OBJECT-BASED CLASSIFICATION OF SPOT AND ASTER DATA COMPLEMENTED WITH DATA DERIVED FROM MODIS VEGETATION INDICES TIME SERIES IN A MEDITERRANEAN TEST-SITE

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ABSTRACT:

A multi-scale object-based classification was carried out using data from three different sensors to map classes of interest in the framework of the EPISTIS project. This project aims to highlight the spatio-temporal patterns that underlie the epidemiology of certain diseases and more particularly of bluetongue in this case-study. A SPOT5 10m XS image of Sardinia taken in the springtime was segmented and the land-cover/land-use classes that are the most easily discriminated were mapped using a thresholding approach. Subsequently, a DEM was used as ancillary data to map the riparian vegetation. The remaining vegetation classes were then mapped using a nearest-neighbour algorithm. ASTER features, notably derived from the SWIR bands, were used in addition to SPOT in the feature space to improve vegetation discrimination. Images taken in the springtime allow for a good discrimination between semi-natural vegetation and arable land, which was the initial objective. However, project developments implied further discrimination within the arable land. Due to their spectral similarity at this resolution in a patchy Mediterranean landscape, a number of classes could not be sufficiently well classified even using additional textural and contextual features. Therefore, data derived from MODIS vegetation indices time series were included in the classification process so as to account for the vegetation dynamics and improve the classification results.

1. INTRODUCTION

The EPISTIS project aims to highlight the spatio-temporal patterns that underlie the epidemiology of certain diseases, and more particularly of bluetongue in this case-study. Bluetongue is an arthropod-borne viral disease of ruminants. All ruminant species - sheep, goats, cattle, buffaloes, antelopes and deer - are susceptible. Of the domestic species, sheep are the most severely affected. The vectors of bluetongue are culicoides (biting midges). Over the last 10 years, the bluetongue virus has dramatically spread throughout southern Europe (OIE WAHID, 2009). In Italy, bluetongue first appeared in August 2000 and the biting midge *Culicoides imicola* is considered to be the major vector of the disease in the country (Conte et al., 2009). EPISTIS investigates, among other questions, the landscape descriptors associated with *C. imicola*'s successful population development in Sardinia. This region was chosen as a priority area due to (i) the high level of *C. imicola* abundance and (ii) the availability of an extensive database with longitudinal density data for *C. imicola*. In this framework, the main objective of the use of remote sensing is to provide land use/land cover maps with relevant classes of interest, from which landscape descriptors will be derived in a later stage. Initially, the focus was on the distinction between semi-natural vegetation and arable land, but the requirements evolved towards further detail within the arable land.

Notwithstanding the required degree of detail in the classification, high resolution data (SPOT5 and ASTER) were preferred to very-high resolution data since wide areas should be mapped so as to cover a sufficient number of *C. imicola* trapping sites. Moreover, considering that a number of classes of interest relate to vegetation dynamics, we opted for a method combining single date high-resolution data with multi-temporal medium resolution data (MODIS).

An object-based image analysis approach (OBIA) was chosen, because of the spatial resolution of the SPOT5 images (10m in the visible and NIR bands) and the high heterogeneity of the vegetation classes. The basic difference with pixel-based procedures is that OBIA does not classify single pixels, but rather image object primitives (regions) that are extracted in a prior image segmentation step. Beyond spectral information, the regions carry many additional features (shape, texture, and contextual features) (Blaschke and Strobl, 2001; Benz et al., 2004). The fact that the resulting classification is to serve as input for patch analysis is also in favour of OBIA.

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2. STUDY AREA AND DATA

2.1 Study area

Sardinia is a mountainous Italian island, with plains constituting only one fifth of the territory. Over the XXth century, malaria eradication, river monitoring and irrigation allowed previously under-utilized lands to be transformed into intensively cultivated lands. The splitting of cultivated areas into smaller parcels, because of the subdivision of the land through inheritance, brought about many changes in landscape patterns. The present agricultural landscape of the Sardinian plains is a typical Mediterranean open land, often treeless and sometimes interrupted by gentle slopes. The main products are wheat in the open lands, grapes and olives in the enclosed lands and artichokes in the market gardens (Pungetti, 1995). Dairy sheep farming represents an important source of agricultural income in Sardinia, where about 3.5 million of dairy ewes are raised at pasture. Quite recently, irrigation has spread in the Sardinian lowlands, which resulted in the development of highly-intensified farms. Irrigated forage crops represent an excellent tool for increasing stocking rate and animal performance per hectare (Fois et al., 1999).

The area we selected to develop the classification method is located in north-western Sardinia near the cities of Sassari, Porto Torres and Alghero. The SPOT5/ASTER overlapping zone covers about 1200 sq km (Figure 1). The main land use/land cover types are Mediterranean maquis and garrigue, arable land, human settlements and water bodies. In this paper we will focus on this area only, although the classification will be applied to other areas as well.
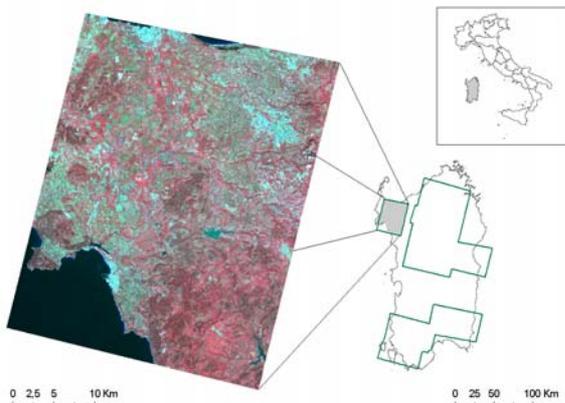
Figure 1: The study area selected for developing the classification method, shown here as a SPOT5 false colour composite (SPOT Image distribution/OASIS programme, Copyright CNES). The green polygons represent the areas where the classification method will be applied.

2.2 Data

2.2.1   Imagery: Three types of images were used in this study: SPOT5 XS, ASTER and MODIS.

The SPOT5 XS image was acquired in April 2003. The green, red and NIR bands have a spatial resolution of 10m, whereas the MIR band has a spatial resolution of 20m. This image was obtained thanks to the OASIS programme.

As a complement, we used an ASTER image acquired in June 2003. The spatial resolution of the VNIR, SWIR and TIR bands is 15m, 30m and 90m, respectively. The rationale for complementing SPOT5 with ASTER is to combine the higher spatial resolution of SPOT5 with the higher spectral resolution of ASTER (14 spectral bands), which is an asset for discriminating the different vegetation types. These images were acquired in springtime, a favourable period to discriminate (semi-)natural vegetation from cultivated areas, which was the initial objective of the classification. The images cover farms where *C. imicola* catches have been recorded for several years.

In addition, a time series of images from the global 250m 16 day Vegetation Index Product (MOD13Q1, version 5, EVI and NDVI) was downloaded for the year 2003, covering the entire study area. These data are distributed by the Land Processes Distributed Active Archive Center (LP DAAC), located at the U.S. Geological Survey (USGS), Earth Resources Observation and Science (EROS) Center.

2.2.2   Ancillary data: A 20m resolution DEM was used to orthorectify the high resolution images and to derive the stream network.

3. METHODS

3.1 Field survey and sample collection

A field survey was conducted in 2007 in order to collect training and validation sets. The samples were collected using a GPS in farms where *C. imicola* catches are being recorded, around these farms in a surrounding neighbourhood corresponding to the flight range of *C. imicola* (a few hundred meters) and also farther away in order to encompass the landscape diversity that is present in the images. To ensure consistency, the class assigned to each sample was validated by two researchers present in the field thus limiting the risk of error. A further check was performed using the very-high resolution images that can be viewed in Google Earth. Additional samples were also collected using Google Earth when necessary. This was made possible thanks to the knowledge of the landscape acquired during the field survey.

One difficulty was to collect samples for some of the subclasses of arable land. Indeed, we intend to make a distinction between (i) agricultural land that is irrigated permanently or periodically and (ii) agricultural land that is never irrigated. During the field survey, a note was made for irrigated parcels and parcels equipped for irrigation (sprinklers etc.). However, a parcel that was not irrigated and not equipped at the time of the field survey can be periodically irrigated, and a parcel equipped for irrigation might not be irrigated anymore. We therefore used the MONIDRI database as a complement to the field survey (Fais et al., 2004). This database is available online through a web mapping interface and contains, among others, detailed land use layers with information on irrigation.

3.2 Image pre-processing

3.2.1   SPOT5 and ASTER: Since (i) indices had to be derived and (ii) we intend to apply the method to a set of images acquired at different dates, the images were atmospherically corrected. We used ATCOR2 (Richter, 2003), an algorithm that includes the MODTRAN radiative transfer

model. Beside the atmospherically corrected reflectance bands, a series of layers were generated, i.e. SAVI, LAI, FPAR, Surface Albedo and Absorbed Solar Radiation. SAVI (Soil Adjusted Vegetation Index) is a vegetation index designed to minimize the effect of the soil background; LAI (Leaf Area Index) is a measure of the green leaf density; FPAR (Fraction of Photosynthetically Absorbed Radiation) is correlated to LAI. It measures the amount of photosynthetically active radiation absorbed by a plant canopy; Surface Albedo is the fraction of the incoming solar radiation reflected by the land surface; Absorbed Solar Radiation flux measures the shortwave solar radiation absorbed by the surface (PCI Geomatics, 2009 ; Bannari et al., 1995). The high resolution images were also orthorectified with topographic maps and a 20m DEM, using Toutin's model embedded in the Geomatica software. The corrected ASTER bands were then cut and resampled to fit the extent and resolution of the SPOT5 image. The resampling option selected is the nearest neighbour that does not alter the pixel values.subject

3.2.2 MODIS: A cubic spline interpolation was applied to de-noise MODIS data series. Indeed, in a recent paper by Scharlemann et al. (2008), a cubic spline interpolation technique was tested for seasonality extraction to be used as input for species distribution modelling. This novel algorithm of spline interpolation followed by regular resampling of the composited satellite data was developed to produce a 5-day interval MODIS time series that could then be subjected to standard temporal Fourier processing methods. This algorithm was found to capture the input amplitude and phase information correctly. The algorithm was programmed in 'R' and applied to the MODIS NDVI and EVI image time series. Fourier analysis is ideally suited for summarizing seasonal variables (Rogers et al., 1996) because seasonal activity is a driving factor for e.g. vegetative status, vector abundance etc. It was performed on the de-noised MODIS data series with the Sat-geoTools software package.

3.3 Legend

The land use/land cover legend was designed according to the class significance for the vector of bluetongue and the landscape descriptors to be derived, taking into account the results of an exploratory unsupervised classification carried out on a subset of SPOT5 images. It was subsequently refined during the 3-week field survey in Sardinia. A parallel was made with CORINE Land Cover to guarantee a more generic character of the classification scheme, although one-to-many and many-to-one relationships do exist. The legend is presented with the classification result in Figure 4.

3.4 Image segmentation

The segmentation was carried out using the multiscale bottom-up segmentation algorithm embedded in eCognition (Definiens AG, 2007). The parameters used in this process are summarized in Table 1. We used only the SPOT5 bands since they have the best spatial resolution. Scale is a parameter without unit that determines the size of the resulting image objects (regions). Smoothness/compactness are weighting factors ranging from 0 to 1. The parameter values were determined by visual inspection of the segmentation result, so as to avoid under-segmentation and excessive over-segmentation of the objects composing the different classes.

Segmentation level	Bands	Scale Parameter	Smoothness/ Compactness	Number of objects
Fine segmentation	SPOT Green, Red, NIR, SWIR	10	0.1/0.5	180135
Coarse segmentation	SPOT Green, Red, NIR, SWIR	50	0.1/0.5	8509

Table 1: Parameters used to create two segmentation levels

3.5 Image classification – step 1

A multi-sensor, mixed rule-based and nearest neighbour approach was implemented, with the integration of ancillary data. Object-based classification was performed using eCognition, which allowed building a rule set that can be applied to similar data with adjustments. The general approach consists in thresholding spectral (including customized features such as NDVI), textural and contextual features to classify the land use/land cover classes that are the more easily isolated, and to use the nearest neighbour classifier for the remaining classes. The nearest neighbour feature space was optimized using the feature space optimization tool and contains features derived from SPOT5 and ASTER. Two levels were classified (fine and coarse) thus allowing the use of the hierarchical properties of image objects. These properties have proven useful in other contexts, e.g. mapping bush densities (Laliberté et al., 2004).

On the fine segmentation level (Figure 2), the 'water bodies' were the most easily isolated by thresholding the mean SPOT Albedo. Classification of the 'riparian vegetation' required the use of the SPOT NDVI and of a stream network layer (drainage) that was generated from the DEM using the hydrologic modelling functions available in ArcGIS. Small bright objects were isolated using the SPOT brightness and used on the coarse level for the classification of 'artificial surfaces'. The other classes were discriminated thanks to the nearest neighbour classifier. It was not possible to further split the classes 'permanent crops and complex cultivation patterns' and 'other agricultural land and natural grassland' according to their irrigation status, due to spectral similarity at this resolution. This split was performed in a second classification step with the adjunction of MODIS data.

The classification on the coarse segmentation level (Figure 3) aims at avoiding the confusion between 'artificial surfaces and open spaces with little or no vegetation' and the bare soils belonging to the agricultural land. Larger objects are more meaningful in terms of textural analysis and different types of texture measures were calculated, i.e. GLCM homogeneity (Haralick et al., 1973) and two texture features based on the sub-objects.

3.6 Image classification – step 2

We introduced MODIS data in the classification scheme in order to subdivide the provisional classes 'permanent crops and complex cultivation patterns' and 'other agricultural land and natural grassland' resulting from the first classification step. We used four amplitude images (A0, A1, A2 and A3) and three phase images (ϕ1, ϕ2 and ϕ3) output from the Fourier transform of both the 2003 NDVI and EVI time series.

(i) Amplitude. The principal component values are greater for classes with constant photosynthetic activity (or higher on average), the first harmonic values for classes with monocyclic photosynthetic activity, the second harmonic values for classes with bicyclic photosynthetic activity and

the third harmonic values for classes with tricyclic photosynthetic activity.

(ii) Phase. The phase values indicate the timing of the first peak of photosynthetic activity.

A first attempt was made to build a rule set based on our relative class knowledge. In this approach, only the amplitude images were used. Using the phase images would imply that we have relative knowledge regarding the timing of vegetation peaks for the different classes, which is not the case. A number of assumptions were formulated, e.g.:

- Irrigated pastures tend to be greener on average than non-irrigated pastures and natural grassland
- Non-irrigated pastures and natural grassland tend to be more monocyclic than irrigated pastures

Increasing linear membership functions on the interval [mean-σ ; mean+σ/2] were designed to distinguish classes with higher amplitude values and decreasing linear membership functions on the interval [mean-σ/2 ;   mean+σ] were designed to distinguish classes with lower amplitude values. With this scheme, the best classification was obtained using data derived from the NDVI time series. Statistical processing of EVI data showed high standard deviation values for A1/A0 and A2/A1, which could indicate that the EVI time series contains more noise, thus explaining the poorer results obtained. However, even the best classification based on NDVI time series did not reach sufficient accuracy and this potentially promising approach using relative class knowledge was abandoned.

A second attempt was made using seasonality parameters extracted with the TIMESAT software. Jönsson and Ekhlund (2004) developed this software to extract seasonality information from noisy time series. TIMESAT first smoothes noisy time series using an adaptive Savitzky-Golay filtering method. The resulting smooth curves are then used for extracting seasonal parameters related to the growing seasons. The parameters extracted are (a) beginning of season, (b) end of season, (c) left 90% level, (d) right 90% level, (e) peak, (f) amplitude, (g) length of season, (h) small integral over growing season, (i) large integral over growing season fall. A classification scheme was built on the same tree-like method and implemented in the object-based classification. Since this attempt did not yield satisfying results, we do not further detail it.

A third attempt was made based on an approach combining membership functions generated using training samples and the nearest neighbour classifier. In this approach both amplitude and phase images of the NDVI time series were used. The feature used to generate the membership functions (A1) was selected by comparing feature histograms and their overlaps. The features used for the standard nearest neighbour classification are the Mean of A0, A1, A2, A3, $\phi 1$, $\phi 2$ and $\phi 3$. They were selected using the feature space optimization tool. The two provisional classes that were to be split were subdivided into four subclasses: 'irrigated arable land and pastures', 'non-irrigated arable land', 'pastures and natural grassland', 'irrigated permanent crops and complex cultivation patterns' and 'non-irrigated permanent crops and complex cultivation patterns'. Arable land in this acceptation excludes the permanent crops and complex cultivation patterns.

4. RESULTS AND DISCUSSION

A subset of the classification is presented in Figure 4.

For the first classification step, an independent accuracy assessment using 127 validation points showed that KIA was at 86%. The best classification result was obtained for the 'water bodies', followed by the 'other agricultural land', the 'artificial surfaces and open spaces with little or no vegetation' and the 'coniferous forests'. For these four classes, KIA was over 90%. The main misclassifications occurred between the 'high maquis and broad-leaved forest' and the 'low maquis and garrigue', but these are not the most critical classes in the framework of our project. The class 'permanent crops and complex cultivation patterns' had the lowest KIA (60%), probably because vineyards are spectrally similar to pastures at that resolution where the vine rows are not detected. In a complex Mediterranean landscape like the one we find in the study area, the use of ASTER bands (and notably the SWIR bands) in the nearest neighbour feature space contributed to the improvement of the classification results for the vegetation classes. However, the limit of the classification using only high resolution single date images is reached when it comes to (i) isolate classes linked to the irrigation status of the plots and (ii) differentiate some vegetation types that are spectrally similar at that resolution.

For the second classification step, an independent accuracy assessment using 147 validation points showed that KIA was at 63%. The best classification result was obtained for the 'irrigated permanent crops and complex cultivation patterns' (81%). The 'irrigated arable land and pastures' has the lowest KIA (52%) and is mostly misclassified as 'irrigated permanent crops and complex cultivation patterns'. On the whole, a visual assessment of the result based on field knowledge shows that the main landscape patterns are reflected in the classification. The influence of the coarser resolution and geo-location error of the MODIS data on misclassifications should still be further investigated, but it is assumed that land use/land cover transition zones and smaller isolated plots are the most affected.

5. CONCLUSION

In this complex Mediterranean landscape, OBIA proved a valuable tool for producing the land use/land cover maps that are needed for further analysis in EPISTIS. It allowed us to combine images with different resolutions, to integrate ancillary data and to use complementary classification approaches. The strategy consisting in classifying the most separable classes in a first stage with thresholded features and the remaining classes in a second stage with the nearest neighbour classifier was effective. The use of textural and contextual features in addition to spectral features also contributed to the improvement of the results. The integration of data derived from MODIS vegetation time series was beneficial for the classes where information on vegetation dynamics is essential. Further work will investigate the integration of uncertainties in the subsequent landscape analysis.
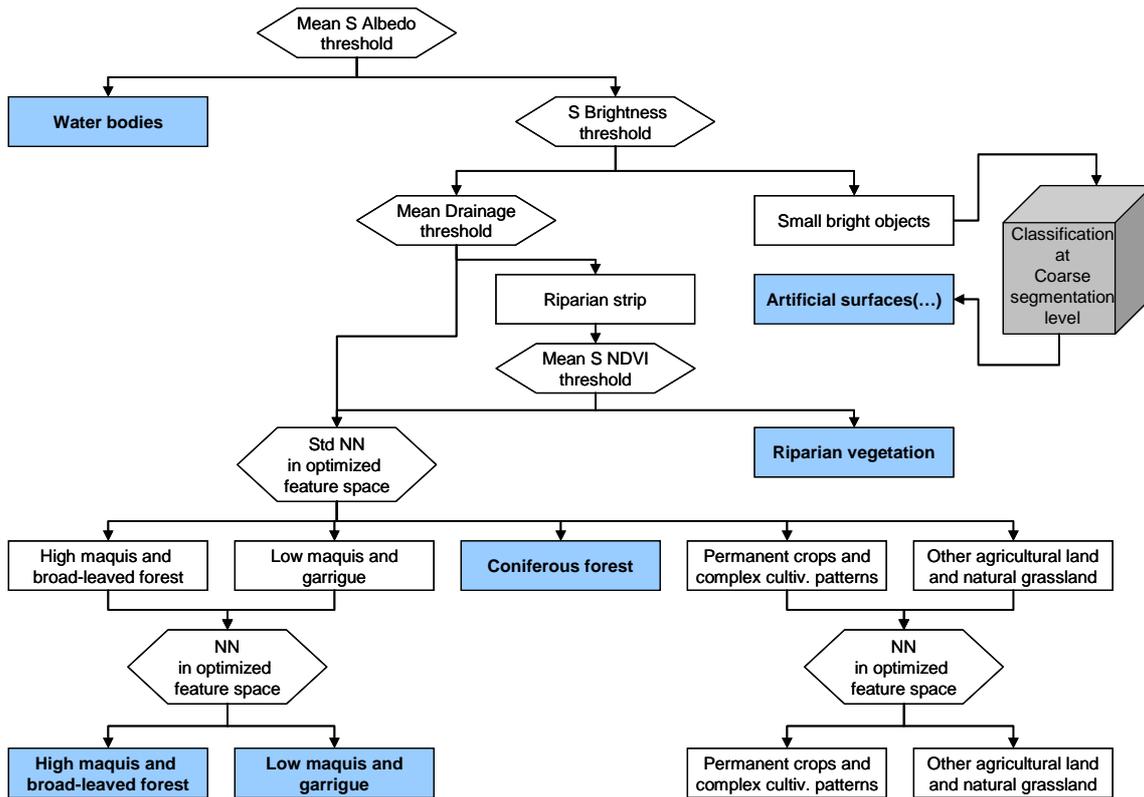
Figure 2: Step 1 - Classification tree of the fine segmentation level. For the thresholded features, values greater than a threshold are split to the right, values smaller are split to the left. Classes in white boxes are provisional results, in blue boxes final (S stands for SPOT).
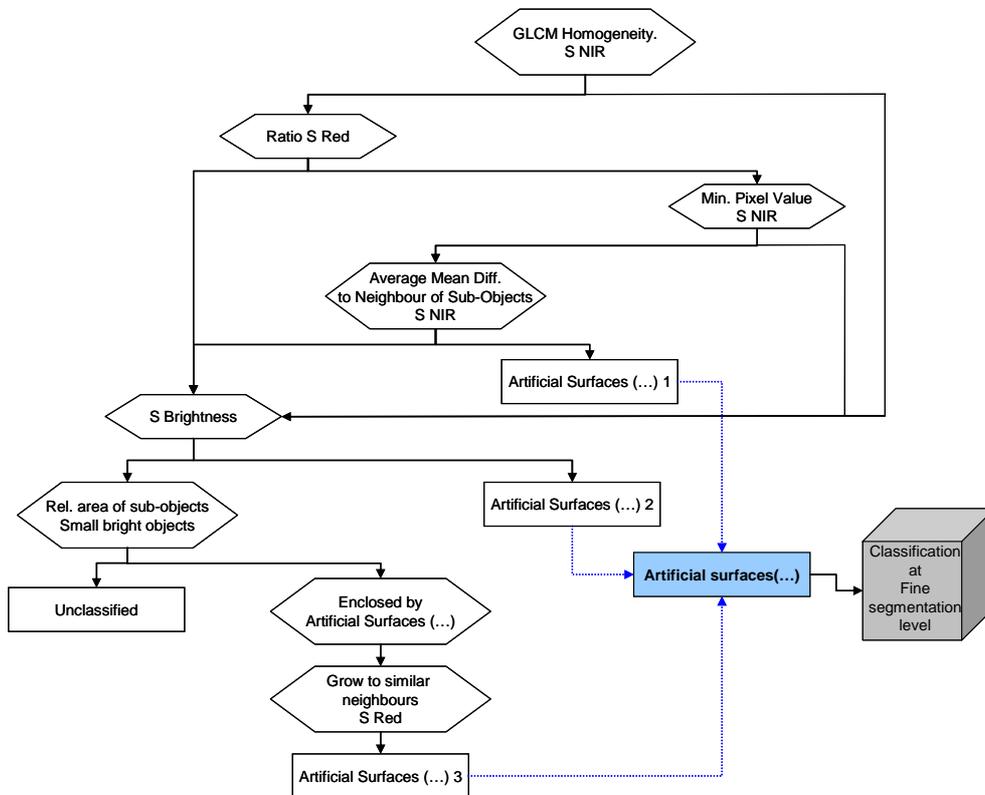
Figure 3: Step 1 – Classification tree of the coarse segmentation level. For the thresholded features, values greater than a threshold are split to the right, values smaller are split to the left. Classes in white boxes are provisional results, in blue boxes final (S stands for SPOT).
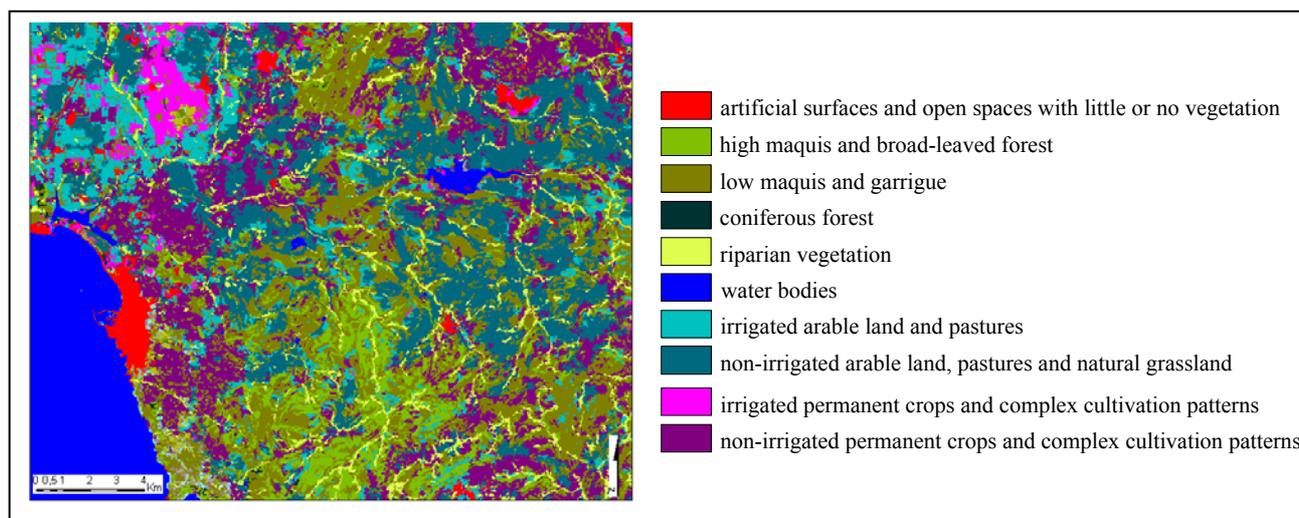
Figure 4: Subset of the classification result. In the legend, the first 6 classes result from the first classification step, the 4 last classes from the second classification step.

REFERENCES

Bannari, A., Morin, D., Bonn, F., and Huete, A.R., 1995. A review of vegetation indices. Remote Sensing Reviews 13:1, pp. 95-120.

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I., Heynen, M., 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry and Remote Sensing, vol. 58, pp. 239-258.

Blaschke, T. and Strobl, J., 2001. What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. GeoBIT/GIS, 14 (6), pp. 12-17.

Conte, A., Gilbert, M., Goffredo, M., 2009. Eight years of entomological surveillance in Italy show no evidence of Culicoides imicola geographical range expansion. Journal of Applied Ecology, 46(6), pp. 1332-1339.

Definiens AG., 2007. Definiens Developer 7 Reference Book. (accessed 14 April 2010)
http://www.ecognition.cc/download/ReferenceBook.pdf.

Fais, A., Nino, P., Dono, G., Severini, S., Bazzoffi, P., Napoli, R., et al., 2004. Monidri - A Participatory Idss for Water Use Management in Agriculture at River Basin Level.
http://www.elet.polimi.it/IFAC_TC_Environment/venice200
4/poster/1v04fais.pdf,http://www.gestcomagensud.it/monidri/index.phtml (accessed 13 April 2010)

Fois, N., Ligios, S., Molle, G., Sitzia, M., Decandia, M., Sanna, L., 1999. Dairy sheep farming in Sardinian irrigated lowlands. Options Méditerranéennes. Série A: Séminaires Méditerranéens (CIHEAM).

Haralick, R., Shanmugan, K. and Dinstein, I. 1973. Textural features for image classification. IEEE Transactions on Systems, Man & Cybernetics 3(1), pp. 610-621.

Jönsson, P. and Eklundh, L., 2004. TIMESAT A program for analyzing time-series of satellite sensor data, Computers & Geosciences, vol. 30, pp. 833-845.

Laliberte, A.S., Rango, A., Havstad, K.M., Paris, J.F., Beck, R.F., McNeely, R., and Gonzalez, A.L., 2004. Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. Remote Sensing of Environment 93(1-2):198-210.

OIE WAHID, 2009. World Animal Health Information Database Interface.
http://www.oie.int/wahis/public.php?page=disease (accessed 14 April 2010).

PCI Geomatics. 2009. Geomatica: User Manual. PCI Geomatics, Version 10.3, Richmond Hill.

Pungetti, G., 1995. Anthropological approach to agricultural landscape history in Sardinia. Landscape and Urban Planning, 31(1-3), pp. 47-56.

Richter, R., Center, D. & Center, R.S.D., 2003. Value adding products derived from the ATCOR models. Unpublished internal report at DLR, German Aerospace Center, Institute for Optoelectronics.
http://www.rese.ch/pdf/atcor_value_adding.pdf (accessed 13 April 2010)

Rogers, D. J., Hay, S. I., Packer, M. J., 1996. Predicting the distribution of tsetse flies in West Africa using temporal, Fourier processed meteorological satellite data. Annals of Tropical Medicine and Parasitology, 90, pp. 225-241

Scharlemann, J. P. W., Benz, D., Hay, S. I., Purse, B. V., Tatem, A., Wint, G. R. W., Rogers, D. J., 2008. A novel algorithm for temporal Fourier processing MODIS data for ecological and epidemiological applications, PLoS ONE, 3(1), e1408.