Remote Sensing for Monitoring the Effects of Agricultural Policies: the Case of the Irrigated Area of Tadla Azilal (Morocco)

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Abstract

The main goal of this paper lies in proposing an efficient 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 remote sensing methodological framework would be essential 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. 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 methodology proposed along this paper has allowed diagnosing the 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 the diagnosis indicated, 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.*

1 Introduction

Along the historical trajectory of agriculture in Morocco, "Le Code des Investissements Agricoles" (CIA or Code of Agricultural Investment), enacted in July 1969, has been one of the main legislative instruments and tools headed up to the control and management of agriculture and irrigation water. This code defines, in a contractual framework, the set of incentives proposed by the State and the obligations of farmers.

Within the broad lines devoted to agricultural policy, as defined by this code, it can be emphasized the establishment of a minimum cultivated area of 5 ha. Also, as a condition for being membership of the beneficiaries of irrigation water, it establishes a rigid crop rotation system that prevents farmers to make their own decisions.

After almost thirty years of application of this statewide planning system, and as a consequence of their ineffectiveness, 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, is characterized by its majority dedication to the production of cereals, sugar beet and fodder, actually being a continuation of the system used during the protectorate.

Following the liberalization of rotating systems, and in accordance with the official data of the “Regional Office of Agricultural Development of Tadla Azilal” (ORMVAT), there were many changes with regards to the crops grown largely, although some fluctuations in cultivated areas have mainly depended on the drought that this area has suffered. However, there are not rigorous studies of the region which provide specific information on the spatio-temporal distribution of the main crops after the process of liberalization. Thus the main objective of this work would try to answer the following question: what was actually the effect of the process of liberalization applied to the agricultural system in Tadla Azilal? And, from this diagnosis, what measures should be implemented to improve socio-economic and environmental aspects of this representative irrigated arid zone where water availability is the main limitation?

The methodology adopted for the multitemporal monitoring of agricultural crops in the region was based on the application of Remote Sensing technology. Spatial information extraction from remote sensing images can be carried out manually, but these tasks are slow, require well-trained operators, and are therefore expensive. So it is required to count on new techniques which automate as much as possible the extraction of spatial information from remote sensing images. Nowadays, scientific community is continuously working on improving efficiency and productivity, emulating human reasoning by computer systems that provide automatic classifications based on prior training or supervised classification (e.g. [1], [2], [3], [4]). The review paper published by Mayer [5] presents a good compilation of techniques that focus on building extraction based on images with different degrees of geometric and spectral resolutions, while [6] reviewed the techniques developed in the field of image processing of remote sensing aimed to monitor land use evolution.

1.1 Fundamentals

Most techniques used for the extraction of information are classifications based on statistical parameters deduced from image areas whose reality is known (spectral signatures), and that can be applied to simple pixels or to homogeneous objects previously defined. In this sense, it is important to point out the pioneering work of Ketting and Landgrebe [7] in which was developed the technique called Extraction and Classification of Homogeneous Objects. The application of this technique demonstrated that classification of groups of pixels (called objects) with certain characteristics turned out to be more robust, efficient and accurate than traditional per-pixel classification. Since then, there have been many studies comparing both techniques to validate the initial results, especially when processing high resolution images [8]. In fact, the recent digital image classification techniques generally called OBIA (Object Based Image Analysis) have burst with enormous force on the scene of the automatic classification of satellite imagery ([9] and [10]), especially in the case of high resolution satellite images.

1.2 Main Hypothesis

The hypothesis constituting the base of this work states that OBIA techniques could also be successfully applied on satellite images of medium resolution, such as Landsat series, in the case of regional multitemporal studies. The main difference with the techniques of traditional image classification based on per-pixel classification stems from OBIA works on objects (i.e. groups of pixels with similar spectral signature) which have previously been segmented by specific algorithms. In this way, it can use average values of different characteristics for each object (called features) such as spectral signature, shape, size, texture and neighborhood as parameters for training supervised classifiers.

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 archeology*" based on the appropriate temporal and spatial resolution satellite imagery from Landsat series.

1.3 Objectives

The application of the proposed approach should allow diagnosing the effects due to 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. In accordance with the diagnosis indicated, a series of recommendations for improving socio-economic and environmental sustainability of the agricultural system could be conducted to serve as guidance for other similar agricultural systems also located in arid areas.

2 Study site description

The irrigated area of Tadla Azilal belongs to the region of Tadla Azilal (Fig. 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 (Fig. 2): 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 excessive salinity. 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.

The area occupied by the irrigated area of Tadla Azilal is close to 325095 ha, being managed by the ORMVAT, and can be classified as agricultural land, forest and uncultivated areas.

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

3 Material and methods

3.1 Economic benefits of irrigation water

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. In Table 2 are shown data regarding the use of irrigation water depending on the type of crop [11].

It can be highlighted that, 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 margins of horticultural crops reach values around 2500 €. To include sociological factors derived from the use of irrigation water, we adopted the indicators of socioeconomic impact of human pressure and water proposed by [12], which includes irrigation water consumption, economic performance and potential employment generated, formulated through the next expression:

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

Where SEP is the Socio-Economic Productivity of irrigation water (€/m^3), EP is the Economic Productivity (measured as the ratio between the production value and the water consumption) and SP means the Social Productivity (i.e. the ratio between the demanded working days and the water consumption multiplied by the corresponding Day's wage).

	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

Tab. 1 Estimates of the socio-economic productivity for the crops located at Tadla Azilal by applying equation (1).

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, 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.

Finally, tab. 1 shows the results coming from the application of the proposed indicators for each crop. According to these data it is worth noting that vegetables crop presents the highest socioeconomic productivity of all crops (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, this time, by cereals.

3.2 Satellite imagery for multitemporal crop monitoring

Landsat satellite images, covering the study area distributed by USGS through Global Visualization Viewer [13], 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 [14], spring-summer season would be usually preferred to acquire Landsat images headed up to inventory and spatially locate irrigated crops over the working area (tab. 2). Indeed, in late spring to early summer, all target crops are in a suitable growth stage to be detected by remote sensing techniques [15].

As can be seen in tab. 2, the maximum planimetric error after Landsat images georeferencing was always lower to 0.6 pixels (subpixel error), so that may be considered acceptable to achieve the objectives proposed in this work.

Sensor	Date	Number of bands	Ground Pixel Size (m)	RMSExy(*) (m)
Landsat 1-3 MSS	March 7, 1973	4	60	28.5
Landsat 4-5 MSS	April 5, 1987	4	60	30.7
Landsat 7 SLC-on	February 14, 2001	7	30	5.7
Landsat 4-5 TM	May 16, 2002	7	30	3.9
Landsat 7 SLC-on	May 27, 2003	7	30	5.7
Landsat 4-5 TM	May 30, 2007	7	30	4.3
Landsat 4-5 TM	June 4, 2009	7	30	4.1
Landsat 4-5 TM	June 7, 2010	7	30	4.2

Tab. 2 Description of Landsat imagery used in this work. (*) RMSExy means Planimetric Root Mean Squared Error.

3.3 Multiscale Object Based Image Analysis

According to the approach proposed in this paper, the application of OBIA classification would include 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. These four steps can be grouped into two groups of processes: manual and automatic. Thus, 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 segmentation process is crucial to obtain useful information from an image because it splits an image into unclassified object primitives that form the basis for the image objects and the rest of the image analysis. 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. Therefore all objects are linked to neighboring objects on the same level, super-objects on higher (coarser scale) levels, and to sub-objects on lower (finer scale) levels.

The software used to carry out objects segmentation and classification was eCognition Developer 8.0 ©. It implements a powerful segmentation 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 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 except for the thermal layer. In fact, it is worth noting that the segmentation weight for the spatially coarser thermal layer was set to 0 in order to avoid deterioration of the segmentation results by the blurred transient between image objects of this layer. Furthermore, the weight of color was set to 0.8 (and so shape factor = 0.2). Anyway, it is important to highlight that the best settings for segmentation parameters vary widely, and are usually determined through a combination of trial and error, and experience.

This initial segmentation has permitted to obtain super-objects of large scale which were binary classified by means of thresholds based on several features designed to identify the vegetation that will be discussed later. The threshold for each Landsat scene was set by means of a trial and error process according to the visual results. Thus, we have obtained two major macro-levels called vegetated and non-vegetated areas (urban areas, bare earth, roads and channels and water). From the initial super-objects, and applying a top-down segmentation (scale = 10), homogeneous sub-objects of the appropriate size containing approximately the different types of crops (target classes) were obtained.

Subsequent to the process of binary macro-classification by thresholds, and working at sub-object level, it was applied a supervised classification by using Nearest Neighbor (NN) classifier to obtain a finer classification from the vegetated macro-level class. It is worth noting that NN is a widely known nonparametric classifier which essentially stands for its simplicity, flexibility and to provide appropriate results with a low number of training samples [16].

In the case of OBIA techniques, training samples are objects which will be used to train the classifier in order to properly classify other objects that have been previously segmented in the image. 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 (e.g. [17]) was employed to automatically take into account potential divergences between the multidimensional features vector (based on the vegetation features described later on) 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 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 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 Neighbor 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 approach addressed in this section was separately applied to each of the Landsat scenes described in tab. 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).

3.4 Description of the features used to carry out crop classification

In OBIA, a feature is a numeric value that measures various characteristics (shape, size, color, texture and context) of image objects. In this paper they are defined as the combination of several Landsat bands. The choice of indices and their combinations mainly depends on the purpose of analysis, so that should be used to integrate the right characteristics to discriminate objects of interest and “background” that makes up the scene. In our particular case it comes to performing the detection of plant biomass. For that reason the so-called vegetation indices were used to achieve two objectives: i) improving the discrimination between two covers with very different reflective behavior regarding the bands normally implied to compute vegetation indices (e.g. to separate bare soil and vegetation by means of Red and Near Infrared bands) and ii) to reduce the effect of the relief (slope and orientation) in the spectral characterization of different land covers.

Below are presented the features or vegetation indices that form the feature vector used in this paper to carry out the classification task (both unsupervised and supervised):

- **a) Normalized Difference Vegetation Index (NDVI).** It is one of the most widely indices used in the area of remote sensing vegetation detection. Typical values found for vegetation range usually within the interval 0.5 to 0.8, while bare soil normally presents values close to zero. Starting from the spatial distribution of NDVI, it can be produced an image that delineate clusters of green plants (photosynthetically active), reducing the possible negative effects caused by an erroneous calibration of the sensor and/or the distorting effect of the atmosphere itself. Several studies have shown that accumulated NDVI correlates well with crop production in semiarid areas [14]. Other studies conclude that the absence of blue band in NDVI helps to mitigate atmospheric effects [18].

$$NDVI = \frac{Nir - R}{Nir + R} \tag{2}$$

b) Ratio Vegetation Index (RVI) It is sensitive to soil optical properties and less sensitive to light conditions:

$$RVI = \frac{Nir}{R} \tag{3}$$

c) Soil Adjusted Vegetation Index (SAVI). Developed by [19], 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 commonly used value is L = 0.5 corresponding to a middle plant cover. This index has proved very effective in reducing the influence of ground to cover in a wide range of plants.

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

d) Infrared Percentage Vegetation Index (IPVI). It was developed by [20] 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:

$$IPVI = \frac{Nir}{Nir + R} \tag{5}$$

e) Difference Vegetation Index (DVI). Proposed by [21], it includes only the numerator term of NVDI:

$$DVI = Nir - R \tag{6}$$

Due to the limited number of bands available in sensor MSS, only NDVI, RVI, SAVI, IPVI and DVI indices took part on the feature vector corresponding to the analyzed Landsat scenes.

4 Results

In Fig. 2 and 3 are shown two graphical examples of the classification results obtained by means of the tested OBIA approach on Landsat images for multiemporal monitoring of the main crops cultivated in the irrigated area of Tadla Azilal (classifications corresponding to 1973 and 2010 satellite data respectively).

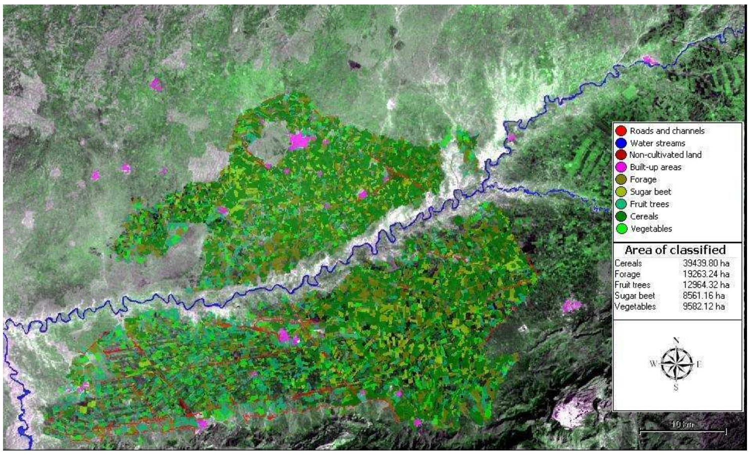

Fig. 2 Results from OBIA classification corresponding to 1973. Landsat MSS imagery (four bands)

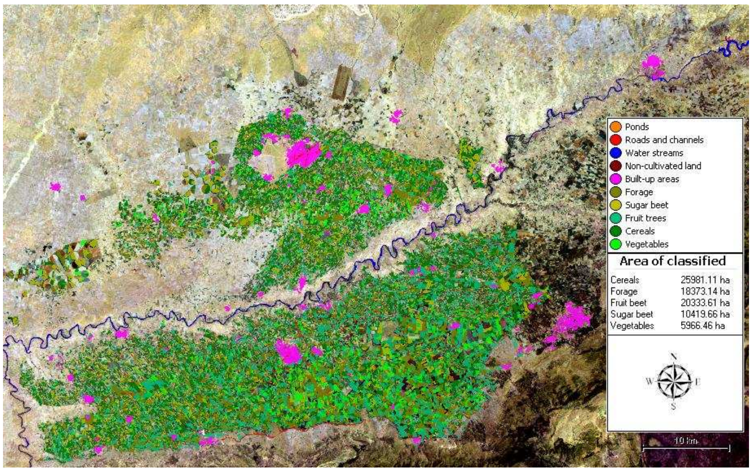

Fig. 3 Results from OBIA classification corresponding to 2010. Landsat TM imagery (seven bands)

The comparison between the area covered by each crop from the values estimated by OBIA techniques and data registered in the Official Agricultural Inventories of ORMVAT (tab. 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.

In previous mapping studies such as LCM2000 [22], Landsat sensor data from one or two dates (typically winter and summer) have been used for classification. 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 [23]. 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, we strongly recommend using scenes taken within May to July season in order to optimize the overall classification results at Tadla Azilal irrigated area.

From the results shown in Figures 2 and 3, and especially in Figure 4, it can be stated that, without any doubt, the liberalization of crop rotation has not significantly influenced the evolution of agricultural production in the irrigated area of Tadla Azilal. The main crop of the area, according to covered area over the total, turned out to be cereals, with an efficiency in water use, measured as socio-economic productivity (SEP), of 0.27 € m-3. Vegetable crop, which presented the highest efficiency index (SEP = 0.69 € m-3), only occupies the last position regarding covered area.

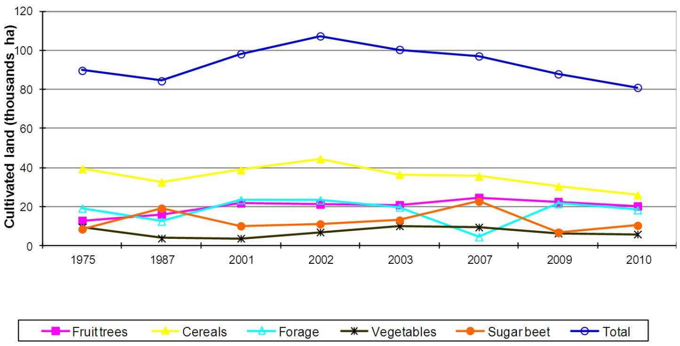

Fig. 4 Temporal evolution of cultivated land over Tadla Azila irrigated area

Attending to the spatial distribution of major crops, 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.

From data shown in Fig. 4, 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.

5 Discussion

After the promulgation of the Code of Agricultural Investment (CIA) in 1969, 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. This caused a significant increase in the price of irrigation water, representing a major obstacle to the development of the irrigated crops with greater added value because of lack of capital available for investment in structural improvements to enable its transformation. In this sense, this tax may be considered as a limitation of the income of small farmers which, in addition to the low profitability of production and obstacles to access to the state subsidies aimed at the improvement of farms, may explain the agricultural stagnation of the region.

From the beginning of the 80's it began the problem of shortage of irrigation water, aggravated by a succession of droughts from 1981 to 1984. This resulted in the need to use the groundwater as an alternative resort. In this case, farmers counted on the government subsidy to finance the opening of wells. It is at least paradoxical to indicate how an area originally planned to take advantage of its abundant surface water, became an area where water resources turned to focus on the exploitation of groundwater, which entails more pressure on non-renewable resources.

As shown in results section, 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 hectares 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.

6 Conclusions

The study of the socioeconomic performance of the main crops and their multitemporal monitoring by means of remote sensing techniques using Landsat imagery has proved useful for analyzing the effect of agricultural policies at a regional scale. In this sense, multiscale segmentation and supervised classification with classifier training based on tabular data, which has been called in the context of this paper training and validation based on instances of non-graphic nature, turned out to be an original method highly recommended for the multitemporal reconstruction of crops and land cover spatial distribution.

From that analysis, it can be stated that the liberalization of the agricultural productive system and the remaking of Le Code des Investissements Agricoles of 1969, which meant, inter alia, the liberalization of traditional crop rotation system, has not produced the expected effects. 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.

In short, and as a general conclusion, it urges the restructuring of the system production to ensure a sustainable, efficient and higher socio-economic production. This involves a change of main crops, introducing more profitable products adapted to the national and international demands, in addition to rethink the rules governing the subdivision of land (land planning). The final idea stems from ensuring the sustainability of the system and therefore its future.

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