Use of remote sensing and geographic information tools for irrigation management of citrus trees

Jiménez-Bello M.A., Ruiz L.A., Hermosilla T., Recio J., Intrigliolo D.S.

in

Use of remote sensing and geographic information tools for irrigation management of citrus trees

M.Á. Jiménez-Bello*, L.Á. Ruiz**, T. Hermosilla**, J. Recio** and D.S. Intrigliolo*

*Instituto Valenciano Investigaciones Agrarias, Ctra Moncada-Náquera km 4.500,
P.O. Box 46113 Moncada, Valencia (Spain)
**geo-Environmental Cartography and Remote Sensing Group. Universitat Politècnica de València,
Camino de vera s/n 46022 Valencia (Spain)

Abstract. The most widely used method for estimating crops water requirements is the FAO approach, which takes into account: (i) climatic variables included in the reference evapotranspiration and (ii) the crop type, characterized by the crop coefficient (Kc). In citrus trees, Kc is mostly function of the tree ground covers (GC). In large areas tree ground covers (GC) can be estimated by means of remote sensing tools, and once tree water needs are calculated, this information can be implemented in geographic information systems. The present article summarizes some of the research conducted in order to estimate citrus water needs in large irrigated areas. It describes first how tree ground covers (GC) can be obtained by using image analysis tools applied to multispectral images. Tree water needs are obtained and they are compared with the real water applications for a case study of citrus water use associations. The results obtained allowed to conclude that the tools developed might be useful for improving irrigation efficiency showing some of the deficiencies currently found in irrigation management of collective water networks.

Keywords. Crop coefficient – Ground cover – Image analysis – High-resolution remote sensing.

Utilisation des outils de télédétection et d'information géographique pour la gestion de l'irrigation en vergers d'agrumes

Résumé. *La méthode la plus largement utilisée pour estimer les besoins en eau des cultures est l'approche de la FAO, qui tient compte : (i) des variables climatiques incluses dans l'évapotranspiration de référence et (ii) du type de culture, caractérisé par le coefficient de la culture (Kc). Chez les agrumes, Kc est principalement fonction de la couverture végétale au sol (GC). Sur de vastes étendues, la couverture végétale au sol (GC) peut être estimée par des outils de télédétection, et après avoir calculé les besoins en eau des arbres, cette information peut être mise en place dans des systèmes d'information géographique. Le présent article résume certains des travaux de recherche menés afin d'estimer les besoins en eau des agrumes dans de vastes zones irriguées. D'abord il est décrit comment calculer la couverture végétale du sol (GC) en appliquant des outils d'analyse d'image aux images multispectrales. Les besoins en eau des arbres sont obtenus et comparés aux irrigations réelles pour une étude de cas concernant l'utilisation de l'eau par les associations de cultivateurs d'agrumes. Les résultats obtenus ont permis de conclure que les outils développés pourraient être d'utilité pour améliorer l'efficience d'irrigation car ils montrent certaines des lacunes rencontrées actuellement en matière de gestion de l'irrigation dans les réseaux d'eau collectifs.*

Mots-clés. *Coefficient de culture – Couvert du sol – Analyse d'images – Télédétection à haute résolution.*

I – Introduction

Irrigated agriculture has a noticeable importance with more than 45% of the total agriculture production in the world (Molden, 2007). Water demand has been steadily increasing during the last years and future forecasts indicate that water scarcity will become a major problem in many areas of the world (Fereres and González-Dugo, 2009). It is then very important to achieve optimum effi-

Options Méditerranéennes, *B no. 67, 2012 – The use of remote sensing and geographic information systems for irrigation management in Southwest Europe*

147

ciency in irrigation applications both on and off farm. It is striking that despite much effort has been done in order to improve efficiency of water distribution along the whole chain, less attention has been paid in terms of irrigation efficiency at the farm level. In this sense, the first crucial step is to perform irrigation application in order to match as much as possible the plant water needs.

The most widely used method for estimating crops water requirement is the FAO approach (Allen *et al.*, 1998), which takes into account: (i) climatic variables included in the reference evapotranspiration (ETo), and (ii) the crop type, characterized by the crop coefficient (Kc). The crop evapotranspiration (ETc), which is the sum of the plant transpiration (T) and soil evaporation (E), is then calculated as ETo by the Kc. The ETo is an estimation of atmosphere evaporation defined as the evapotranspiration rate from a reference surface. Owing to the difficulty of obtaining accurate field measurements, ETo is commonly computed from weather data. The principal weather parameters affecting ETo are radiation, air temperature and humidity and wind speed. Nowadays the FAO Penman-Monteith equation is the standard method for the definition and computation ETo (Allen *et al.*, 1998). With this model the ETo (mm/day) is obtained as

$$ETo(mm/day) = (0.408\Delta(R_n-G)+\gamma(900/T+273)U_2(e_s-e_a))/(\Delta+\gamma(1+0.34U_2))$$

where ET_o reference evapotranspiration [mm day^{-1}], R_n net radiation at the crop surface (MJ m^{-2} day^{-1}), G soil heat flux density (MJ m^{-2} day^{-1}), T mean daily air temperature at 2 m height (°C), u_2 wind speed at 2 m height (m s^{-1}), e_s saturation vapour pressure (kPa), e_a actual vapour pressure (kPa), e_s - e_a saturation vapour pressure deficit (kPa), Δ slope vapour pressure curve (kPa °C^{-1}), γ psychrometric constant (kPa °C^{-1}).

The other variable used for computing the ETc, the Kc takes into account those characteristics that differentiate each crop from the reference crop (Allen *et al.,*1998). Differences in resistance to transpiration, crop height, crop roughness, reflection, ground cover and crop rooting characteristics result in different ETc levels in different types of crops under identical environmental conditions. Most of these parameters depend on the plant ground cover (GC). In the case of citrus, Castel (2000) obtained an average yearly Kc based on the GC (Table 1).

Table 1. Crop Coefficient (Kc) according ground cover (GC,%) for citrus and fruit trees

GC(%)	Citrus
20 > GC	$K_c = 0.021 + GC * 0.0174$
20 < GC < 70	$K_c = 0.274 + GC * 0.005$
70 < GC	$K_c = K_{c70}$

Citrus trees crop coefficient also vary along the season with minima in spring and maxima in autumn (Table 2) reflecting mainly changes in ground cover produced by pruning and by growth of new leaves in spring and autumn, but also changes in soil evaporation produced by rainfall.

Table 2. Monthly citrus crop coefficient as reported in Castel (2000)

Average	Jan	Feb	Marc	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0.68	0.66	0.65	0.66	0.62	0.55	0.62	0.68	0.79	0.74	0.76	0.73	0.63

For computing irrigation water requirements rainfall contributions to the orchard water balance should be also taken into account. Since, the total amount of rainfall is often not entirely available for tree transpiration the effective rainfall (P_{ef}) should be estimated. This is because some rainfall water might not be stored in the orchard due to runoff or drainage (FAO, 1978). In addi-

tion, in modern drip irrigated orchards, it is considered that the entire soil allotted per tree is not colonized by roots that should be more localized within the dripper zone. In order to consider P_{Ef} is estimated by means of a factor (Fpe) that relates the effective rainfall with the GC (Table 3).

Table 3. Effective rainfall for citrus and fruit trees according to season

Season	Fpe factor
Winter	Fpe = 1.25 * GC / 100
Summer	Fpe = 1.25 * GC / 100
	(as maximum Fpe = 0.8)

It is then clear that for optimum irrigation management is crucial to precisely estimate tree ground covers that will be then used to both computing tree water requirements and rainfall contributions to the net water orchard balances. Plants ground cover can be directly measured with a sampling mesh as Wünsche *et al.,* (1995) proposed. On another hand, Castel (2000) used a ruler to measure canopy dimensions and GC was estimated as the horizontal projection of the canopy and it was expressed as ratio to the planting spacing. GC can also be estimated by indirect methods which are based mainly in the light interception measured by sensors (Giuliani *et al.,* 2000) and its representation in three dimension models (López-Lozano *et al.,* 2011). For the determination of a stand's LAI (Leaf Area Index), there are direct techniques like harvesting of the whole canopy or some samples of the vegetation, which are destructive and laborious. Taking samples of litter is non-destructive but also very time-consuming (Holst *et al.,* 2004). Due to the difficulties of the direct techniques, indirect techniques are preferred. Tools such as hemispherical photography and cover photography (Macfarlane *et al.,* 2007), the LAI 2000 and LAI 2200 (LI-COR Biosciences), LAI ceptometer (Decagon Devices) and Tracing Radiation and Architecture of Canopies (TRAC; Chen, 1996) allow measuring LAI in a non-destructive way.

However, for the determination of GC and LAI for large extensions, like irrigation areas, the use of these techniques entails a large amount of samples and long processing time. For this reason, remote sensing techniques become valuable tools in order to estimate these parameters. Due to the physiologic features of tree crops, high resolution images are required to estimate with accuracy these parameters.

High spatial resolution images have been available since the beginning of aerial photography, but their application to agriculture and forestry dramatically increased with the first near-infrared (NIR) photographs, and even more with the use of digital cameras that reduced acquisition costs and provided more homogeneity in terms of radiometric calibration of the scenes. Additionally, at the end of the 20th century and the very beginning of the 21st a new generation of high resolution satellites brought availability of data with a high frequency of acquisition. Among these satellites with onboard high resolution sensors, the series of Ikonos (2000), EROS-A and B (2000, 2006), QuickBird (2001), OrbView-3 (2003), WorldView-1 and 2 (2007 and 2009), GeoEye (2008) or RapidEye (2008) are very representative, typically having panchromatic and/or multispectral sensors, the former with spatial resolutions ranging from 0.5 to 1 m/pixel and the latter from 2 to 4 m/pixel. Panchromatic images have one band with spectral sensitivity in the visible and very near infrared, while the multispectral images from these high resolution sensors usually have four bands centred on the visible and NIR regions of the electromagnetic spectrum. Furthermore, the image fusion techniques allow for the combination of both types of images, obtaining a new image with the spatial detail of the panchromatic and the spectral bands of the multispectral, while preserving most of the information contained in the original images. These techniques are continuously improving and provide an excellent alternative and complement to the digital aerial colour-infrared imagery, several of them being reported in Wald *et al.,* (1997), Nuñez *et al.,* (1999), Ranchin and Wald (2000) and many other authors. Regarding new remote sensing sensors that

can be used in ground cover determination, it seems appropriate to mention the new Aerial Laser Scanning (ALS) or Light Detection and Ranging (LiDAR) systems, thoroughly described by Baltsavias (1999). LIDAR technology works by continuously sending energy pulses to the ground, that impact on Earth's surface and return to the sensor. The return time allows registering the position and coordinates of the recorded points and, therefore, measures terrain, vegetation, and other elements in 3D. The final point cloud data can be processed and analyzed for ground cover estimation, as well as many other applications. However, current unavailability of these data on a regular basis, as well as their high cost, make it out of the scope of this chapter.

II – Remote sensing tools for estimation of citrus tree ground cover

Automated detection of trees and ground cover from multispectral imagery has been mainly focused on forest applications (Wulder *et al.,* 2000; Culvenor, 2002; Pouliot *et al.,* 2002; Wang *et al.*, 2004), but some image processing methods have also been reported for olive tree detection, both semi-automated (Kay *et al.*, 2000) and automated (Karantzalos and Argialas, 2004; García-Torres *et al.*, 2008), and for Citrus and fruit tree identification (Recio *et al.,* 2009). In general, methods for ground cover estimation from images are based on classification techniques, supervised or unsupervised, on tree identification algorithms using local maxima approaches from vegetation indices or other band combinations and filtering approaches, or on hybrid methods combining segmentation, classification and the application of a variety of filters. In this section, a review and brief description of these techniques is made, focusing on the case of agricultural tree plots.

1. Overall methodology

Independently of the efficiency or performance of the method used, an important and practical aspect to consider in ground cover estimation is the fact that it is very sensitive to the binomial ground *tree size* and image *spatial resolution*. In small trees, the relative error due to the tree perimeter uncertainty becomes higher. Analogous effect occurs when the spatial resolution of the image is smaller (pixel size larger), that is, the tree border error quantifying the ground cover increases (Fig. 1a). Therefore, in the selection of the appropriate spatial resolution of the images, the average size of the trees to be processed is an important factor to be considered.

0.25 m/píxel   1.5 m/píxel
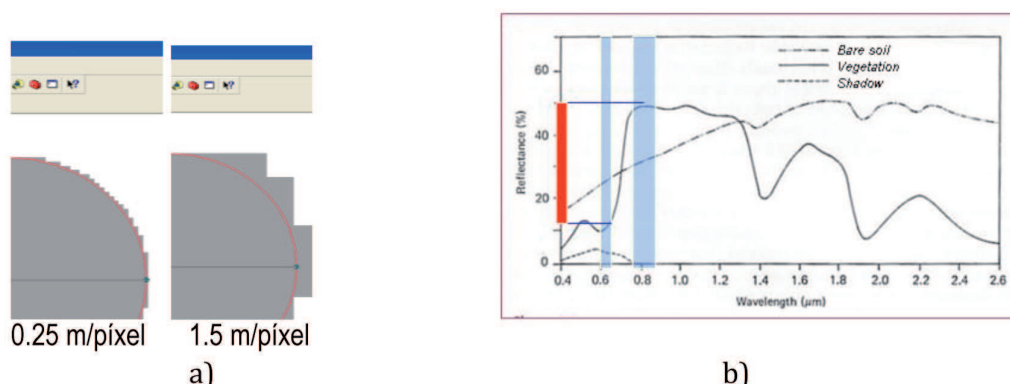
a)   b)

Fig. 1. (a) Effect of the image spatial resolution on the accuracy of the estimation of the ground cover area on the border of the tree; and (b) average spectral response curve of bare soil, vegetation and shadow, showing in blue the sensitivity of red and NIR bands, and in red their sharp difference in reflectance for vegetation.

Another important factor is the spectral information provided by the image. Since the spectral reflectance of the vegetation increases sharply in the infrared, due to the scattering of this radiation caused by the random arrangement of the cells and the intercellular air spaces in the spongy mesophyll layer of the leaves, the availability of visible and NIR bands is very important to accurately differentiate soil or shadow from a tree, and subsequently to obtain good ground cover estimations. Figure 1b illustrates this effect.

After the selection of the most appropriate images, and depending on the source and distribution institution or agency, a set of pre-processing operations must be done before applying any algorithm to the analysis of the data:

– The radiometric adjustment of the different scenes to be used, consisting of the reduction of the differences between scenes in terms of illumination or calibration of the sensors. This is usually more noticeable in aerial images, where images from different strips present distinct observation angles. The adjustment can be carried out by means of histogram matching, histogram specification, regression of radiometric values or similar techniques.

– Geometric corrections are needed to eliminate geometric distortions generated on the image due to the acquisition process. They are variable depending on the platform (satellite or aerial), and on the topography of the terrain.

– Fusion techniques refer to the combination of panchromatic and multispectral images to obtain a new image with the spatial resolution of the first and the spectral information of the second. They may be applied if these two types of images are available.

– Finally, some smoothing filtering processes may be applied to remove noise from the images and to enhance the differences between the trees and the background, facilitating the performance of the tree detection algorithms. These filters are variable depending on the authors and the characteristics of the agricultural plots.
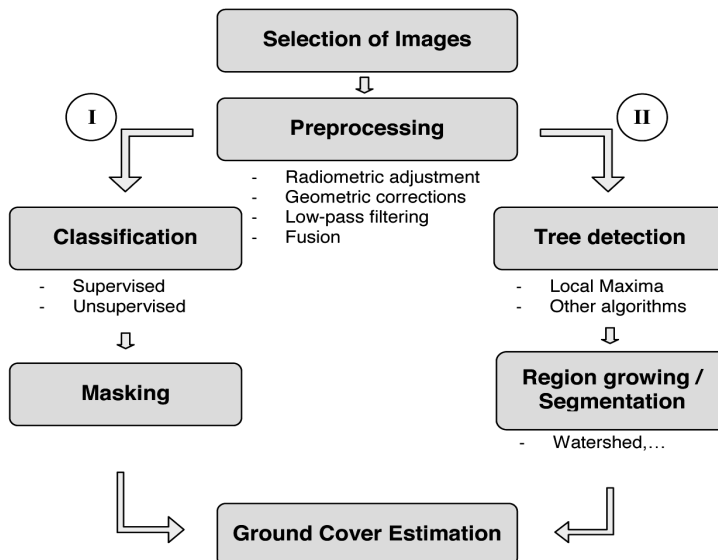

Fig. 2. **Overall methodology for tree ground cover estimation from satellite and aerial images. (I) Procedures based on classification; (II) Procedures based on tree detection algorithms and segmentation.**

Figure 2 shows a generic procedure for ground cover estimation, where two different types of approaches are distinguished (branches "I" and "II") after the pre-processing steps. The next two sections describe these general alternatives, one of them based on the multispectral classification of the images, and the other based on the detection of the trees followed by region growing procedures or analogous segmentation techniques.

2. Methods based on image classification

Image classification is the process used to produce thematic maps from imagery, and consists of the extraction of descriptive features from the pixels or objects in the image, and their assignation to a class or category according to that quantitative information. Two main types of image classification techniques can be considered: *supervised* and *unsupervised*. In supervised classification, the analyst selects representative sample sites of known cover type, called training areas, compiling a numerical description of each class. Each pixel or object in the data set is then compared to them and is labelled with the most similar class. Many different algorithms or classification methods can be used to measure this similarity and generate decision rules, such as minimum distance, maximum likelihood, other based on decision trees, neural networks, etc. The maximum likelihood classifier, a statistical standard method, quantitatively evaluates both the variance and covariance of the category spectral response patterns when classifying an unknown pixel, assuming that the distribution of the cloud points forming the category training data is Gaussian. Given the mean vector and the covariance matrix of each category pattern, the probability of a given pixel or object being a member of a particular land cover class can be computed (Lillesand and Kiefer, 2000). Figure 3b shows the result of classifying a citrus plot in three classes: tree, shadow and soil.

Unsupervised classifiers do not utilize training data as the basis for classification. Rather, they involve algorithms that examine the pixels in an image and aggregate them into a number of unknown classes based on the natural groupings or clusters present in the image values. In these approaches, spectrally separable classes are automatically determined and then their informational category is defined by the analyst. There are numerous clustering algorithms, one of the most common is the K-means, an iterative method that arbitrarily creates K clusters and each pixel is assigned to the class whose mean vector is closest to the pixel vector. This step is iterated until there is not significant change in pixel assignments. A common modification is known as the ISO-DATA algorithm, which includes merging the clusters if their separation is below a threshold, and splitting of a single cluster into two clusters if it becomes too large. These algorithms present the advantage, compared to the supervised, that they work in an automatic manner, since no previous information is needed to classify the images. However, several parameters must be initially set by the user, such as number of classes, number of iterations, or some thresholds used to stop the iterations. Figure 3c shows the result after classifying a plot in tree, shadow and soil.
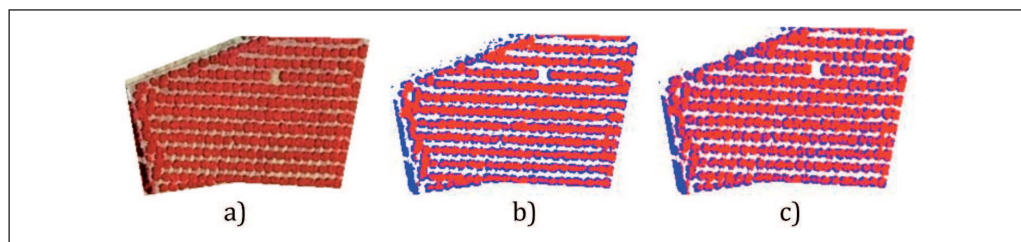

Fig. 3. Example of the classification of a citrus plot in 3 classes: tree (red), shadow (blue), soil and background (white). (a) Original colour-infrared image; (b) supervised classification using *maximum likelihood* algorithm; and (c) unsupervised (*ISODATA*) classification using the following parameters: 3 classes, 5 maximum iterations, 5% change threshold.

Classification methods for ground cover estimation are not considered as fully automated, since they require selection of training samples (supervised methods) or definition of parameters (unsupervised methods). However, the main handicap of supervised classification is the large variability of tree and soil response in different plots even from the same area, which makes the extrapolation of the training samples and the decision functions very difficult, making this technique by itself limited to small areas with homogeneous plantations. On the other side, the definition of parameters required by unsupervised approaches is difficult and involves uncertainty, yielding results that are only approximate. Finally, other limitation is that since they are usually based on the spectral response of the vegetation, weeds may be often misclassified as trees, with the subsequent commission error in tree coverage determination.

3. Methods based on tree detection and segmentation

These methods prioritize the identification and localisation of the trees that are present in a plot, and then use these locations as seeds for the definition of the tree crowns. Although there is a variety of methods that are used for tree detection, especially in forest applications, the most used are those based on the *local maximum filtering* (LMF) algorithm (Gougeon, 1995). This algorithm assumes that NIR reflectance has a peak at the tree apex and decreases towards the crown edge. Thus, after computing the *Normalised Difference Vegetation Index* (NDVI), that enhances the different reflectances of vegetation canopy in the NIR and red (NIR-Red/NIR+Red), a moving window can be applied over the NDVI image (Fig. 4a), considering a tree when the central value in the window is higher than the other values. The size of the filtering window can be either determined as a function of the average size of the trees, or automatically defined for each plot by the position of the first maximum on the semivariogram curve (Ruiz *et al.,* 2011). Figure 4b shows the result of the application of the LMF over a citrus plot.

After tree detection, region growing or segmentation algorithms are applied to define the crown surrounding each tree. Region growing is an iterative process which starts at "seed" pixels from the set generated using the LMF algorithm. Pixels from the neighbourhood of each seed are progressively classified as belonging or not to the same crown as the seed (Hirschmugl *et al.,* 2007). Classification criteria are typically based on absolute distance from the seed, brightness gradient thresholds, spectral coherence, etc. Figure 4c shows the ground cover mask resultant after the application of the region growing process.
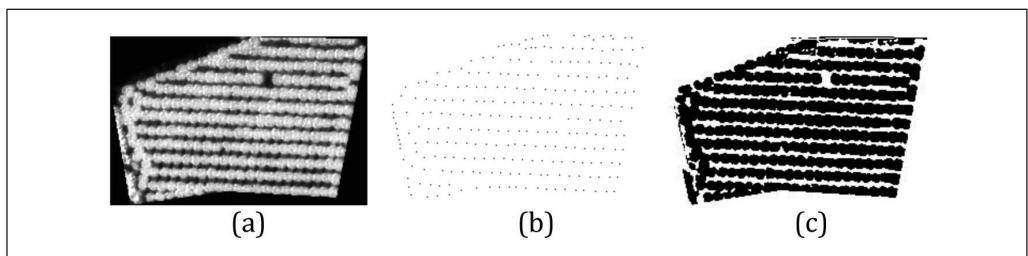

(a)   (b)   (c)

Fig. 4. **Extraction of ground cover area on the image example of Fig. 3a using a tree detection approach. (a) NDVI image; (b) application of the local maxima on the NDVI image; (c) cover area after region growing.**

Finally, other approaches are based on the application of hybrid methods, such as the combination of unsupervised classification, local maxima filtering, region growing, etc. An example of these combined techniques for ground cover estimation in citrus orchards is described in detail

in other chapter of this book. In addition, new sensors like airborne LiDAR allow for the integration of these data with multispectral images to provide a better accuracy in tree detection and crown cover. This will very likely be the trend during the next several years to increase the reliability of these methodologies. The methodology involves the preprocessing of LiDAR data to create a digital surface model (DSM), digital terrain model (DTM), and normalised digital surface model (nDSM). Then, the integration of spectral information from the images and height data from LiDAR, allows for a better estimation of ground cover (Fig. 5).
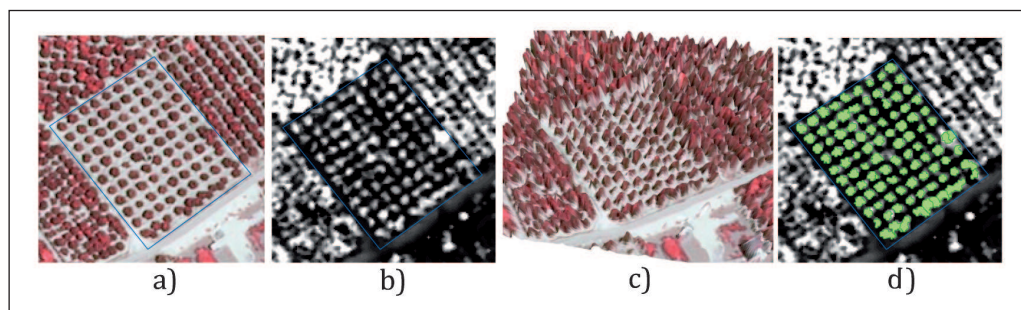

Fig. 5. **Example of the combination of aerial images and LiDAR data for ground cover estimation. (a) Colour-infrared image; (b) nDSM directly computed from low density LiDAR data (source: PNOA 2009); (c) 3D perspective with the image draped over the DSM; and (d) tree crowns (in green) automatically delineated after region growing.**

III – Integral irrigation water management at farm and district level

1. Implementation in Decision Support Systems

To optimize the use of all inputs involved in irrigation (water, energy and fertilizers) it is necessary to keep track of all the processes that are involved, with the aim of detecting weaknesses in management and try to improve them. Given the large amount of information required to do so, it is advisable to use a Decision Support System (DSS), which feeds the processes with different alternatives assessing the results in each case. Since most of the information used is spatial, Geographic Information Systems (GIS) are shown as the best working tool for this purpose.

The required data to be implemented in a DSS comes from different sources. Data can be grouped in two categories, according if they are used for agronomic or hydraulic purposes.

The agronomic processes deal with crop water requirements, irrigation scheduling and fertilization. To simulate these processes the needed data are:

– Cadastral information. This data let to know plot features as area and location. It can be obtained from public databases in standard formats.

– Soils. This information supplies soil characteristics like texture to calculate water crop requirements.

– Crops. In the case of citrus trees, planting spacing, ground cover, and root depth are required to estimate water crop requirements.

– Irrigation subunits. These data are useful to calculate irrigation time for scheduling. For example, in drip irrigation, emitter flow is required to calculate theoretical irrigation time. Moreover depending of the subunit and its management, net water crop requirements are increased to supply a minimum water amount to all plants (Arviza, 1996).

– Agroclimatic information. ETo ad Pe are required to compute net water crop requirements. Irrigation Advisory Services from local governments make available agroclimatic information obtained from station networks with daily frequency. Figure 6 shows the network of agroclimatic stations of the Valencia region (Spain).

This information can be incorporated to the DSS to calculate daily water crop requirements.
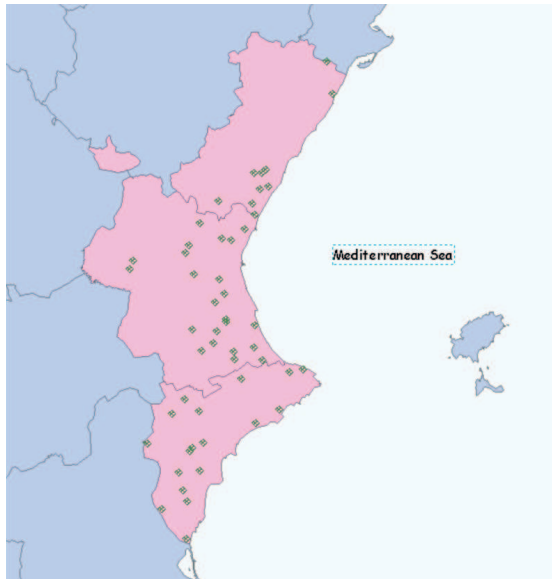

Fig. 6. Net of meteorological weather stations belonging to the Irrigation Technology service of the Instituto Valenciano Investigaciones Agrarias.

The hydraulic processes give information about how water is delivered and if it is done with the required guarantees of pressure, amount and quality. Also by means of performance indicators the system can be assessed (Córcoles *et al.,* 2010).

The required data about are the network layout, pumps, control devices (control systems, valves), hydrants, intakes, flow meters and irrigation scheduling. Figure 7 summarizes the data required for the agronomic and hydraulic management.

Focussing on the agronomic management, a DSS can calculate the crop water requirements and the irrigation time of all plots for irrigation scheduling.

In order to assess irrigation performing a DSS can give information about how water has been delivered to plots to meet crop water requirements. An indicator used for this purpose is the Seasonal Irrigation Performing Index (SIPI) that relates the crop water requirements with the water supplied (Faci *et al.,* 2002). Values lower than 100 mean that a crop it is being irrigated more than required. Values higher than 100 means that a crop is being irrigated less than required.
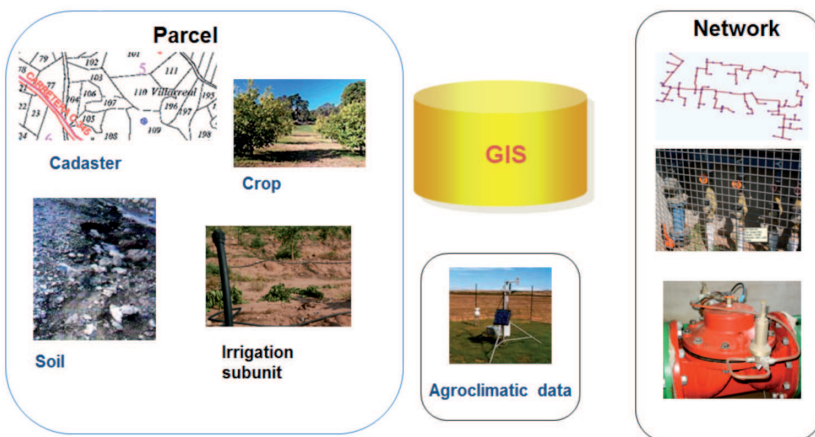
Fig. 7. Data required to be implemented in a DSS for the agronomic and the hy-draulic management.

2. Application to a case study

Next it is showed the implementation of a case study of a DSS called HuraGIS (Jiménez-Bello, 2010) in the Water User Association (WUA) of Senyera in Valencia (Spain) a region with Mediterranean climate. The total irrigated area was 104 ha, cropped entirely with citrus. Water was allocated by a pressurised irrigation network. There were 280 operating intakes that irrigated 356 plots. The average plot size was 3093 m^2. Crops were dripping irrigated.

GC was calculated using techniques depicted in above with the 2006 and 2008 ortophotos from the Spanish National Plan of Aerial Photography. Water crop requirements were calculated using agroclimatic data from the nearest station of the network of Valencia region.

Figure 8 shows the monthly SIPI (%) for four irrigation seasons (2006, 2007, 2008, 2009) for all parcels of the WUA. The annual SIPI (%) for these years were 117, 80, 81, and 67, respectively.
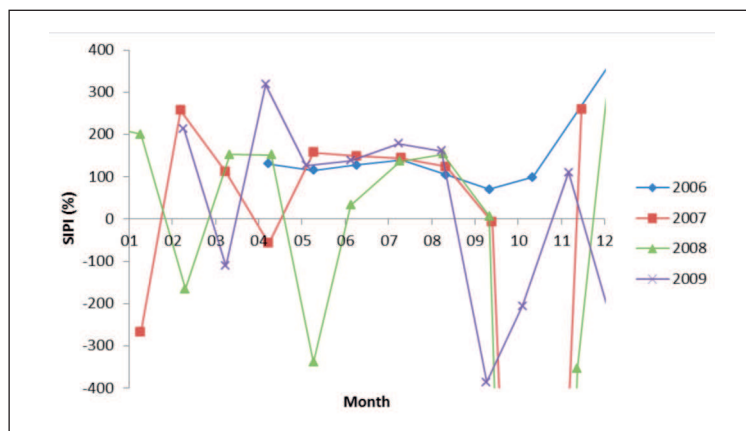

Fig. 8. Seasonal Irrigation Performing Index (SIPI) for the study case of Senyera for four seasons (2006, 2007, 2008, 2009).
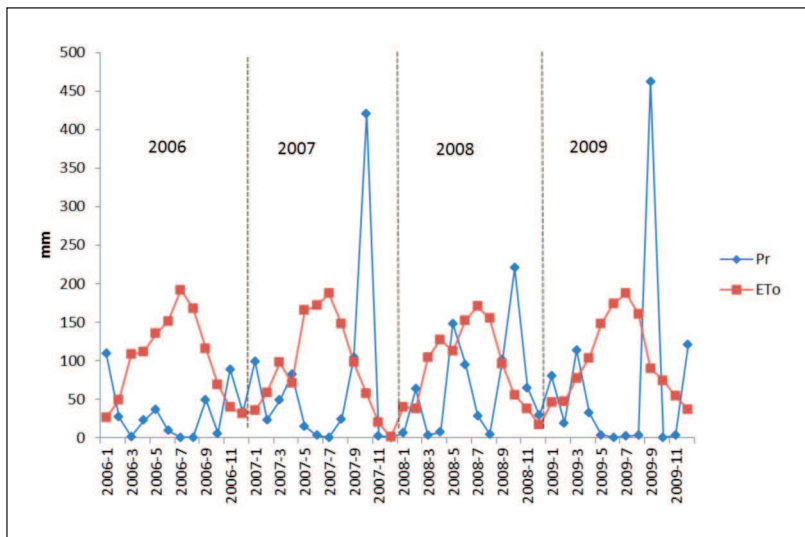
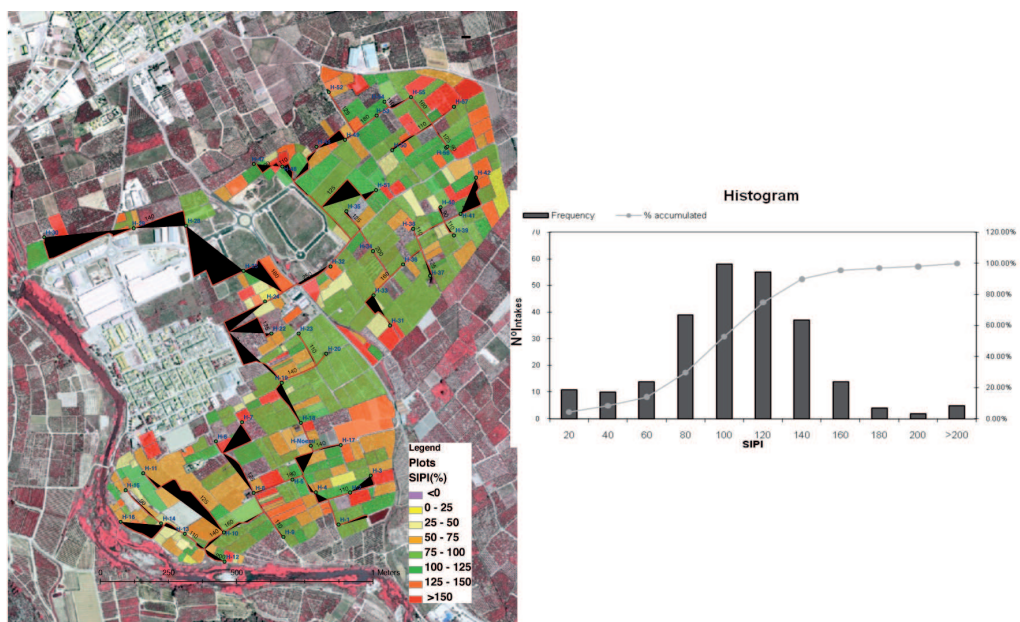Fig. 9. Monthly ETo (mm) and Pr (mm) for the study case of Senyera.

Fig. 10. (A) Map of Seasonal Irrigation Performance Index (%) for the 2010 of the study case of Senyera. (B) Histogram of SIPI(%) for the irrigation intakes of the study case.

Those values close to 100% mean that crops were properly irrigated. As it can been seen these values are around 100% in summer, the months with higher demand. Values below 0 are due to rainfall, which was not properly taken into account for irrigation scheduling as it can be seen in Figure 9. The lower values of monthly SIPI(%) correspond to the months of rains.

The map of Fig. 10 shows the annual SIPI(%) for each irrigated parcel in 2010 of the study case. The histogram shows the existing variability at WUA level. Most of plots irrigated by the network intakes have SIPI values that range from 80% to 120% which means that are properly irrigated. But 20% of plots are overirrigated. On the other side 20% of plots are underirrigated.

With this information obtained via performance analysis, recommendations can be given to users to improve their irrigation efficiency. For example, in plots which are under-irrigated, users can modify either their irrigation time or increase the emitter number with the aim of increasing the received water amount.

References

Allen R.G., Pereira L.S. and Raes D., 1998. Crop evapotranspiration. Guidelines for computing crop water requirements. *FAO Irrigation and Drainage Paper 56*. Food and Agriculture Organization of the United Nations, Rome.

Arviza J., 1996. *Riego localizado*. Universidad Politécnica de Valencia. Departamento de Ingeniería Rural y Agroalimentaria. Valencia. Spain.

Baltsavias E.P., 1999. Airborne laser scanning: basic relations and formulas. In: *ISPRS Journal of Photogrammetry and Remote Sensing*, 54, p. 199-214.

Castel J.R., 2000. Water use of developing citrus canopies in Valencia, Spain. In: *Proc Int. Soc. Citriculture, IX Congr.*, p. 223-226.

CGCtel J.R. 2000. Water use of Developing Citrus Canopies in Valencia, Spain. In: *Proceedings of the international Society of Citriculture. IX Congress.* 2000, p. 223-226

Chen J.M. and Blanken T.A, 1992. Defining leaf area index for non flat leaves. In: *Plant Cell Environ.*, vol. 15, p. 421-429

Chen J.M., 1996. Optically-bGCed methods for meGCuring seGConal variation in leaf area index of boreal conifer forests. In: *Agricultural and Forest Meteorology*, 80, p. 135-163

Corcoles J.I., de Juan J.A., Ortega J.F., Tarjuelo J.M. and Moreno M.A., 2010. Management evaluation of Water Users Associations using benchmarking techniques. In: *Agricultural Water Management*., 98, p. 1-11.

Culvenor D. S., 2002. TIDA: an algorithm for the delineation of tree crowns in high spatial resolution remotely sensed imagery. In: *Computers & Geosciences* 28 (1), p. 33-44.

Faci J.M., Bensaci A., Saltni A. and Playán E., 2000. A case study for irrigation modernisation. I. Characterisation of the district and analysis of water delivery records. In: *Agric. Water Manage*., 42, p. 315-334.

FAO, 1978. *Effective rainfall in irrigated agriculture*. FAO irrigation and drainage paper. N.G. Dastane

Fereres E. and Goldhamer D.A. 1990. Deciduous fruit and nut trees. In: Stewart BA, Nielsen DR, eds. *Irrigation of agricultural crops*, Agronomy 30. Madison, WI: ASA, CSSA, SSSA, p. 987-1017.

Fereres E. and Gonzalez-Dugo V., 2009. Improving productivity to face water scarcity in irrigated agriculture. In: Sadras VO, Calderini DF (eds) *Crop physiology: applications for genetic improvement and agronomy*. Academic Press, San Diego, p. 123-143.

García-Torres L., Peña-Barragán J.M., López-Granados F., Jurado-Expósito M. and López-Escobar R., 2008. Automatic assessment of agro-environmental indicators from remotely sensed images of tree orchards and its evaluation using olive groves. In: *Computers and Electronics in Agriculture*, 61 p. 179-191.

Giuliani R., Magnanini E., Fragassa C. and Nerozzi F., 2000. Ground monitoring the light-shadow windows of a tree canopy to yield canopy light interception and morphological traits. In: *Plant Cell Environ.* 23, p. 783-796.

Gougeon F.A. 1995. A crown-following approach to the automatic delineation of individual tree crowns in high spatial resolution aerial images. In: *Canadian Journal of Remote Sensing*, 21, p. 274-284.

Hirschmugl M., Ofner M., Raggam J. and Schardt M., 2007. Single tree detection in very high resolution remote sensing data. In: *Remote Sensing of Environment*, 110, p. 533-544.

Holst T., Hauser S., Kirchgäßner A., Matzarakis A., Mayer H., Schindler D. and Spiecker H., 2003. Measuring and modelling Plant Area Index in beech stands. In: *International Journal of Biometeorology*, 48 (4), p. 192-201.

Jiménez-Bello M. A., Martínez Alzamora F., Bou Soler V. and Bartoli Ayala H.J., 2010. Methodology for grouping intakes of pressurised irrigation networks into sectors to minimize energy consumption. In: *Biosystems Engineering*, 105, p. 429-438.

Karantzalos K. and Argialas D., 2004. Towards the automatic olive trees extraction from aerial and satellite imagery. In: *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences*, 35(5), p. 360-365., p. 1173-1177, Istanbul, Turkey.

Kay S., Léo O., Peedell S. and Giardino G., 2000. Computer assisted recognition of olive tree in digital imagery, Space Applications Institute, JRC of the European Commission, Ispra, Italy.

Lillesand T.M. and Kiefer R.W., 2000. *Remote Sensing and Image Interpretation*. John Wiley & Sons, Inc. New York.

López-Lozano R., Baret F., García de Cortázar Atauri I., Lebon E. and Tisseyre B. 2011. 2D approximation of realistic 3D vineyard row canopy representation for light interception (fIPAR) and light intensity distribution on leaves (LIDIL). In: *European Journal of Agronomy*, 35-3, p. 171-183.

Macfarlane C., Grigg A. and Evangelista C., 2007a. Estimating forest leaf area using cover and fullframe fisheye photography: thinking inside the circle. In: Agricultural and Forest Meteorology 146 (1-2), p. 1-12.

Molden D., 2007. *Water for Food, Water for Life: A Comprehensive Assessment of Water Management in Agriculture.* Earthscan, London.

Nuñez J., Otazu X., Fors O., Prades A., Palá V. and Arbiol R. 1999. Multiresolution-based image fusion with additive wavelet decomposition. In: *Transactions on Geoscience and Remote Sensing.* IEEE. 37(3), p. 1204-1211.

Pouliot D. A., King D.J., Bell F.W. and Pitt D.G., 2002. Automated tree crown detection and delineation in high-resolution digital camera imagery of coniferous forest regeneration. In: *Remote Sensing of Environment*, 82 (2-3), p. 322-334.

Ranchin T. and Wald L., 2000. Fusion of high spatial and spectral resolution images: the ARSIS concept and its implementation. In: *Photogrammetric Engineering and Remote Sensing,* 66(1), p. 49-61.

Recio J.A., Ruiz L.A., Fernández A. and Hermosilla T., 2009. Extracción de características estructurales en un sistema de clasificación de imágenes basado en parcelas. In: *XIII Congreso Nacional de la Asociación Española de Teledetección*, 23-26 septiembre 2009, Calatayud, p. 577-580.

Ruiz L.A., Recio J.A., Fernández-Sarría A. and Hermosilla T., 2011. A feature extraction software tool for agricultural object-based image analysis. In: *Computers and Electronics in Agriculture*, 76 (2), p. 284-296.

Wald L., Ranchin T. and Mangolini M., 1997. Fusion of satellite images of different spatial resolutions: assessing the quality of resulting images. In: *Photogrammetric Engineering and Remote Sensing*, 63 (6), p. 691-699.

Wang L., Gong P. and Biging G.S., 2004. Individual Tree-Crown Delineation and Treetop Detection in High-Spatial-Resolution Aerial Imagery. In: *Photogrammetric Engineering and Remote Sensing*, 70 (3), p. 351-357.

Wulder M., Niemann K.O. and Goodenough D.G., 2000. Local Maximum Filtering for the Extraction of Tree Locations and Basal Area from High Spatial Resolution Imagery. In: *Remote Sensing of Environment*, 73 (1), p. 103-114.

Wünsche J.N., Lakso A.N. and Robinson T.L., 1995. Comparison of four methods for estimating total light interception by apple trees of varying forms. In: *HortScience*, 30, p. 272-276.