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Land Use Cover Mapping of Water Melon and Cereals in Southern Italy

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Abstract

The new high-resolution images from the satellites as IKONOS, SPOT5, Quickbird2 give us the opportunity to map ground features, which were not detectable in the past, by using medium resolution remote sensed data (LANDSAT). More accurate and reliable maps of land cover can then be produced. However, classification procedure with these images is more complex than with the medium resolution remote sensing data for two main reasons: firstly, because of their exiguous number of spectral bands, secondly, owing to high spatial resolution, the assumption of pixel independence does not generally hold. It is then necessary to have a multi-temporal series of images or to use classifiers taking into account also proximal information.

The data in this study were (i) a remote sensing image taken by SPOT5 satellite in July 2007 and used to discriminate the water melon cover class and, (ii) three multi-temporal remote sensing images taken by SPOT5 satellite in May, June and July 2008 used to discriminate water melon and cereal crop cover classes.

For water melon recognition, providing a single image in 2007, an object-oriented technique was applied instead of a traditional, per pixel technique obtaining an increase of overall accuracy of 15%.

In 2008, since it was available a multi-temporal data set, a traditional 'Maximum Likelihood' technique was applied for both water melon and cereal crop cover class. The overall accuracy is greater than 95%.

Key-words: land use, maximum likelihood, object-oriented, crop recognition.

1. Introduction

In a context characterized of high evaporative demand of the atmosphere and decreasing water resources, the irrigation management at district scale is becoming a major issue and accurate information on crop spatial distribution is vital as a prerequisite to optimize the water allocation based on a scientific support for land use planning with reliable information relating to current resource conditions.

In the past, air-photo interpretation has played an important role in detailed vegetation mapping (Sandmann et al., 2003), while applications of medium spatial resolution satellite imagery such as LandsatTM and SPOT4 alone were often insufficient or inadequate for differentiating species-level vegetation in detailed vegetation studies (Kalliola et al., 1991; Harvey et al., 2001). However, high spatial resolution remote sensing is becoming increasingly available; airborne and space-borne multispectral imagery can be obtained at spatial resolutions at or better than 1 m. From high resolution imagery, the features can be extracted through visual means with hand delineation procedures (Lillesand et al., 2004). However, these approaches are very time consuming and subjected to human error, furthermore the high resolution imagery is collected in digital format and is multispectral, this makes it a good candidate for an automated approach of feature extraction.

High spatial resolution imagery initially thrives on the application of urban-related feature extraction (Jensen et al., 1999; Benedikts-

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son et al., 2003; Herold et al., 2003a), this preference for urban areas is partly due to proximity of the spectral signatures for different species and difficulties in capturing texture features for vegetation (Carleer et al., 2004).

The increasingly smaller spatial resolution does not necessarily benefit classification performance and accuracy (Hay et al., 1996; Hsieh et al., 2001) of the traditional unsupervised or supervised techniques. With the increase in spatial resolution, single pixels no longer capture the characteristics of classification targets. Moreover, adopting traditional pixel-based classification approaches, the increase in spectral variability within a class causes a significant reduction of statistical separability between classes. Consequently, classification accuracy is reduced, and the classification results show a 'salt-and-pepper' effect, with individual pixels classified differently from their neighbours.

To overcome this problem, some pixel-based methods have already been implemented. The main characteristic of these methods is that they incorporate spatial information to characterize each class using neighbourhood relationships. To improve classifications, size, shape, texture, context, and pattern can be incorporated into classification methods. New algorithms, such as nearest neighbour analysis, neural networks, decision trees and the mixing of spectral and textural data, can be applied (Donnay et al., 2001, Herold et al., 2003). These approaches improve the results, but further increase the skill level required for use (Herold et al., 2003), and require intensive computation especially for high-resolution imagery.

Object-based classification may be a good alternative to the traditional pixel based methods because it overcomes the problem related to per-pixel classifiers analyzing groups of contiguous pixels as objects instead of using the conventional pixel-based classification unit (Geneletti and Gorte, 2003). In theory, this will reduce the local spectral variation caused by crown textures, gaps, and shadows. Moreover, with spectrally homogeneous segments of images, both spectral values and spatial properties, such as size and shape, can be explicitly utilized as features for further classification (Yu et al., 2006).

Few studies have been reported with the objective to compare the efficiency of an object based approach respect to the conventional pixel-based one for high-resolution remote sensing imagery.

It was found that the accuracy of detailed vegetation classification with very high-resolution imagery is highly dependent on the sample size, sampling quality, classification framework, and ground vegetation distribution (Yu et al., 2006).

To produce a reliable cover map, multi-temporal series of images can be necessary, because the pixel-based classification methods frequently group dissimilar pixels with the largest and surrounding class. Multitemporal images for a specific study area, with the correct spatial and temporal resolution, are not always available. Therefore, for a new case-study, it could be necessary to order new time-series acquisitions of satellite images, but it could be very expensive. Therefore studying on detailed vegetation mapping with high-resolution multispectral imagery presents some difficulties. The Feature Analyst (FA) tool, implemented in ERDAS Imagine 9.2 software, approaches the object recognition and feature extraction overcoming these shortcomings by using inductive learning algorithms and techniques in order to model the feature recognition process.

The purpose of this work is to evaluate and discuss positive and negative aspects of two available techniques, the object-oriented and the traditional 'Maximum Likelihood' (ML), applied in order to: (i) quantify the extension and spatial distribution of water melon (*Citrullus lanatus*, Thunb.) and cereal crops and, (ii) to assess how in two years, 2007 and 2008, the land use of fields has changed in the Jonical costal area, an important agricultural district of Southern Italy.

2. Materials and methods

2.1 The study area and data

The study site is located along the coast of the Ionian Sea (Southern Italy) in an area of approximately 620 km^2. The area, with 4303 ha and 21672 ha for permanently and no- irrigated lands, respectively, is mainly cropped with cereals (durum wheat in particular), horticultural crops, orchards and vineyards.

SPOT5 images, with a spatial resolution of ten meters and four bands in visible and near/medium infrared spectrum, has been used to produce land cover maps.

The data in this study were a remote sensing image taken by SPOT5 satellite in July 2007 and used to discriminate the water melon cover class and three multi-temporal remote sensing images taken by SPOT5 satellite in May, June and July 2008 used to discriminate the water melon and the cereal crops cover classes.

In both investigated years, firstly, a data set of ground truths was collected on the scene, that was, then, split into a training data set, to recognise pattern on the study area, and a test data set, to validate the land cover maps.

The accuracy of the each classification map has been evaluated computing the overall accuracy that consists of the number of correct observations divided by the number of total observations for each thematic class. Overall accuracy allows to compare and evaluate different classification techniques applied to the same study area.

2.2 Methodology

In 2007, providing a single image, an object-oriented technique was applied (Fiorentino et al., 2008).

In 2008, since it was available a multi-temporal data set, a traditional ML technique was applied for both water melon and cereal crop recognition. The class of cereal includes in particular the durum wheat, *Triticum durum* Desf., (widely cultivated in the study area), barley (*Hordeum vulgare* L.) and some grass species as oats (*Avena sativa* L.), fescue (*Festuca arundinacea* Schreb.) and ryegrass (*Lolium perenne* L.), which can hardly be distinguished from information by remote sensing.

The multi-temporal information has enhanced the accuracy of classification, as it exploits the different crop reflectance in the visible and near-infrared spectrum range, due to the different crop phenological states.

In both cases, to obtain a more reliable classification map, the algorithms were trained with the recognition of other crops present in the study area. For example the vineyards, broadly spread on the investigated scene is easily confused with water melon.

2.2.1 The object-oriented technique. The Feature Analyst (FA) uses an inductive learning based approach to object-recognition and feature extraction. The FA workflow (VLS, 2004) includes the following four steps:

1. User digitalizes several examples of the feature to collect (training data set). Feature Analyst is an approach similar to traditional supervised classifier, because the user needs to supply ground truth sites of each feature of interest. However, the main difference is that it uses these sites to find areas in the image that are similar, not only on the basis of spectral signature but also of geometrical shape parameters. Typically, to start only a few examples are required.
2. User selects the feature type, which automatically sets all of the learning parameters behind the scene. The contextual classifier can be adjusted based on the feature to be extracted. It is possible to define the spatial context for the feature of interest and it is important to use an input pattern that captures the essence of the feature you are trying to extract. In our case study the geometrical pattern applied is represented in Figure 1 because it would work well for extracting land cover features on 10 meter imagery (VLS, 2004). The input representation describes the pattern of pixels considered around a target pixel to classify it. The key is to use an input representation that captures the essential spatial structure of the feature of interest. In general, the more complex the pattern is (this relates also to image resolution) the more input pixels are required. The algorithm was used by the following supplementary settings: (i) the imagery had four available bands and all of them were used, (ii) objects with less than 5 pixels were automatically aggregated with the most appropriate neighbouring object and, (iii) rotated instances were included so that classification of similar objects oriented

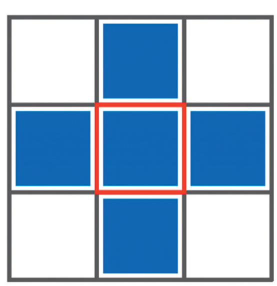

Figure 1. Pattern recognition in supervised classification of water melon field.

differently was allowed. Then, user extracts feature.

3. Results analysis and, if required, the user provides “positive” and “negative” examples to remove clutter and improve classification. This tool allows the user to define new examples of “correct,” “incorrect,” and “missed” areas so to produce a new output more refined than the previous one. This process can be repeated as many times as necessary. Clutter is the most common form of error in feature extraction. The objective of clutter mitigation is to remove false positives. Thus, the learning task is to distinguish between false positives and correctly identified positives. The user generates a training set by labelling the positive features from the previous classification as either positive or false positive. The trained learner then classifies only the positive instances from the previous pass. The false positives from the previous pass are considered correct in clutter mitigation and are thus masked out.

The classification is improved in successive passes, where each new pass is designed to remove one form of error from the results of the previous pass.

The classification maps were then further corrected by applying a median filter and using the cadastral maps to more precisely delineate the complex particles.

2.2.2 Maximum Likelihood algorithm. This approach is a conventional statistical classification technique that allocates each pixel of an image to the class with which it has the highest likelihood or “a posterior” probability of membership. Let the spectral classes for an image be represented by the categorical variable $\{\omega_i; i=1, \ldots,\}M$ with M mutually exclusive categories and let $\mathbf{X} = \mathbf{X}(\mathbf{u}_\alpha)$ be B-variate random vectors (B = number of spectral bands of the image), the pattern observations describing a point at the position $\mathbf{u}_\alpha$.

In remote sensing the measurement vector **X,** referred to the pixel of spatial coordinates $\mathbf{u}_\alpha$ ($\alpha = 1, \ldots, n$), is a column of brightness values for the image and the training data for ground cover type are associated to the sample of $\mathbf{u}_\alpha$.

To determine the class or category (Duda, 1973) to which a generic pixel vector **X(u)** belongs, it is strictly the conditional probabilities:

$$P(\omega_i/X(u)) \text{ i} = 1,\ldots\ldots\text{,M}$$

that are of interest. This probability gives the likelihood that the class prevails for the pixel at the position **u.**

Maximum Likelihood algorithm assigns each pixel to the class whose ‘a posteriori’ probability is maximised:

$$\textit{assign the position } \mathbf{u} \textit{ at the class } \omega_i \Leftrightarrow$$
$$P(\omega_i/X(\mathbf{u})) = max^{\omega}\ P(\omega/X(u))$$

$P(\omega_i/\mathbf{X}(\mathbf{u}))$ are unknown, but suppose we have sufficient training data for each class that can be used to estimate a “spectral” probability density function $P(X(u)/\omega_i)$ for a cover type, i.e. the chance of finding a pixel from class ω_i, say, at the position **X(u).** $P(\omega_i/\mathbf{X}(\mathbf{u}))$ is then obtained by applying the Bayes rule:

$$P(\omega_i/X(u)) = \frac{P(X(u)/\omega_i)P(\omega_i)}{P(X(u))}$$

where $P(\omega_i/\mathbf{X}(\mathbf{u}))$ represents the posterior probability of a pixel with data vector **X(u)** to belong to class i, $P(X(u))$ is the unconditional probability that the pixel **u** occurs in the image, $P\omega_i$ is the ‘a priori’ probability of the class ω_i. It is assumed that spectral probability density function is of the form of multivariate normal model.

3. Results

Figure 2 shows the SPOT5 image of July 2007 obtained by relating the bands 3, 2, 1 to the red green and blue channel (RGB) respectively.

The data sets of ground truths in 2008 were obtained through a visual inspection of the fields and were split, respectively, into the training data set and the validation data set. The validation data, within the target cover class, were selected by randomly drawing a given proportion (1/3) of the overall class occurrence. The data sets of training and validation have been used to produce and validate the land cover maps, obtained by applying the FA algorithm in 2007 and the traditional multitemporal ML technique in 2008.

During the collection of the ground truth data, in both 2007 and 2008 years, it was observed

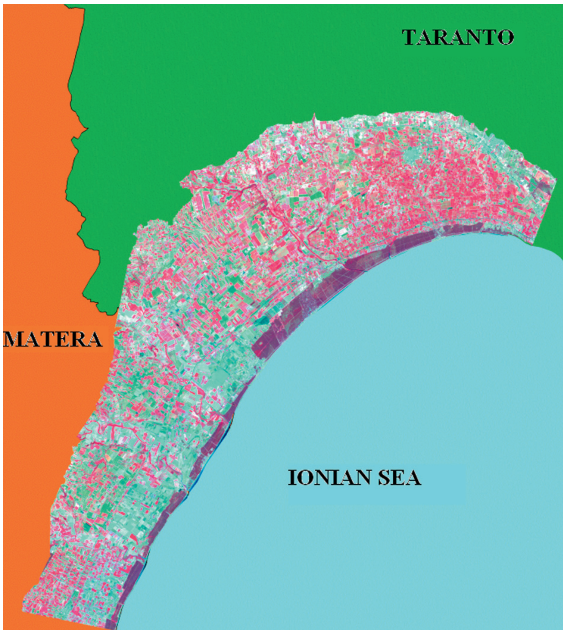

Figure 2. Image (July, 2007) from SPOT5 satellite in combination of colours 321RGB.

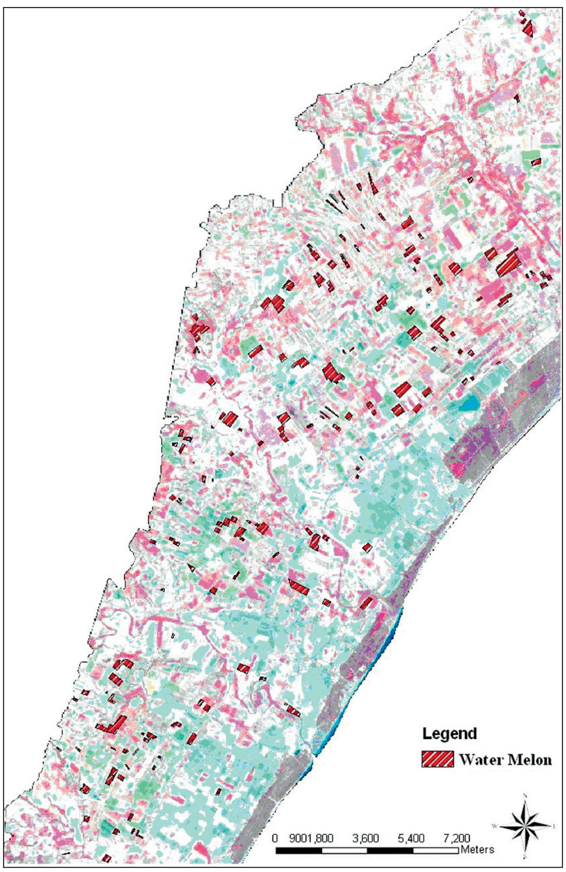

Figure 3. Map of water melon land cover in 2007. The crop is represented in red.

that the dimension of water melon fields was always larger than 1 ha. This is the reason we chose to acquire SPOT images with 10 m spatial resolution than higher spatial resolution satellite images.

Figure 3 shows the classification map of water melon in 2007, obtained after the classification process of ERDAS FA algorithm, with only two post processing steps being necessary to improve the resulting map, in order to distinguish between false positive and correctly identify positives on the basis of expert knowledge.

To ensure that FA classifier had the better performance, using the same training and test areas, a map of water melon land cover was elaborated by applying ML traditional technique (Fiorentino et al., 2008). The overall accuracy obtained in test increased from 78% for ML to 93% for FA. Therefore, the object-based methods created a classification that more closely resembles the field spatial distribution in agricultural landscape, while the pixel-based classification has the typical noise of pixels being mixed in with other cover types. The better performance of FA classifier, compared with the ML one, was evaluated not only on the basis of an objective statistical test, but also of the expert knowledge of the study area. This stresses the role of the expert knowledge in improving the classification by manually adding new polygons to initial training data set. However, this can also be assumed as a drawback of FA classifier, revealing the mostly heuristic character of such approach.

In Figure 4 the land cover map for cereal crop and water melon in 2008 obtained by applying ML classifier is shown. A probability threshold equal to 70% value was set, which allows to determine those pixels that are most likely to be incorrectly classified, so that they can be masked. However, ML has no possibility to improve classification by successive steps of a hierarchical feature extraction, but multitemporal data improves the accuracy of the classification because it provides information on the presence or absence of a crop and its status at different phenological periods. In fact, on May, when the first image acquisition was made, the cereals (in particular durum wheat) were still present in the fields and still green, while the water melon plants were still covered by plastic white tunnel, or recently discovered; in June

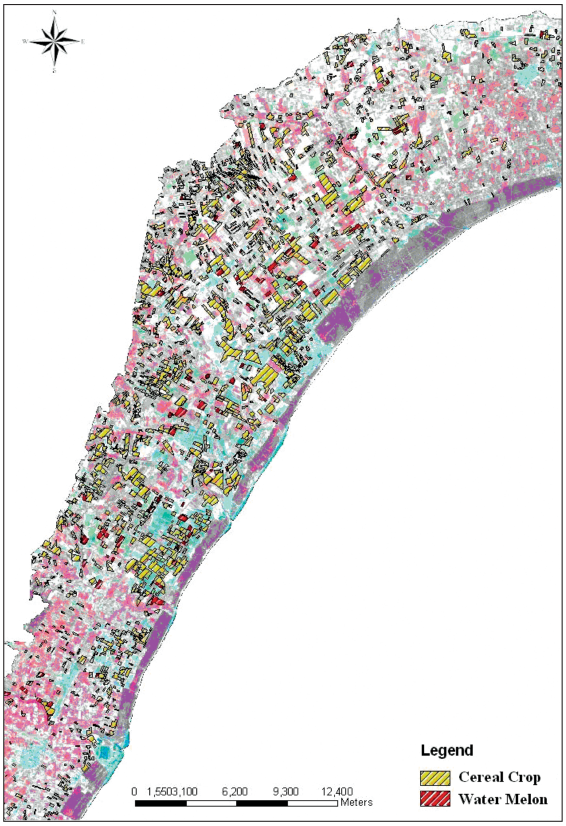

Figure 4. Land cover map of water melon (red colour) and cereal crops (yellow colour) in 2008.

the cereals had been harvested, while the plants of water melon were in vegetative phase. Finally, in July the fields, where the water melon was transplanted later, had a homogeneous vegetation cover. The overall accuracy calculated for water melon crop was equal to 97%, while for cereal crop the accuracy was equal to 95%. These high accuracy values are due not only to the use of multispectral information available in 2008, but also to a data set of ground truth larger than that collected in 2007. In both cases (2007 and 2008 maps), as the spectral signature of water melon is similar to that of vineyard, it was necessary to train the classification algorithm to recognise this cover class.

Analysing both 2007 and 2008, water melon classified maps, it was found that fields smaller than 1 ha represented a percentage lower than the 4% of the total area classified as water melon, validating the ground truth observation.

The land use classification described here uses a set of rules based on the phenological growth profiles of agricultural crops. These profiles can be observed through an analysis of the Normalized Difference Vegetation Index (NDVI) over time (Basso et al., 2004).

NDVI is an indicator for the amount of plant biomass at a location and is useful for tracking the amount of living vegetation in a field during a growing season. Higher values indicate greater amounts of vegetation while lower amounts indicate a bare soil or canopy characterized by less growth (low cover fraction), less green color or high senescence.

For each of the SPOT5 scenes in 2008, NDVI was calculated using ERDAS Imagine software. The resulting maps are shown in Figure 5 in which the decreasing green vegetation is reported from May to July.

In Figure 6, in order to visualize and further analyze the distribution of this indicator, the NDVI temporal patterns in three points of two private farms (Peviani's and Masi's) are plotted on a line graphs. The patterns of crop phenology illustrate the NDVI values during the water melon growing season. For Peviani's farm it's

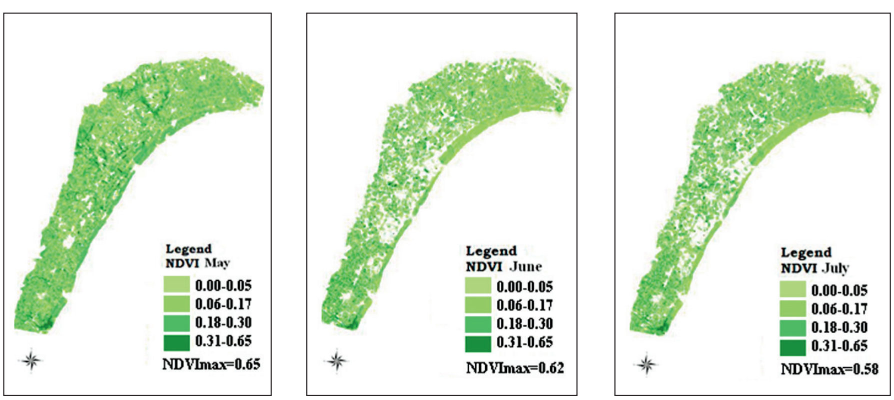

Figure 5. Maps of NDVI in May, June and July 2008.

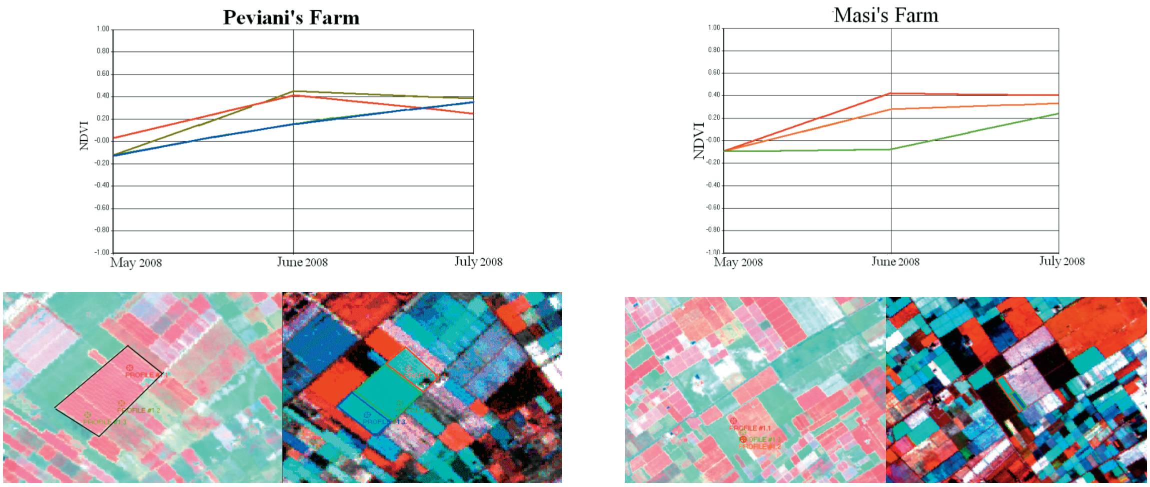

Figure 6. Phenological growth profile of water melon in two farms in 2008.

possible to distinguish three times of transplanting: the area corresponding to the red line has the most advanced transplanting time with positive values of NDVI, but very low in May when the transplanting was carried out recently. The NDVI reaches its maximum value in June and then declines in July with the beginning of the harvest, because of repeated passages of machineries in the field, necessary for the harvest and that leave a higher proportion of bare soil. The other two fields were not vegetated in May, in fact, the transplanting was performed at the end of May in the field outlined in green, while in the blue outlined region, the transplanting took place later, as confirmed by the graph of NDVI that reaches the maximum value only in July. For the Masi's farm, it's possible to distinguish only two transplanting times. The area and red line correspond to the first time of transplanting, with a values of NDVI peaking in June and remaining stable in July. In the green area, the water melon is transplanted in June with the NDVI reaching significant values in July.

4. Conclusions

In 2007, using a single SPOT5 image to produce the classification map, the Feature Analyst approach seems to be more accurate in water-melon pattern recognition, while in 2008 providing multitemporal information, the traditional ML algorithm has produced accurate results. The main drawback of FA approach is the difficulty in defining the input pattern which captures most spatial structure of the feature being classified. This representation may be relatively easy for an isolated object, but may be more complex for a cropped field.

Another disadvantage of FA relies on the ability of the user to introduce additional information into the initial training data set and then on the empirical nature of this approach. FA may perform better when more detailed information, as individual plants and trees, are supplied.

The classification map of water melon produced in 2007 was compared, using GIS techniques, to that of water melon and cereal crops elaborated in 2008.

From the comparison of the results obtained for 2007 and 2008, it is possible to draw interesting considerations from agronomical point of view. It was found that 925 ha in 2007 and 850 ha in 2008, of 62000 ha of the study area, were cropped with water melon. The area cultivated with water melon in 2007 changed in 2008 as follow: 295 ha (32%) have retained the same crop, 607 ha (66%) were cropped with cereal crop (particularly durum wheat) and the other 23 ha (2%) remained fallow or for other crops. In the study area, the use of rootstock is widespread and this increases the resistance of water melon to soil born diseases allowing the continuous cropping for 2 or 3 years without adverse effects on yield and soil fertility.

Such results indicate that the availability of accurate remote sensing information and the present technology can be considered useful tools in order to optimize agronomical practices at district scale, as land use planning and crop rotation. They can also to improve the spatial allocation of irrigation requirements and the management of water resources for spring/summer crops, as water melon, that, in areas characterized by high evaporative demand, require a scheduled irrigation in order to obtain a sustainable yield.

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