mixing linearity in the NDVI signal (CENTER, 2000; Genovese et al., 2001; Hansen et al., 2002; Kerdiles and Grondona, 1995; Lobell and Asner, 2004), the total NDVI observed at the sector-level for each time step can be calculated as the weighted sum of the reference NDVI values for each cropping class at a specific time and weighted by their relative coverage inside the sector. The mixing approach was run at the monthly level during a 10-year period and can be summarized in the following equation (similar to Busetto et al., (2008)):

$$\mathrm{NDVI\_}acc^{i} = S^{i}_{\mathrm{tree}} \times \mathrm{NDVI}_{\mathrm{tree}}(t) + S^{i}_{\mathrm{row}}(t) \times \mathrm{NDVI}_{\mathrm{row}} + S^{i}_{\mathrm{nc}}(t) \times \mathrm{NDVI}_{\mathrm{nc}}(t) \quad (4)$$

In which,

- $\mathrm{NDVI\_acc}^{i}$ is the sum of NDVI of all pixels within the sector,
- $\mathrm{NDVI}_{\mathrm{tree}}(t)$ is the NDVI calculated at each monthly time step by selecting 25 "unmixed" MODIS pixels with tree coverage higher than 95% and extracting the NDVI signal for each month.
- $\mathrm{NDVI}_{\mathrm{row}}$ is calculated by selecting 25 "unmixed" pixels that are >95% covered with row crops. Of this sample of pixels, the 95-percentile value is taken, assuming that this value corresponds to a month with maximum cover.
- $\mathrm{NDVI}_{\mathrm{nc}}(t)$, similarly to $\mathrm{NDVI}_{\mathrm{tree}}(t)$, is calculated from a selection of 25 pixels that are permanently non-irrigated (rainfed and natural vegetation).

The selection of the MODIS pixels was based on visual inspection of high-resolution optical satellite imagery of the platform Quickbird, from mosaics of the study area that are provided freely for download by the regional agricultural research institute IMIDA (http://www.imida.es). By using imagery corresponding to the start (year 2003) and the end (year 2011) of the study period it was made sure that no significant changes in pixel composition occurred meanwhile.

From (4) equation (3) and, it follows that the row cropping area for each month and sector can be calculated as follows:

$$S^{i}_{\mathrm{row}}(t) = \frac{\mathrm{NDVI\_}acc^{i} - S^{i}_{\mathrm{tree}} \times \mathrm{NDVI}_{\mathrm{tree}}(t) + \left(S^{i}_{\mathrm{tree}}(t) - S^{i}_{\mathrm{ti}}\right) \times \mathrm{NDVI}_{\mathrm{nc}}(t)}{\mathrm{NDVI}_{\mathrm{row}} - \mathrm{NDVI}_{\mathrm{nc}}(t)} \quad (5)$$

Then$S^{i}_{\mathrm{nc}}(t)$ follows from eq. (3). The above equation provides the cropping area of the seasonal row crops for each month in the time period and for each sector.

2.4. Crop evapotranspiration

Several authors have shown that Vegetation Indices (VIs) obtained from multispectral imagery can be related to the ratio of crop evapotranspiration ($\mathrm{ET_c}$) and reference crop evapotranspiration ($\mathrm{ET_o}$), similar to the crop coefficient K_c used in the the FAO-56 Penman Monteith method (Allen et al., 1998). Crop coefficient estimation from VIs for irrigation purposes has been broadly studied in herbaceous crops (Er-Raki et al., 2007; González-Dugo and Mateos, 2008; Jayanthi et al., 2007; Kamble et al., 2013; Sánchez et al., 2012) and in woody crops (Samani et al., 2009). VI-based crop coefficient estimates for natural vegetation have been provided by Groeneveld et al. (2007). Maselli et al. (2014) studied the use of global VI-based evapotranspiration estimates from MODIS products. Glenn et al. (2011) provides a review of the relationships between VIs and ET and Consoli and Vanella (2014) carried out a comparison between different ET-methods for a crop in a Mediterranean area.

Deficit irrigation and under-irrigation practices, especially in perennial crops, are common in this area during drought periods (Martínez-Alvarez et al., 2014). Prolonged drought and stress conditions affect the vegetative development of crops and the NDVI. Several authors have shown that for monthly assessments, it can be assumed that NDVI-based ET estimates are close to actual evapotranspiration ($\mathrm{ET_a}$) (Glenn et al., 2011; Pereira et al., 2014) because the stress effects at this time scale are observed in the NDVI.

Thus, the derived cropping areas for the two crop types for each month as described previously can be used to estimate the actual crop evapotranspiration for each month and for each sector:

$$\mathrm{ET}^{i}_{\mathrm{a}}(t) = \left(S^{i}_{\mathrm{tree}} \times \hat{k}_{\mathrm{tree}}(t) + S^{i}_{\mathrm{row}}(t) \times \hat{k}_{\mathrm{row}}(t)\right) \times \mathrm{ETo}(t) \quad (6)$$

where $\mathrm{ET}^{i}_{\mathrm{a}}(t)$is the actual evapotranspiration for sector i in month t in volumetric units (hm^3), $\hat{k}_{\mathrm{tree}}(t)$ is the mean crop coefficient for tree crops, $\hat{k}_{\mathrm{row}}(t)$ for row crops, and $\mathrm{ETo}(t)$ is the reference crop evapotranspiration for month t, assumed to be the same in all sectors.

The crop coefficients were derived directly from the NDVI-values of the selected unmixed pixels, by using the following equation (González-Dugo and Mateos, 2008):

$$k_{c-VI} = k_{\mathrm{c,max}}\left(1 - \frac{\mathrm{NDVI}_{\max} - \mathrm{NDVI}}{\mathrm{NDVI}_{\max} - \mathrm{NDVI}_{\min}}\right) \quad (7)$$

where the subscripts max and min refer to the maximum NDVI value observed for the cropping type, and the minimum value under bare soil conditions, respectively. The factor $k_{\mathrm{c,max}}$ is crop specific and a value of 1.0 for seasonal row crops was adopted (reference value typical for a lettuce crop, being the principal seasonal crop in the area) and 0.7 for perennial tree crops (taking citrus crops as a reference) (Contreras et al., 2014). The equation assumes (i) linearity between k_{c} and NDVI (e.g. Campos et al., 2010; Kamble et al., 2013), (ii) that problems of "saturation" of NDVI values are not significant (Duchemin et al., 2006), and (iii) that there is no significant contribution of bare soil evaporation. This last assumption is reasonable as drip irrigation technology is fully implemented in this irrigation scheme.

2.5. Irrigation water applied

To calculate the irrigation water applied (IWA) according to eq. 1 for each month and irrigation sector, an estimate is needed for the non-productive fluxes (F in eq. 1) which are considered losses from the farmer's point of view. The fluxes were estimated from the following equations:

$$e = e_{\mathrm{app}} \times e_{\mathrm{distr}} \times (1 - l) \times (1 - l_{\mathrm{rsv}})$$

where,

$$F^{i} = \left(\frac{1}{e} - 1\right) \times \left(ET^{i}_{\mathrm{a}} - P_{\mathrm{eff}}{}^{i}\right)$$

with e is the total efficiency coefficient, e_{app} the application efficiency, e_{distr} is the distribution efficiency, l is the salt leaching fraction, and l_{rsv} is the fraction of the water in the system lost through evaporation from the on-farm agricultural reservoirs. For the application efficiency a locally estimated and accepted value of 0.9 was taken (CENTER, 2000). The distribution efficiency was assumed to be 1 given the high level of modernization in this district (Soto-García et al., 2013). For the salt leaching fraction, values were taken from the survey-based analysis carried out by Martínez-Alvarez et al. (2014). Here a distinction was made between periods with normal water availability conditions and drought conditions. For normal conditions (years 2002–2005 and 2009–2011) a leaching fraction of 10% was assumed, and for drought conditions (2006–2008) a value of 15%. The higher leaching fraction during drought periods in this area is related to groundwater quality. The loss fraction through evaporation losses of water in agricultural water reservoirs were obtained from estimates for this irrigation scheme from (Martínez-Alvarez et al., 2008) and ranged from 0.95 in winter to 0.9 in summer.

Effective monthly precipitation estimates were computed according to the FAO method (Allen et al., 1998; Brouwer and Heibloem, 1986) and using rainfall data monitored at the

Table 1
Performance statistics of the inter-comparison between survey-based and satellite-based values for IWA.

Performance indicator	Row crops –normal	Tree crops – normal	Row crops – drought	Tree crops – drought
R2	0.76	0.90	0.85	0.96
PBIAS	1.00	1.16	0.88	0.98
RMSE	2.1	0.7	1.8	0.4
NRMSE	13%	11%	12%	7%
NSE	0.68	0.83	0.79	0.95

local agrometeorological stations belonging to the SIAM network (http://siam.imida.es).

The IWA estimates were finally cross-checked with estimates reported by Martínez-Alvarez et al. (2014). They estimated IWA from extensive-field surveys carried out in the study area during 2008 (drought period) and 2011 (normal precipitation period). Martínez-Alvarez et al. (2014) provides data on irrigation water use patterns for different crop types. Martínez-Alvarez et al. (2014) up-scaled the surveyed farm-level data using statistical information on cropping areas, cropping cycles and water supplies to obtain IWA estimates at the irrigation scheme level. The period covered by Martínez-Alvarez et al. (2014) is the same as the one of our study.

The evaluation was done by determining for both time series the regression coefficient of determination (R^2), the percent bias (PBIAS), the root mean square error (RMSE) and the RMSE normalized by the range between the maximum and minimum vales (NRMSE). Besides, the Nash and Sutcliffe (1970) efficiency (NSE) criterion is used: a normalized statistic, commonly used in streamflow modelling assessments to determine the relative magnitude of the residual variance against the measured variance. The NSE ranges between $-\infty$ and 1.0, with NSE = 1.0 being the optimal value. For computing NSE coefficients, survey-based data was used as the "measured" variables.

3. Results

3.1. Inter-comparison of outcomes

The monthly irrigation water applied values obtained through the satellite-based method as described previously were compared with the survey-based values from Martínez-Alvarez et al. (2014). This comparison was done at the district level, as the survey was designed to be representative at that level. Fig. 3 shows a scatter plot of the monthly survey-based and satellite-based IWA values. A distinction was made between the values corresponding to years with normal water availability and drought years (2006–2008). There is aclear relationship for both crop types and for both water availability conditions. Table 1 provides the performance statistics. The coefficient of determination (R^2) ranges between 0.76 for row crops under normal conditions and 0.96 for tree crops under drought conditions. R^2 is higher under drought conditions than under normal conditions. The slope, or bias (PBIAS), is near to one for row crops under normal conditions, meaning that the survey-based average is almost the same as the satellite-based average. For tree crops, under normal conditions the satellite-based estimate is generally higher, while for drought conditions generally lower. Also for row crops, the satellite-based estimates are generally lower than the survey-based values. The RMSE is around 2 hm^3/month for row crops, and around 0.5 hm^3/month for tree crops, being somewhat lower during the drought period. The NRMSE gives an indication of the relative deviation between both series and is between 7% and 13%.

The NSE performance indicator (Table 1) endorses a good correspondence for both crop types, although for tree crops slightly better than for row crops. Fig. 4 confirms that the temporal pattern for both crops is well captured. The figure indicates the drought and non-drought period. Clearly, satellite-based IWA estimates during drought periods are slightly lower than survey-based values, in spite of the fact that a higher salt leaching fraction was assumed during the drought period. The deviation highlights a critical difference between both methodologies, further discussed in Section 4.

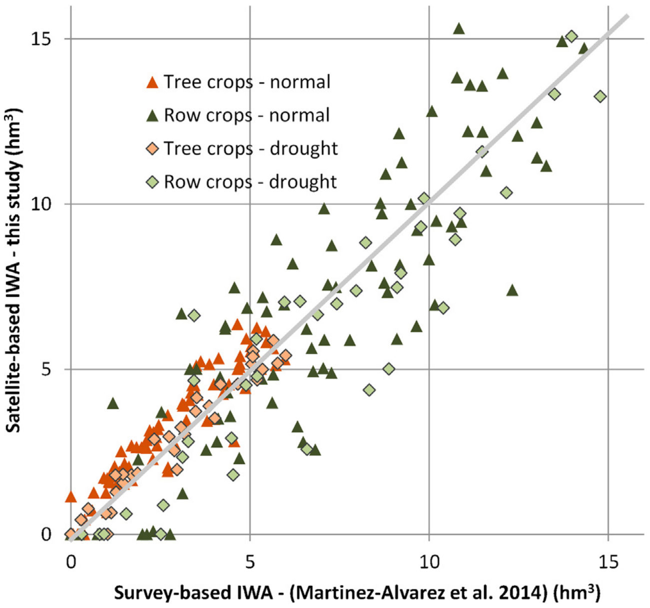

Fig. 3. Scatter plot of irrigation water applied (IWA) from the survey and from the satellite-based method for row and tree crops.

3.2. Spatial and temporal patterns of groundwater use

The remote sensing-based water balance method provided monthly time series for each sector of irrigation water applied and groundwater use. Fig. 5 shows the monthly averages of the water balance components of eqs. 1 and 2, separately for the years with normal (left panel) and drought (right panel) conditions. The positive items correspond to the incoming fluxes of the water balance (effective precipitation, groundwater and surface water supply) and the negative to the outgoing fluxes (actual evapotranspiration and losses).

Fig. 5 shows that under normal water availability conditions, surface water and groundwater supply are comparable in the total balance (43% and 41%, respectively) while effective precipitation contributes only 16% to the total balance. In drought years precipitation contributes the same percentage, but surface water supply is drastically reduced (20%) while groundwater provides 64% of the total balance. It has to be noted that drought conditions in this area are concomitant with a drastic reduction in surface water supply and a substantial increase in groundwater abstraction. This feedback makes that during drought years the total annual water balance is reduced on average by only 7% compared to years with normal surface water availability.

The time series of irrigation water applied, and the portion obtained from groundwater were averaged annually for both normal and drought conditions, and mapped (Fig. 6). The map shows

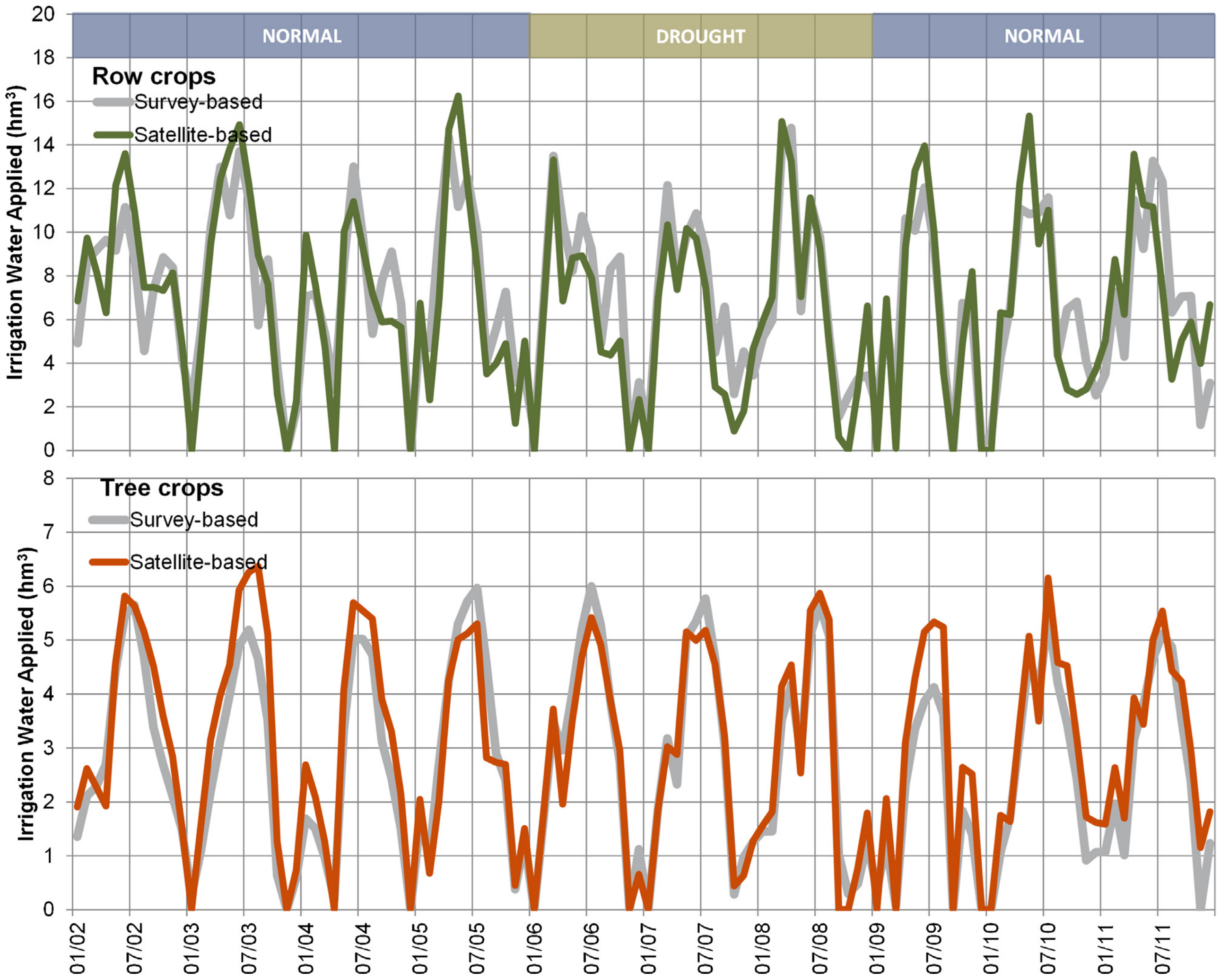

Fig. 4. Monthly irrigation water applied (hm3) for tree crops from the survey and from the satellite-based method.

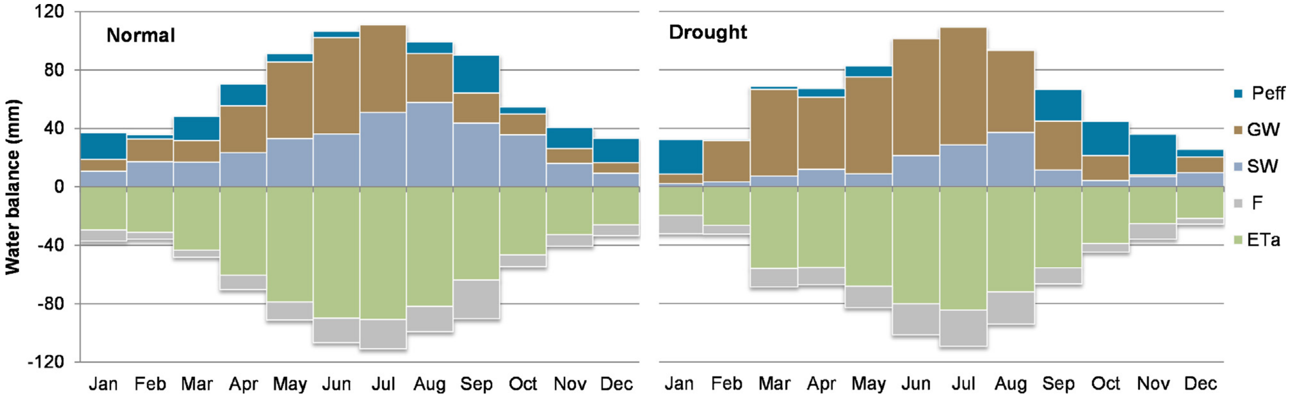

Fig. 5. Monthly surface water and groundwater use for the entire study area. P_{eff}: effective precipitation, GW: groundwater supply, SW: surface water supply, F: drainage losses; $\mathrm{ET_a}$: actual evapotranspiration.

that (1) certain areas have a higher dependency on groundwater than others, and (ii) that there is no direct relationship between IWA and groundwater dependency. Especially during years with normal water availability, areas with similar irrigation intensities can have very different groundwater dependencies because farmers tend to have plots in different sectors and can use their water rights where they prefer (correlation coefficient $r = 0.20$). Groundwater use increases considerably for all irrigation sectors during drought years, and some correlation exists between IWA and groundwater dependency ($r = 0.57$).

3.3. Precipitation and crop evapotranspiration versus groundwater use

Groundwater abstractions depend on surface water availability and local precipitation amounts. The relationship between ground-

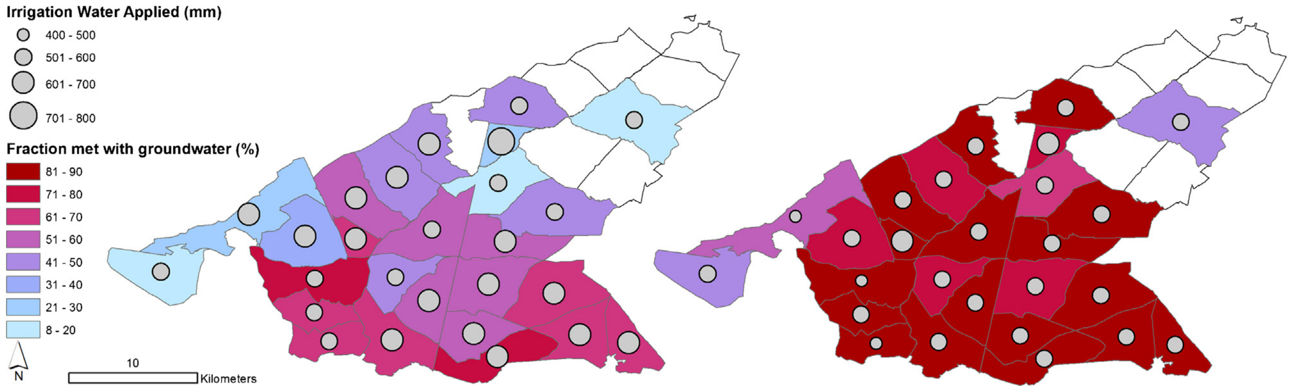

Fig. 6. Map of irrigation sectors with irrigation water applied (mm) and percentage obtained from groundwater (average over entire period) for normal (left) and drought (right) years. The irrigation sectors that appear as blank in this map are those that were excluded from the analysis due to the dominance of greenhouses.

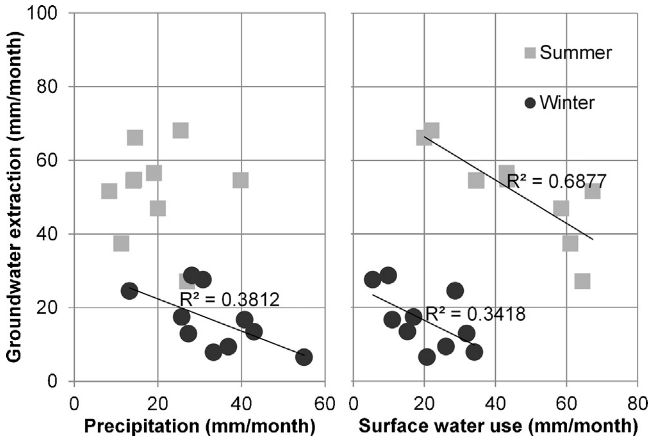

Fig. 7. Precipitation (left panel) and surface water supply (right panel) against groundwater abstractions in summer and winter.

water use and surface water availability is apparent from Fig. 5. There is not a direct relationship between local precipitation and groundwater usage in semi-arid irrigation areas. Rainfall is highly erratic and amounts highly variable. Farmers adapt their irrigation applications depending on the rainfall intensities and amounts, crop growth stage and climate water demand.

The left panel of Fig. 7 shows a scatter plot of total precipitation amounts against groundwater abstractions in summer (grey squares) and winter (black dots). The summer period is taken here as April to September and winter period from October to March. There is no apparent relationship between summer precipitation amounts (about half of winter amounts) and groundwater usage. Higher rainfall amounts do not lead to lower groundwater abstractions. For winter rainfall there is a relationship with groundwater use ($R^2 = 0.38$, p-value <0.05). During years with more rainfall in winter, farmers do rely less on the groundwater resource in general, although the variability in the relationship confirms that other factors also can play a role.

The relationship with surface water availability is more evident, as shown in the right panel of Fig. 7. More surface water availability leads to lower groundwater abstractions, as expected, both in summer as in winter. The relationship is weaker in winter, but still significant.

3.4. Cropping area and groundwater use

Cropping area and groundwater use should obviously be well correlated, especially under drought conditions when the majority of IWA is obtained from groundwater. Comparing such relationships for normal and drought conditions showed different strengths in relationships in different crop types. Fig. 8 shows the relationship between groundwater use vs cropping area for the two crop types, averaged over the period 2002–2011. As expected, both variables are well correlated, and the slope gives an indication of the irrigation depth that corresponds to groundwater abstractions. Thus, the change in slope is an indication of how groundwater use differs between normal and drought conditions. Table 2 shows the relative and absolute differences between the slope values calculated from Fig. 8, revealing that both the relative as the absolute differences are higher in tree crops than in row crops.

4. Discussion and conclusion

The difficulties in obtaining reliable ground-based data on groundwater use at the irrigation sector level motivated the exploration and potential of remote sensing data for mapping the groundwater abstraction rate at that scale. The products from the MODIS satellites are often used for water management applications as they provide a good compromise between temporal availability and spatial resolution. Their daily overpass generates reliable NDVI products without being affected too much by cloudiness, depending on the season and location. An important advantage of remote sensing information is its spatial resolution and its ease of application. The spatial resolution of the NDVI products is suitable for certain agricultural water management applications, depending on the heterogeneity of the area. For this study, this resolution was considered sufficient, as the irrigation sectors cover on average 250 pixels. The smallest sector contains only 85 pixels, which can still be considered enough for a representative estimate of the crop coverage at this spatial level.

Another aspect related to the pixel size of the MODIS product and the methodology, is the need for a representative sample of "unmixed" pixels, i.e. with homogeneous crop types. If the irrigation scheme is large enough, and agricultural plots are not too small, such pixels can be easily identified. Also, the climate should be relatively homogeneous over the area in order to exclude it as a significant variable in determining the influence of crop type and crop growth stage on NDVI-variability.

The NDVI-based approach presented in this work is applicable to areas where soil evaporation can be neglected, i.e. where rainfall is erratic and irrigation practices have reduced soil evaporation losses to practically zero as is the case with drip irrigation in the study area of this work. However, in case soil evaporation is a significant term in the water balance, NDVI fails to be a reliable proxy for the crop coefficient (Johnson and Trout, 2012; Pereira et al., 2014). Remote sensing information can still be useful to establish the water balance but more complex energy balance algorithms to derive actual

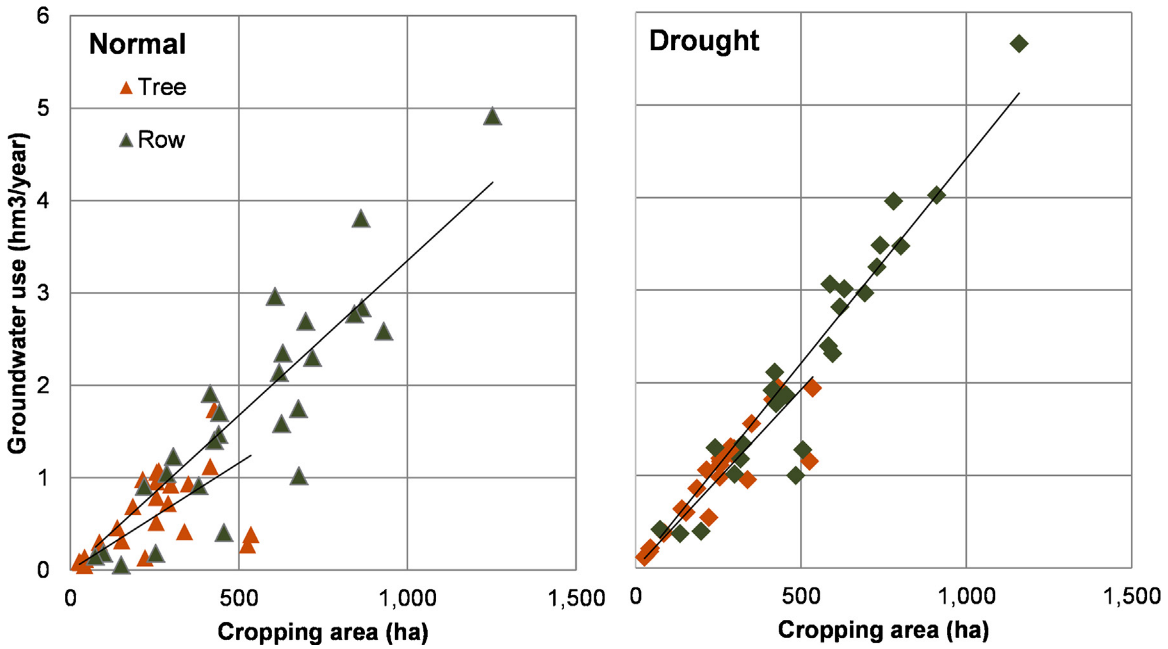

Fig. 8. Average annual groundwater use (hm^3) against average annual cropping area (ha) of tree and row crops for the entire study period (left panel) and during drought period (right panel). Each point corresponds to an irrigation sector.

Table 2
Slopes (including 95% confidence intervals) of linear fits between cropping area and groundwater use based on Fig. 8, and the absolute and relative between normal and drought period.

	Slope normal (m^3/ha year)	Slope drought (m^3/ha year)	Difference (drought – normal)	Relative difference (drought/normal)
Tree crops	2313 +/− 774	3851 +/− 667	1538	166%
Row crops	3350 +/− 1040	4421 +/− 614	1071	132%

evapotranspiration are likely to be more appropriate (e.g. Ahmad et al., 2009; Van Eekelen et al., 2015). Poor data on groundwater use in semi-arid irrigation systems makes remote sensing-based methods often the only option to assess groundwater fluxes, derive water accounting indicators and measure irrigation system performance (Alexandridis et al., 2014; Khan et al., 2008; Van Dam et al., 2006).

Evaluation of the satellite-based approach was done by comparing irrigation water applied at the irrigation scheme level with those from a survey-based study. Temporal patterns correlated well, but satellite-based values were, under normal climate conditions, generally slightly higher than the survey-based values, and lower under drought conditions. Lack of useful data on the irrigation and farming practices may be the cause of the difference between normal and drought years. A higher salt leaching fraction was used for drought periods, which indicates that salt leaching is an important factor to consider when using a satellite-based method to estimate IWA and when farmers deal with water of different quality (salinity).

On average, the outcomes show that groundwater accounts for about half of the irrigation water applied during non-drought years. Groundwater use increases considerably (1.5 times) during drought years, in spite of a small reduction in overall water use (7%). However, considerable spatial variability exists in groundwater usage. In part this can be due to the fact that there is some exchange of groundwater among sectors. Overall, the proposed methodology provides important insights in the spatial variability of groundwater use and its relation with cropping and irrigation practices. These insights are necessary as in the study area groundwater levels and quality are declining, threatening the sustainability of the system. The groundwater body is officially declared in poor status and water authorities are required to take action and forced by the European Water Framework Directive to achieve a good status in 2027. In another semi-arid irrigation system in Europe, a similar approach was used to study the sustainability of groundwater management as input for the local decision making process (Alexandridis et al., 2014).

In spite of the relatively small contribution of rainfall (on average 16%) to total water use, a negative relationship was found between precipitation amounts and groundwater use. During years with high rainfall, and independently of surface water availability, farmers tend to rely less on groundwater than during years with low rainfall. This shows that local drought events also influence groundwater use patterns, and not only droughts in the larger, upper Tagus basin which provides water for inter-basin water transfer. Still, local drought conditions are affected mainly by conditions in the larger Tagus basin, and to a much lesser degree by low rainfall amounts in the Segura basin itself.

Mixed farming (seasonal and perennial) in the study area makes it difficult to understand which of the crop types have a higher dependency on groundwater resource than others. However, the relation between cropping area and groundwater use at the sector level sheds some light on how farmers respond to water availability and groundwater use for the two studied crop types. Results suggest that in the study area, under normal water availability conditions, the irrigation demand met with groundwater is higher for row seasonal crops than it is for tree crops. Under drought conditions though, the relation between cropping area and groundwater use becomes very similar for both crop types. While perennial tree crops depend to a lesser extent on groundwater during normal years, their dependency increases sharply during drought periods, more than row crops. Farmers in this area thus tend to adapt to general lower surface water availability by reducing row crops and using groundwater as a major resource for perennial tree crops.

Our results and methodology will help to identify and map the sectors and crop types that are most dependent on groundwater and are vulnerable to deterioration in the quantitative and qualitative status of groundwater. This is useful for water resource managers and policy makers concerned with mitigating drought impacts and understanding the role that groundwater resources play on the sustainability of semiarid agricultural regions.

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