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Remote sensing as a complementary tool for monitoring the effects of agricultural policies: The case of the irrigated area of Tadla Azilal (Morocco)

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Agricultural policies are human driving forces that can influence various processes within the landscape due to land-use assignation. Along this work, an innovative methodological framework based on remote sensing techniques is proposed for the analysis of the effects coming from the implementation of any change in agricultural production and for diagnosing the sustainability of irrigated agricultural systems located at arid regions in developing countries. In this sense, the main goal of this paper lies in proposing an efficient and reliable methodology for the multitemporal mapping of cultivated areas at a regional scale and the calculation of socio-economic performance. The undergoing hypothesis is that the emerging "object-based image analysis" techniques could be successfully applied on medium resolution satellite images such as Landsat series. This approach has been tested on a representative region of intensive cultivation in arid areas such as the irrigated area of Tadla Azilal (central Morocco). The application of the developed methodology has allowed helping, as a complementary tool, in strengthening the underlying hypothesis of a relative failure of the liberalization of agricultural production sector and the refunding of the code of agricultural investment after nearly thirty years of its application. In accordance with this hypothesis, yet to be contrasted through other field-based studies, a series of recommendations for improving socio-economic and environmental sustainability of the agricultural system are conducted to serve as guidance for other similar agricultural systems also located in arid areas.

Key words: Object based image analysis, socio-economic impact, remote sensing, developing countries, arid regions, sustainability.

INTRODUCTION

The conservation of agricultural land resources, either in developed or developing countries, is linked to a sustainable and thus profitable agriculture (Ore and Bruins, 2012; Thapa and Gila, 2012). In fact, sustainable agricultural systems must be resource-conserving, environmentally compatible, socially supportive, and commercially competitive (Ikerd, 1990). The challenge for developing countries is to develop land management programs to increase the availability of high-quality fertile lands in areas where population growth is high, poverty is endemic, and existing institutional capacity is weak (World Bank, 2006). Making right decisions largely depends on the quality of the available information. Agricultural policies, through their effect on Land-use, act as strong driving forces that can influence various processes within the landscape and can have an impact on landscape functions (Debolini et al., 2013; Fleskens and Stringer, 2014). In fact, land use, ecosystem service values and local economy have a close relation (Zhang et al., 2013). In this sense, people migrate from degraded to more fertile areas, from the countryside to cities, from regions that cannot provide sufficient resources to sustain people’s livelihoods to more fortunate places. This is one of the main drivers of agricultural land abandonment and the subsequent soil degradation of previously very productive irrigated areas in developing countries. As a case study, we have focused our work on the irrigated area of Tadla Azilal, located at central Morocco. This area actually constitutes an oasis within an arid region due to its water availability coming from the Atlas mountain range. However, the problem of shortage of irrigation water in Tadla Azilal began to be especially worrying at early 80's, being aggravated by a succession of droughts from 1981 to 1984. This resulted in the need to use the groundwater as an alternative resort, which entailed more pressure on non-renewable resources.

Regarding the historical trajectory of agriculture in Morocco, "Le Code des Investissements Agricoles" (CIA or Code of Agricultural Investment), enacted in July 1969, can be considered as one of the main legislative instruments and tools headed up to the control and management of agriculture and irrigation water in this country. The aforementioned code is presented as a contract between farmers and the State, defining rights and duties in public Large Scale Irrigation schemes. Historically, this policy has been coined as “*Politique des Barrages*” which consisted of huge investments by the State in public irrigation infrastructure (that is, building of huge dams) with the objective of reaching the milestone of 1 million ha of irrigated agricultural land by 2000 (Diao et al., 2005). In short, the State held the equipment and the management of large irrigated areas in exchange for a financial contribution of the farmers in the form of a tax, which was a function of the volume of water used, to defray operating costs, maintenance and amortization of irrigation infrastructures. In addition, agricultural land-use in these potentially very productive areas has been rigidly regulated by the State during a long time. For example, it was established a rigid crop rotation system that prevented farmers to make their own decisions.

After almost thirty years of application of the aforementioned state wide planning system, Moroccan agricultural sector did not significantly improve mainly due to the heavy and selective intervention of the State to regulate markets and control prices for so-called “strategic” commodities, which translated technically into controlling the flow of imports and exports. The combined effect of these policies has led to an implicit taxation of the sector, especially when accompanied with the overvalued exchange rate at the time (Doukkali, 2006). Consequently, Moroccan Ministry of Agriculture, Rural Development and Fisheries proceeded to the liberalization of agricultural sector.

The production system adopted throughout the kingdom of Morocco, and particularly in the irrigated area of Tadla Azilal, has been traditionally characterized by its majority dedication to the production of cereals, sugar beet and fodder, actually being a continuation of the agricultural system applied during the protectorate. After the liberalization of rotating systems, it is advocated the implementation of a more profitable and sustainable agriculture that can ensure its future continuity by setting population-based and preventing emigration. However, there are not rigorous studies of the region which provide specific information regarding the spatio-temporal distribution of the main crops neither before nor after the process of liberalization.

This paper seeks to contribute a methodological framework at regional scale to help evaluate the effects of agricultural policies in developing and arid/semiarid areas (scarcity of field data and available water). Therefore it is crucial both to count on indices to measure the efficiency of water use and effectively know their spatio-temporal dynamics. In this context both Remote Sensing and the Socio-Economic Productivity (SEP) indicator proposed by García Lorca (2009) could be seen as very useful tools to help decision makers in the analysis of the agricultural system. Taking into account that mapping and monitoring of vegetation species using traditional field-based methods is costly and time-consuming (Mansour et al., 2012), Land-use (LU) monitoring based on Remote Sensing and an Object Based Image Analysis (OBIA) approach has been applied in this work. In fact, there are many works related to remote sensing applications for mapping multi-year cropping patterns from Landsat imagery based on either traditional per-pixel approach (Martínez-Casasnovas et al., 2005; Alexandridis et al., 2008) or OBIA techniques (Vieira et al., 2012).

Regarding OBIA techniques, they rely on aggregating similar pixels to obtain homogenous objects (image segmentation stage), which are then assigned to a target

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Figure 1. Location of the study site (irrigated area of Tadla Azilal, Morocco).

class (classification stage). Using objects instead of pixels as a minimum unit of information minimizes the salt and pepper effect due to the spectral heterogeneity of individual pixels. Unlike traditional pixel-based methods that only use spectral information, object-based approaches can use shape, texture, and context information associated with the objects and thus have the potential to efficiently handle more difficult image analysis tasks (Blaschke, 2010; Marpu et al., 2010), thus improving the performance of supervised classifiers, both for high (Lee and Warner, 2006; Blaschke, 2010; Myint et al., 2011) and low spatial resolution satellite imagery (Flanders et al., 2003; Dingle and King, 2011; Ceccarelli et al., 2013). The application of the proposed approach should allow the detection of potential spatio-temporal changes in cropping patterns over the irrigated area during the period studied and therefore help evaluate, together with complementary and necessary field-based data, the success or failure of the policy measure consisting in the liberalization of Moroccan agricultural production sector and the refunding of the code of agricultural investment after nearly thirty years of its application.

MATERIALS AND METHODS

Study site description

The irrigated area of Tadla Azilal belongs to the region of Tadla Azilal (Figure 1), located at the Southeast area of Morocco, 200 km from the economic capital of Morocco (Casablanca). The region covers an area of 17125 km^2, while the irrigated area under study represents 21% of this area, lying in a plain with an average height of 400 m. Tadla Azilal is divided by the river Oum Er Rbia in two sub-areas: Beni Moussa and Beni Amir. Regarding quality of the irrigation water used in the area of Beni Amir, it comes from the river Oued Oum Er Rbiaa and it is characterized by slight salinity with values ranging from 0.6 to 1.3 g/L (Nemmaoui, 2011). In the case of Beni Moussa, the principal source of irrigation water is the dam of Bin El Ouidan-Oued el Abid, generally contributing good irrigation water quality (Nemmaoui, 2011).

The area occupied by the irrigated area of Tadla Azilal is close to 325095 ha and can be classified as agricultural land, forest and uncultivated areas. Tadla Azilal is subject to environmental constraints such as low and unpredictable seasonal rainfall, high mean annual temperatures and high evaporative demand, which severely limit water supplies for agricultural use. Moreover, existing constraints are likely to be exacerbated by climate change, with temperatures expected to rise and water supplies to become increasingly scarce (Rosenzweig et al., 2004), particularly in Africa (Orindi and Murray, 2005).

Economic benefits of irrigation water

To include sociological factors derived from the use of irrigation water, we adopted the indicator "*Socio-Economic Productivity (SEP) of irrigation water*" proposed by García Lorca (2009), which includes irrigation water consumption, economic performance and potential employment generated, formulated through the next expression:

$$SEP = \frac{[(60 \times SP) + (40 \times EP)]}{100} \tag{1}$$

Where SEP is the socio-economic productivity of irrigation water

Table 1. Description of Landsat imagery used in this work. (*) RMSExy means Planimetric Root Mean Squared Error.

Sensor	Date	Number of bands	Ground Pixel Size (m)	RMSExy(*) (m)
Landsat 1-3 MSS	March 7, 1973	4	60	28.5
Landsat 4	April 5	4	60	30.7
Landsat 7 SLC	February 14	7	30	5.7
Landsat 4	May 16	7	30	3.9
Landsat 7 SLC	May 27	7	30	5.7
Landsat 4	May 30	7	30	4.3
Landsat 4	June 4	7	30	4.1
Landsat 4	June 7	7	30	4.2

(€/m3), EP is the economic productivity (measured as the ratio between the production value and the water consumption) and SP means the social productivity (that is, the ratio between the demanded working days and the water consumption multiplied by the corresponding Day's wage). The assessment of the demanded working days and day's wages for every crop was carried out by using a representative survey over 79 farmers in the area (Nemmaoui, 2011), of which 97% used the traditional method called "Robta" or surface irrigation. 66% of farmers polled worked in Beni Moussa and 34% in Beni Amir.

Satellite imagery for multitemporal crop monitoring

Landsat satellite images, covering the study area distributed by USGS through Global Visualization Viewer (Glovis, 2013), were employed to undertake the multitemporal analysis of the agricultural crops spatial distribution in the irrigated perimeter of Tadla Azilal. Taking into account that the date of acquisition of images is crucial and directly linked to the type of phenomenon to be studied (Doraiswamy et al., 2004), spring-summer season would be usually preferred to acquire Landsat images headed up to inventory and spatially locate irrigated crops over the working area (Table 1). Indeed, in late spring to early summer all target crops are in a suitable growth stage to be detected by remote sensing techniques (Chuvieco, 2008). As can be seen in Table 1, the maximum planimetric error after Landsat images georeferencing was always lower to 0.6 pixels (subpixel error), so it may be considered acceptable to achieve the objectives proposed in this work.

Multiscale object based image analysis

According to the approach proposed in this paper, the application of OBIA classification includes the following steps: i) image segmentation and retrieval of objects, ii) selection of training samples (objects), iii) classification based on supervised features computed for each object in the training sample, iv) where applicable, subsequent edition of the supervised classification. The steps 1º and 3º are executed automatically after choosing appropriate parameters and values, while the steps 2º and 4º are basically manual and fundamental processes, since the final results depend, to a large extent, on the precise selection and review of the samples.

The value of the scale parameter affects image segmentation by determining the size of image objects. If the scale value is high, the variability allowed within each object is high and image objects are relatively large. Conversely, small scale values allow less variability within each segment, creating relatively smaller segments. The point is that all image objects are part of the image object hierarchy, which may consist of many different levels at different scales but always in a hierarchical manner (from coarser to finer scales).

The software used to carry out objects segmentation and classification was eCognition Developer 8.0©. It implements an algorithm called multiresolution segmentation which is a bottom-up segmentation algorithm based on a pairwise region merging technique trying to locally minimize the average heterogeneity of image objects for a given resolution of image objects. The workflow adopted in this paper to apply OBIA techniques on Landsat images started with a coarse segmentation of the scene (scale = 65) using an equal weight to all Landsat bands excluding the thermal layer. The weight of colour (spectral heterogeneity) was set to 0.8 and, therefore, its complementary shape heterogeneity weight equalled 0.2.

This initial segmentation produced super-objects of large scale which were classified in non-vegetated (urban areas, bare earth, roads and channels and water) and vegetated areas (Figure 2) by means of thresholds based on vegetation indices which will be described later. The threshold for each Landsat scene was set by means of a trial and error process according to the visual results. From the initial super-objects classified as vegetated, and applying a top-down segmentation process (scale=10), homogeneous sub-objects of the appropriate size for containing approximately the different types of crops (target classes) were obtained. Working at this sub-object level, a supervised classification based on Nearest Neighbour (NN) classifier was applied to obtain a finer classification from the vegetated macro-level class (Figure 2).

Unfortunately it was not available an adequate *Ground-Truth* to train the classifier and validate the final results, since we are working on Landsat archival images where, for obvious reasons, it is impossible to make the corresponding field work. On the other hand, it was impossible to achieve (maybe even they do not exist) higher resolution images of the irrigated area of Tadla Azilal from satellite or photogrammetric flights that can help the extraction of samples for training or validation. This situation, relatively common in developing countries, forced us to test an alternative and novel approach based on the consultation of yearly official inventories for target crops (indirect and not georeferenced data). The official inventory used in this study was provided by the Office Régional de Mise en Valeur Agricole du Tadla (ORMVAT; personal communication).

In this case, five main types of crops were analysed: cereals, sugar beet, vegetables, fruit trees (mainly citrus fruits and olive groves) and forages. The widely known K-means clustering method (Spath, 1985) was employed to automatically take into account potential divergences between the multidimensional features vector (based on the 14 features described in the next section) and so classify every sub-object belonging to the super-class vegetated in five a priori unknown clusters or classes. In this way, we are given a dataset of N sub-objects in a p-dimensional space (being p = 14 the dimension of the features vector) and an integer of K (in this case K = 5). The problem is to separate the N sub-objects into K clusters

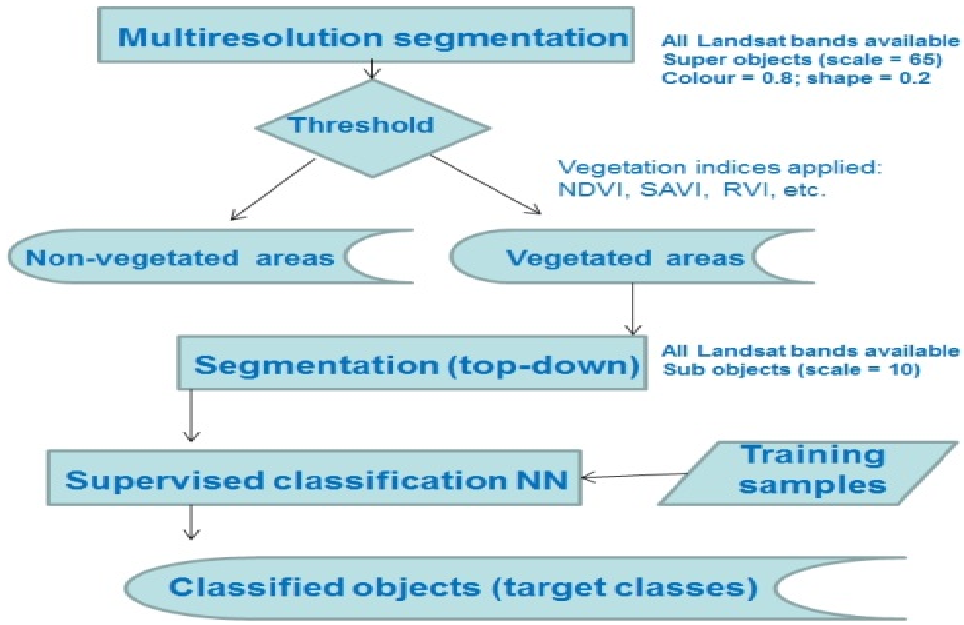

Figure 2. General flow chart of the proposed OBIA based classification algorithm.

by means of an iterative algorithm that minimizes the sum of distances from each sub-object to its cluster centroid over the remaining clusters. This algorithm moves sub-objects between clusters until the sum cannot be decreased any further. Our particular result would be a set of five clusters that are as compact and well-separated as possible and so they should roughly correspond to the five groups of crops we are looking for. Afterwards we can use a certain subset of sub-objects near the corresponding class centroid as training samples for feeding our Nearest Neighbour classifier and compare or validate the classification results against the area assigned to each target crop reported by the official inventory every year. The process turns out to be iterative in the sense that large deviations between classified and official data forces to select a new subset of training samples by simply changing the training samples around every centroid of the initial unsupervised clusters. The iterative process is stopped when computed deviations seem to be reasonably small. After several trials, and in the case of Landsat images and crops analyzed through this work, it is recommended that the number of training samples should be around 25 items for each type of reference (with an average of 200 pixels each one). The flow chart corresponding to the described algorithm is depicted in Figures 2 and 3.

The approach addressed in this section was separately applied to each of the Landsat scenes described in Table 2. The goal consisted of the evaluation of the semi-automatic classification obtained through the use of OBIA techniques to identify signatures based on the multidimensional feature vector explained in the following section for each one of the major crops at the irrigated area of Tadla Azilal. In the case of 1973, we did not have available data of the crop inventory, so it was used the training corresponding to the scene of 1987 (which was taken with the same sensor Landsat MSS).

Description of the features used to carry out crop classification

Selected features have to be suitable to carry out the detection of plant biomass to separate vegetated and non-vegetated areas at largest scale (binary super-object classification by threshold selection at segmentation scale = 65 in Figure 2). For that reason the following widely known vegetation indices were used:

(i) Normalized difference vegetation index (NDVI)

Typical values found for dense vegetation canopy tend to be positive (say 0.3 to 0.8), while bare soil generally tends to generate rather small positive NDVI values ranging from 0 to 0.2. Several studies have shown that accumulated NDVI correlates well with crop production in semiarid areas (Doraiswamy et al., 2004). Furthermore, the absence of blue band in NDVI helps to mitigate atmospheric effects (Ünslan and Boyer, 2004).

$$NDVI = \frac{Nir - R}{Nir + R} \quad (2)$$

(ii) Ratio vegetation index (RVI)

It is sensitive to soil optical properties and less sensitive to light conditions:

$$RVI = \frac{Nir}{R} \quad (3)$$

(iii) Soil adjusted vegetation index (SAVI)

Developed by Huete (1988), it is considered very useful to be applied in semi-arid areas because of it minimizes the disruptive effect of the reflectivity of the soil by introducing the factor L. This factor is an empirical variable coming from the data adjustment to the line of vegetation-soil and ranges from 0 (very high density vegetation) to 1 (low density vegetation). In this sense, the most

Table 2. Estimates of the socio-economic productivity for the crops located at Tadla Azilal by applying equation 1 (compiled by from field survey and data provided by ORMVAT).

Crops	EP (€/m^3)	SP (€/m^3)	SEP (€/ m^3)
Cereals	0.52	0.11	0.27
Sugar beet	0.21	0.09	0.14
Forages	0.16	0.04	0.08
Vegetables	0.82	0.61	0.69
Citrus fruits	0.33	0.08	0.18
Olive grove	0.18	0.15	0.16

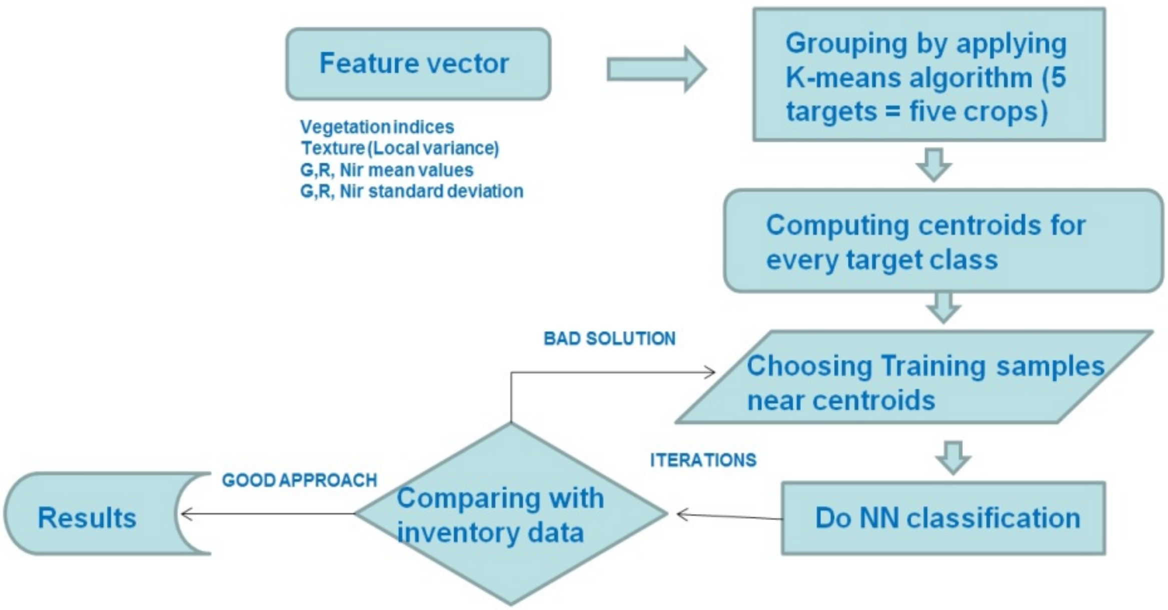

Figure 3. Flow chart corresponding to the proposed training algorithm based on tabular data.

commonly used value is L = 0.5 corresponding to a middle plant cover.

$$SAVI = \frac{Nir - R}{Nir + R + L}(1 + L) \quad (4)$$

(iv) Infrared percentage vegetation index (IPVI)

It was developed by Crippen (1990) from the previously discussed formulation of NDVI, which suggests that the spectral subtraction of the value contained in red band is not relevant. In this case the values are ranged within the interval 0 to 1:

$$IPVI = \frac{Nir}{Nir + R} \quad (5)$$

(v) Difference vegetation index (DVI)

Proposed by Richardson and Everitt (1992):

$$VI = Nir - R \quad (6)$$

Once vegetated areas were identified, a new segmentation-classification process were carried out at a lower segmentation scale (scale = 10) in these vegetated areas as it was described in the last section (Figure 3). Working at the lowest scale segmentation level, sub-objects were classified by applying NN supervised classification from a high-dimensional feature vector constituted of the following features: i) the five vegetation indices previously described, ii) G, R and Nir mean values computed for each sub-object, iii) G, R and Nir standard deviations computed for each sub-object and iv) texture feature based on local variance computed on G, R and Nir bands. Regarding the texture feature estimated from local variance, the approach proposed in Fernández et al. (2013) based on a 3x3 pixels kernel was applied.

RESULTS AND DISCUSSION

Table 2 shows the results coming from the application of the previously described SEP indicator for each crop.

According to these data it is worth noting that vegetables crop presents the highest socioeconomic productivity (0.69 € per m3 of irrigation water consumed), followed by cereals and finding forage crop located at the last place. The same can be said for social productivity, which vegetables crop presenting the highest value and fodder the lowest one. With regards to economic productivity, again vegetables crop reaches the top followed by cereals.

In a context of arid areas where water availability is low, it is crucial to make profitable the agricultural system by increasing production through an efficient and sustainable water use. It can be highlighted that, according to the “Regional Office of Agricultural Development of Tadla Azilal” data (ORMVAT; personal communication), averaged over the 10 seasons ranging from 1994 to 2005, forage crops have been those that presented the largest water consumption, reaching a percentage of 34.4%, although this crop only covers around 18.6% of the irrigated area. Then there are citrus and sugar beet, both together representing 27.8% of total water consumption and covering almost the same area as fodder. Cereals demand less water per hectare although cover an area close to 39.5% of the total irrigated area. Thus they consume around 18.2% of total irrigation water consumption. Moreover, the dominant crops in the perimeter of Tadla Azilal (wheat, sugar beet and fodder) have an annual net profit which fluctuate between 900 and 1700 €, while the net margin of horticultural crops reaches values around 2500 €.

Regarding results coming from the proposed object-based remote sensing approach, in Figures 4 and 5 are shown with two graphical examples of the classification results obtained for multitemporal monitoring of the main crops cultivated in the irrigated area of Tadla Azilal (classifications corresponding to 1973 and 2010 Landsat data respectively). The comparison between the percentage of area covered by each crop with respect to the total area regarding the values estimated by OBIA techniques and data registered in the Official Agricultural Inventories of ORMVAT (Table 3) indicates an acceptable estimation coming from OBIA approach, yielding a mean deviation value of -11.08% (general underestimation of cultivated land) and a standard deviation or uncertainty close to 14.75%. The average for absolute deviations took a value of 13.53%. In this regard, the deviation values were found quite similar for all target crops except in the case of vegetables, where OBIA techniques tended to underestimate the true values, especially during the years 1987 and 2001. This was mainly due to the month when Landsat images were taken in 1987 and 2001, that is April and February respectively. Indeed, the vast majority of crops in the area are usually sown in March and proper crop remote detection would only be effective when plant presents an advanced phenological stage, which would be set up from May to June for Tadla Azilal region. It is important to underline that Landsat sensor data from one or two dates (typically winter and summer) have been used for classification in previous mapping studies such as LCM2000 (Fuller et al., 2002). The idea is to enhance the contrast in the spectral reflectance associated to different phenological stages. However, optical imagery from more than two dates within an annual cycle have rarely been used for classification due to the prevalence of cloud cover in winter and the logical requirement for multitemporal observations, which makes this alternative more cumbersome and costly (Lucas et al., 2007). Furthermore, and for the study area of Tadla Azilal, earlier or later June-July Landsat scenes would likely produce a more variable reflectance of vegetation because of leaf production and senescence usually occurs outside this time interval. Thus, it is strongly recommended using scenes taken within May to July season in order to optimize the overall classification results at Tadla Azilal irrigated area.

Attending to the spatial distribution of major crops, one of the main advantages of the proposed approach, it can be noticed the presence of specialized clusters. For example, the area of Beni Amir is specialized in growing cereals and fodder, while sugar beet is mainly grown in the area of Beni Moussa and especially in the eastern zone. Vegetable crops, the more profitable from the standpoint of efficiency in water use, do not exceed 8% of the total cultivated area, being situated mostly in the sub-perimeter of Beni Moussa where a higher quality of irrigation water from the dam of Bin El Ouidan-Oued el Abid is available.

Regarding fruit crops, and as it was already defined during the protectorate period, they are mainly distributed in the area of Beni Moussa. Again the difference in quality of irrigation water may explain this spatial distribution and, thus, fruit crops are the only crops that seem to keep their traditional cultivated area. In both sub-areas can be highlighted the strategic situation of almost all farms devoted to fruit production, always close to main roads of the zone. Another important characteristic refers to the large fluctuations in the location and size of these fruit farms, and its evolution over the analyzed period.

This is due to the fact that fruit farmers are used to intercalate forage crops between fruit trees to increase their benefits. That intercropping application has led to some problems for remote sensing classification of the class fruit crop. In this regard, and to avoid confusion, it was decided to classify these mixed crops according to the majority crops around them (contextual classification) and/or the apparently dominant crop (forage or fruit), although this actually implies some loss of fruit covered area which, in principle, is not significant for the purposes of our study.

It is worth noting that the main crop of the area, according to covered area over the total, turned out to be cereals (Figure 6), with an efficiency in water use,

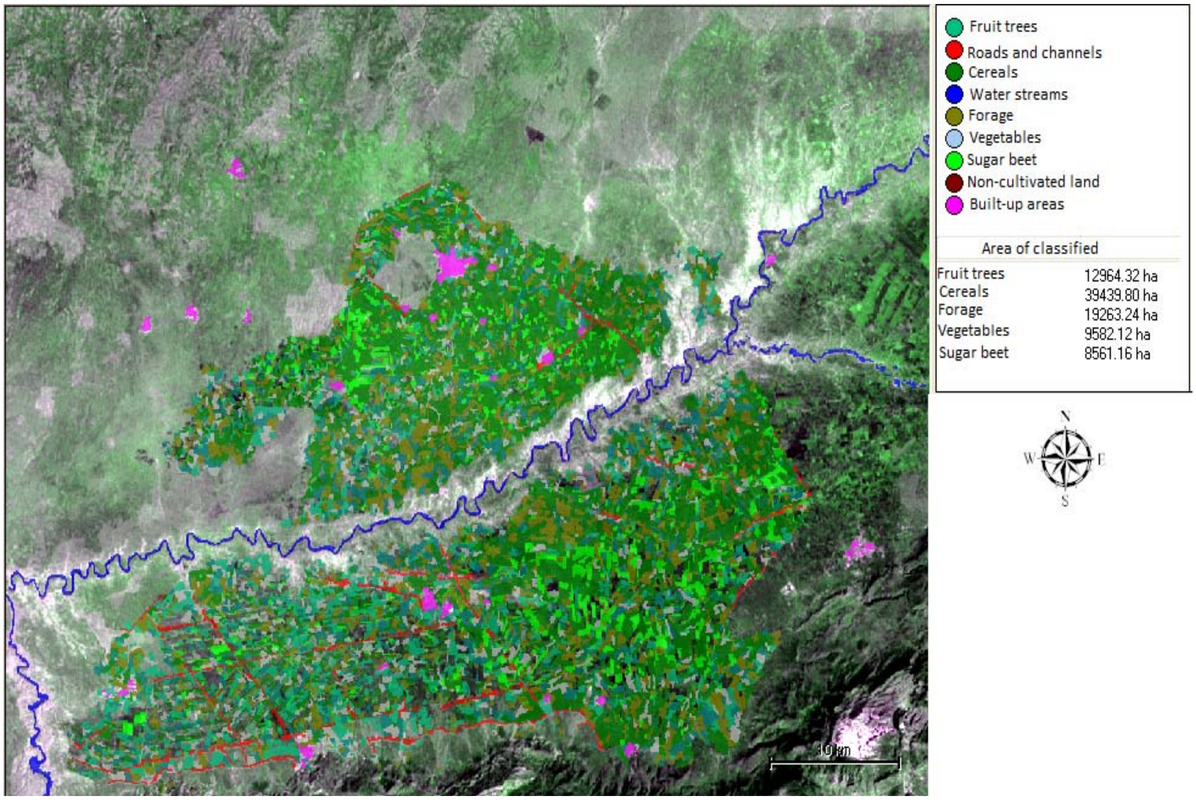

Figure 4. Results from OBIA classification corresponding to 1973. Landsat MSS imagery.

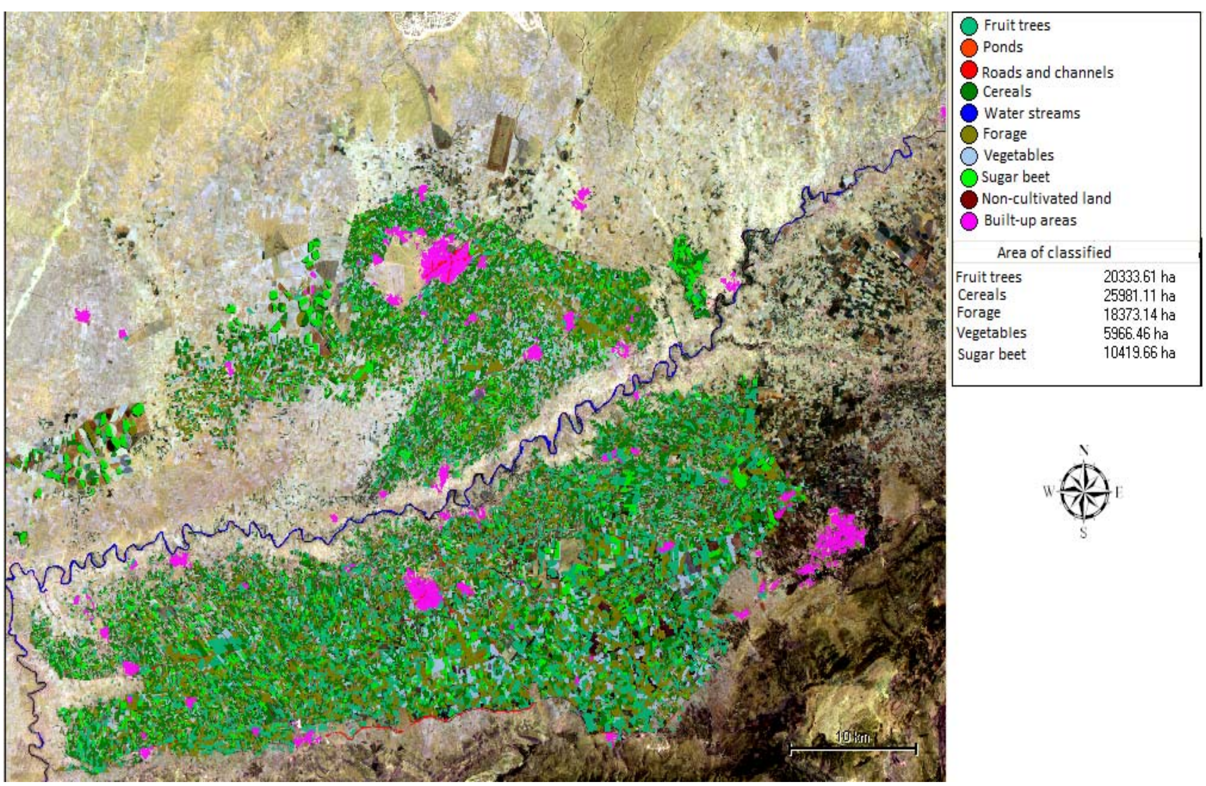

Figure 5. Results from OBIA classification corresponding to 2010. Landsat TM imagery.

Table 3. Deviations between the results estimated from the proposed OBIA method as compared to data from ORMVAT official inventory regarding the area covered by each crop with respect to the total area (100(OBIA-inventory data)/inventory data). No inventory data were available for year 1973.

Crop	Season						
	1987 MSS	2001 ETM	2002 TM	2003 ETM	2007 TM	2009 TM	2010 TM
Cereals	-14.68%	-13.34%	2.76%	-20.55%	-12.90%	-14.94%	-25.76%
Sugar beet	-6.05%	-5.79%	0.82%	-11.01%	1.01%	-24.61%	-6.13%
Vegetables	-44.80%	-56.21%	-7.29%	37.03%	-------	-13.97%	-0.56%
Fruit trees	-6.02%	-5.86%	-8.82%	-11.24%	-11.23%	-7.03%	-22.39%
Forages	-16.90%	-6.16%	-10.45%	-6.82%	-1.10%	-5.79%	-19.94%

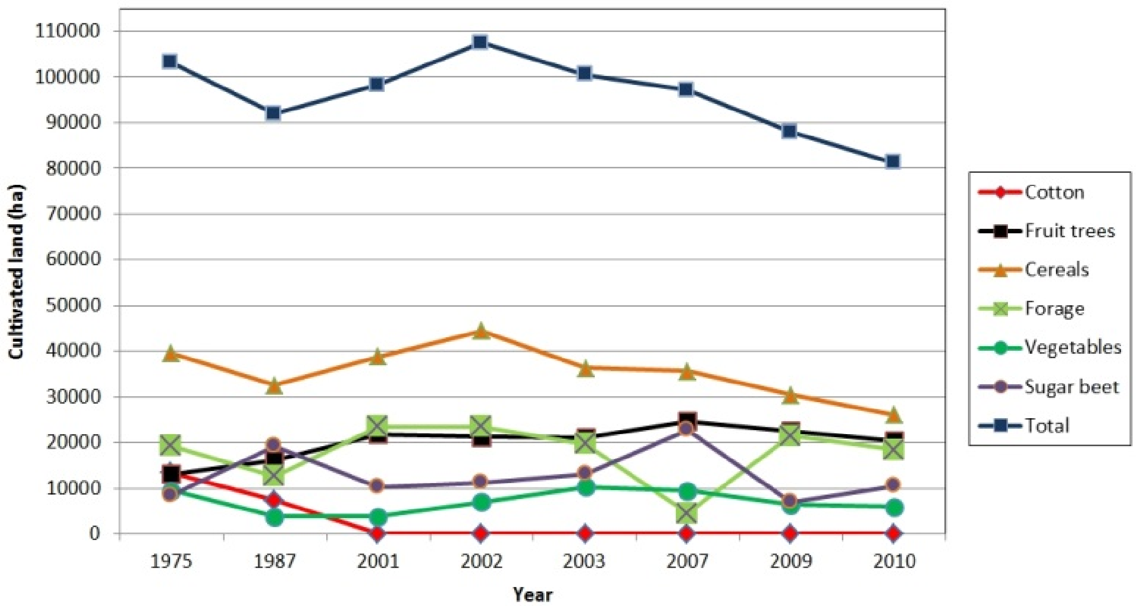

Figure 6. Temporal evolution of cultivated land over Tadla Azila irrigated area.

measured as socio-economic productivity (SEP), of 0.27 € m^{-3}. Vegetable crops, which presented the highest efficiency index (SEP = 0.69 € m^{-3}), only occupied the last position regarding covered area. Also from data shown in Figure 6, it may be noticed a slight decrease of the total cultivated area mainly due to the reduction of cereals and sugar beet. The only crop that has registered an increase over the last three years has been forage what can be attributed to the fact that it is the choice of farmers to cope with drought and especially market fluctuations, as this particular crop ensures a steady income through high demand due to the shortage of pasture.

Finally, it has been checked that vegetable crops offer the greatest efficiency in the use of irrigation water and thus generate larger socioeconomic production, even tripling that of traditional crops. However, vegetable crop is a minority due, among other factors, to the uncertainty related to the policy adopted by the ORMVAT within the framework of the CIA. Indeed, ORMVAT policy in dry years advocates dedicating available water in reservoirs to cereals and sugar beet. Furthermore, horticultural crops demand high technology and expertise for the successful implementation of localized irrigation, diseases control, marketing, etc. Another limiting factor is the setting up of the minimum cultivated surface in 5 ha as it was established by the Dahír 1-69-29 (July 1969). It imposes an unnecessary rigidity to the system that, in many cases, does not allow attending to the diversity of horticultural production. Another problem is the established tradition of cultivating cereals in the region and, especially, the tendency of the ORMVAT experts to focus attention on major crops as is the case of cereals. Notice that liberalization process was expected to allow farmers to make decisions, but this is useless “per se” if it is not accompanied by official State investments headed up to increase innovation, training, commercialization and technology in the agricultural sector.

Conclusions

The study of the socioeconomic performance of the main crops and their multitemporal monitoring by means of object-based remote sensing techniques using Landsat imagery has proven to be a useful tool to help evaluate the effects of agricultural policies at a regional scale, but it should be supplemented with field-based data. Multiscale segmentation and supervised classification with classifier training based on tabular data, which could be called in the context of this paper training and validation based on non-georeferenced data, turned out to be an original method highly recommended for the multitemporal reconstruction of crops and land cover spatial distribution in the absence of a georeferenced ground truth. From that analysis, it can be stated that ORMVAT still gives priority to crops such as cereals, sugar beet and forage crops which are less profitable from a socioeconomic point of view. In this sense, the socioeconomic impact indicators adopted in this paper have enabled an integrated assessment of productivity for each crop in terms of efficiency in the use of a scarce resource such as irrigation water. The social component of the index (SEP) makes it very useful as an indicator for assessing the sustainability of a farming system. The results coming from this study substantiate the hypothesis that the stagnation stage of development which is suffering this region could be partially explained by the adoption of crops with a low socioeconomic productivity. This fact would be aggravated by a numerous of contributing factors like the succession of dry years, which effect turns out to be very sensitive in arid areas, together with various endemics weaknesses of the area such as lack of commercial connection and logistics systems, lack of state initiatives to advise and introduce new farming techniques and rigidity of the system related to the minimum cultivated surface. All these circumstances have obliged the farmers to adopt more traditional crops, thus endangering the future of one of the richest zones of Morocco in natural resources.

Summing up, remote sensing and OBIA techniques could be a very interesting methodological framework for multitemporal mapping of crop irrigation areas in arid regions such as Tadla Azilal. In this sense, it could be considered a true work of “agricultural systems archaeology” based on the appropriate temporal and spatial resolution satellite imagery from Landsat series.

Conflict of Interest

The authors have not declared any conflict of interest.

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