Kernel-based reclassification algorithm applied on very high spatial resolution satellite imagery of complex ecosystems

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ABSTRACT

Kernel-based reclassification algorithm derives information on specific thematic classes on the basis of the frequency and spatial arrangement of land cover classes within a square kernel. This algorithm has been originally developed and validated for the urban environment. The present work investigates the potential of projecting this technique to the classification of very high spatial resolution satellite imagery of natural ecosystems. For that purpose a software tool has been developed. The output, apart from the reclassified image, includes a post-classification probability map which shows the areas where the kernel reclassification algorithm has given valid results. The software was tested on an IKONOS image of Lake Kerkini (Greece), a wetland of great ecological value, included in the NATURA 2000 list of ecosystems. The results show that the algorithm has responded successfully in most cases overcoming problems previously encountered by pixel-based classifiers, such as pixel noise.

1. INTRODUCTION

The implementation of the NATURA 2000 network is currently one of the most challenging issues for European Nature Conservation. Traditional species oriented methods of monitoring are not compliant with the increasing demand of spatially explicit data on the ecological quality of and threats against designated protected sites. Following the increasing concern over the losses in biodiversity and habitats, it is now widely recognized that it is essential to assess and monitor ecological resources objectively in order to formulate appropriate policies.

As very high spatial resolution (VHSR) satellite data (< 10m) have recently become available, the performance of 'traditional' per-pixel image classification methods (such as maximum likelihood) has decreased, as these classifiers do not take into account the vicinity of the pixels. The kernel reclassification algorithm[1] examines labels of adjacent pixels within a square kernel and calculates the so-called adjacency-event matrix, accounting for the spatial arrangement and frequency of the labels. Criterion for pixel re-labeling is the degree of match between the adjacency event matrix and the Template Matrices produced during training. Single land cover labels are attributed to the pixels after the application of a pixel-based unsupervised classifier. Thus, the algorithm accounts for texture and spectral components of the information classes. This approach has been originally developed and applied for the urban environment [1,2].

The method was applied to a single IKONOS 4-m spatial resolution multispectral image of the conservation wetland of Lake Kerkini in Northern Greece, in order to classify it into five classes as determined by the European Nature

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Information System (EUNIS; home site: http://mrw.wallonie.be/dgrne/sibw/EUNIS/home.html) developed by the European Environment Agency (EEA). The EUNIS Habitat classification has been developed to facilitate harmonized description and collection of data across Europe through the use of criteria for habitat identification. It is a comprehensive pan-European system, covering all types of habitats from natural to artificial, from terrestrial to freshwater and marine habitats types.

The study area comprises the catchment of an artificial lake (Figure 1) that has been created between 1928 and 1932. A new dam was built in 1982. The purposes of the damming were flood protection and the provision of water resources for irrigation. The maximum depth of the lake is 10 m with an annual fluctuation of water level between 4.5 and 5 m. The lake and it's riparian areas are important habitats for migratory bird species. In total the area hosts 102 breeding bird species,171 migrating species and 171 wintering species. Fish fauna includes at least 30 species, thereof 2 endemic sub-species.

Figure 1: Panoramic view of the lake in springtime (north to south).
The riparian forest is flooded (at the left hand side).

2. KERNEL RECLASSIFICATION ALGORITHM

The basic steps of kernel reclassification algorithm are illustrated in Figure 2. Input datasets include a very high spatial resolution satellite image and a ground truth map of the same year and season. The user then selects the training sets in order to provide to the system information on the different classes. For each final class, a number of representative clusters is required (maximum number of clusters for each class is 5). The first step is to perform an initial supervised or unsupervised classification to the original image and export it in binary format. The number of initial classes varies between specific test sites, but 6-12 classes are normally sufficient.

Following the definition of training clusters within the originally classified scene, the signature files are generated. These files include the adjacency event matrices, defined as

$$M = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \cdots & f_{ij} & \cdots & \cdots \\ f_{n1} & f_{n2} & \cdots & f_{nn} \end{bmatrix} \quad , \qquad [1]$$

where f_{ij} is the frequency with which pixels belonging to class i are adjacent to those belonging to class j, within the specified kernel. From the definition, in equation [1] $f_{ij}=f_{ji}$. The size of the square matrix M depends on the number of classes present in the initially classified image. The size of the signature file on the other hand is dependent on the kernel size, as it contains all the non-overlapping matrices *M* that can fit in the training cluster. Therefore, if the number of classes is three (Figure 3)- namely A, B and C- the training cluster is 40x40 pixels and the kernel size is 9, then the corresponding signature file contains 16 3x3 adjacency event matrices. The total number of signature files equals the number of training clusters, as there are usually more than one clusters per final class.

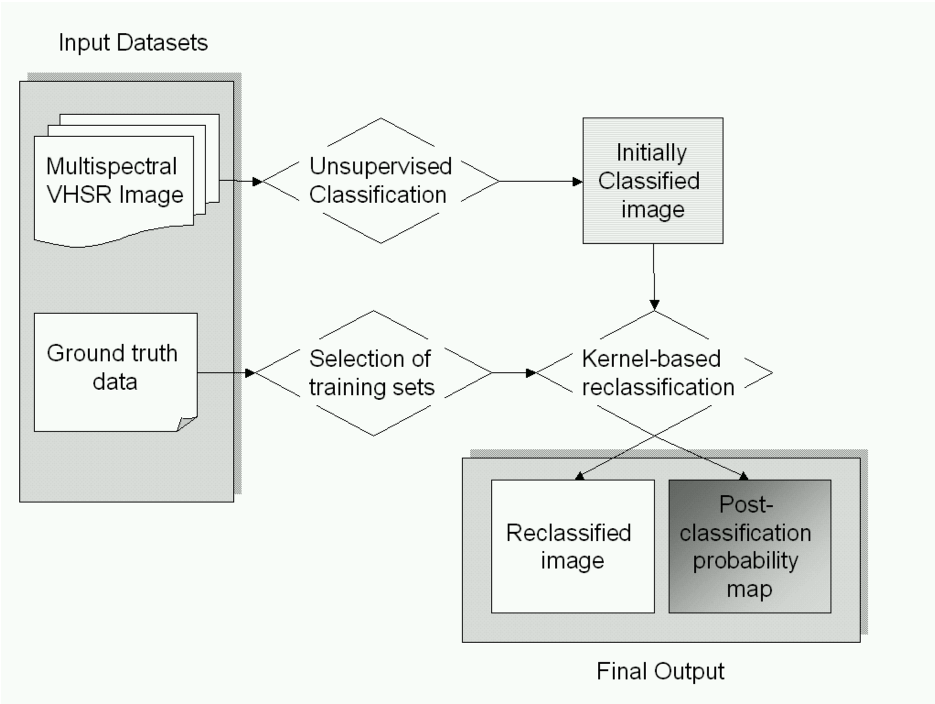

Figure 2: Flow chart of kernel reclassification algorithm

Following the generation of signature files, the algorithm extracts the mean training adjacency event matrices taking into account the most representative ones for each class. During the classification module a kernel of defined size passes over the whole image and computes the so-called similarity index between the current and the training adjacency event matrices. The similarity index is defined as

$$\Delta_k = 1 - \sqrt{0.5 N^{-2} \sum_{i=1}^{C} \sum_{i=j}^{C} (M_{ij} - T_{kij})^2}, \qquad [2]$$

where M_{ij} is defined from equation [1], T_{kij} is the corresponding element for final land-use category *k*, *N* is the total number of adjacency events in the kernel and *C* is the is the number of final land-cover classes in the image.

From the above it is clear that the values of Δ_k fall in the range between 0 (no similarity) and 1 (perfect match), i.e. $0 \le \Delta_k \le 1$. The algorithm assigns to each pixel the thematic land cover class for which Δ_k is maximum. It also provides as a standard output product a *post classification probability map*, each pixel of which equals the maximum Δ_k . Post-classification probability map has the same number of lines and columns as the classified image and is necessary to validate the results of reclassification. It can subsequently be used to create a mask of the areas reclassified with confidence larger than a threshold value specified by the user.

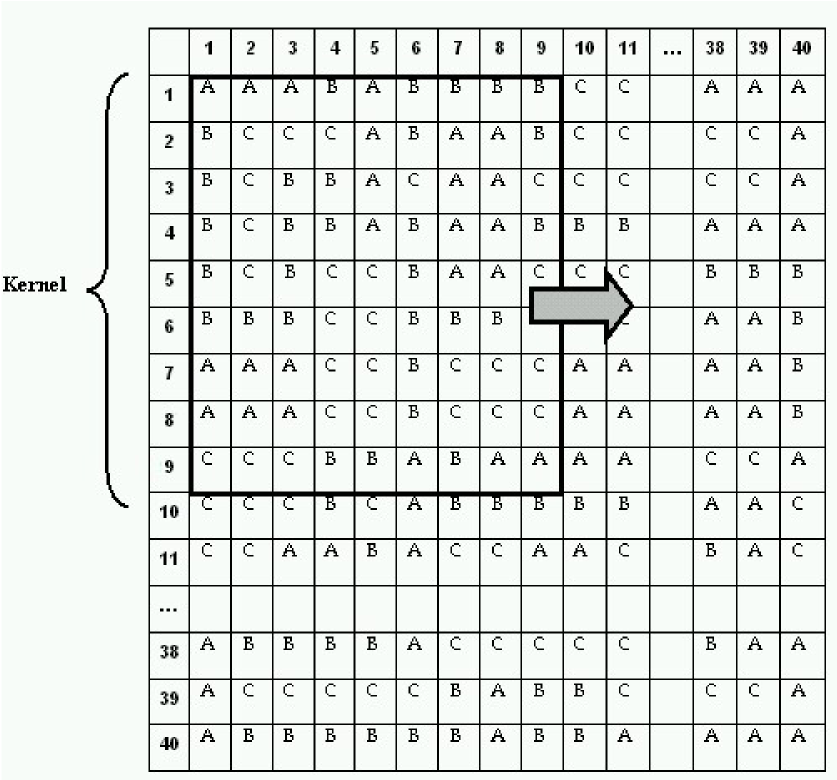

Figure 3: A simplified example of a 3-class 40x40 pixels image with a kernel of 9x9 pixels

3. APPLICATION AREA AND AVAILABLE DATA

The test site is a complex wetland ecosystem and comprises of Lake Kerkini (the core area of the site) and its catchment area. Lake Kerkini is a large, artificial freshwater lake located at the place of a former swamp. It is located in Northern Greece (latitude: 42 12' N, longitude: 23 09' E) as shown in Figure 4, and is proposed to be included in the NATURA 2000 network (code GR1260008). Lake Kerkini is fed by the Strymon River and is used for irrigation and flood control. The water level in the lake falls to a minimum each year between September and February and rises to a maximum level between early May and early June. Thus, two options of the lake exist. Kerkini Lake supports very interesting aquatic vegetation including formations of rooted plants with floating leaves or rooted submerged species. Reed bed formations fringe the lake and the canals. The most important key habitat of the area is the riparian forest at the NE of the lake. It is the nesting and feeding habitat for a lot of rare bird species during long periods. It is also important for reptiles, amphibians and fish.

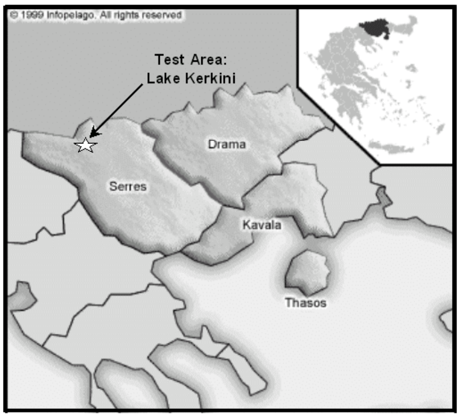

Figure 4: Location of the test site

The satellite image used for the present application was acquired on 28 May 2000 by IKONOS-2 satellite which is on a sun-synchronous low earth orbit at a nominal altitude of 681 km and has a revisiting capability of 3 days. The IFOV is such that it collects images of the earth with a very high spatial resolution of 1 m and 4 m in the panchromatic and multispectral modes, respectively. For the purposes of the present study, a sub-scene of about 18 km^2 centered at the Delta of River Strymon was used. The four IKONOS-2 multispectral channels are tuned to detect spectral radiation in the visible (0.45-0.53 mm Blue, 0.52-0.61 mm Green and 0.64-0.72 mm Red) as well as in the near infrared (NIR; 0.77-0.88 mm) parts of the electromagnetic spectrum.

The selection of training samples for both classification schemes was realized by extracting representative sample areas of same size (30x30 pixels) from each class. This was imposed by the requirements of kernel reclassification algorithm.

4. RESULTS

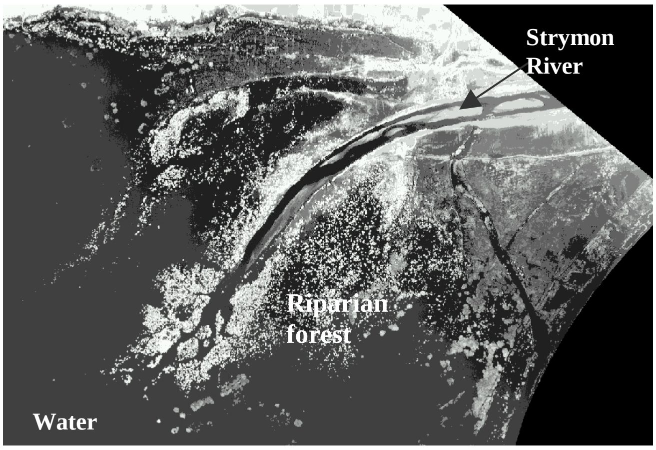

Figure 5: Unsupervised classification of original scene into 8 classes

The first step of the procedure is an unsupervised per-pixel classification. The method used was Iterative Self-Organizing Data Analysis Technique (ISODATA[3]), which uses minimum spectral distance to assign a cluster to each candidate pixel. In the present application a maximum number of 8 spectral classes was specified and a convergence threshold of 0.95 was set. The result is illustrated in Figure 5. The second step involves the selection of 30x30 pixel training clusters based on EUNIS (level 2-3) ground-truth data map. The number of clusters for each class is provided in Table 1. As it is not possible to distinguish free from rooted floating vegetation of eutrophic waterbodies on a satellite image (classes C1.32 and C1.34), these are considered as one class (C1.3). Another point of interest is the exclusion of the river (EUNIS code C2.3) due to the shape of the class, which does not allow the extraction of 30x30 training clusters. Therefore, in total, five different classes will be considered for the reclassification. Following the selection of the appropriate training clusters, the kernel reclassification is carried out. The kernel size was set to 9 pixels. The threshold value for pairs correlation was set to 0.75.

Class code	***Class definition***	***No. of training clusters***
G1.112	Mediterranean tall [Salix] galleries *(Riparian Forest)*	4
C1.32	Free floating vegetation of eutrophic waterbodies	3
C1.34	Rooted floating vegetation of eutrophic waterbodies	
C3.5	Pioneer and ephemeral vegetation of periodically inundated shores	4
G1.1xC3.2	Riparian woodland X water fringing reedbeds and tall helophytes other than canes	1
E5.4	Moist or wet tall herb and fern fringes and meadows	1

Table 1: EUNIS classes present at test site

Figure 6: Reclassified image

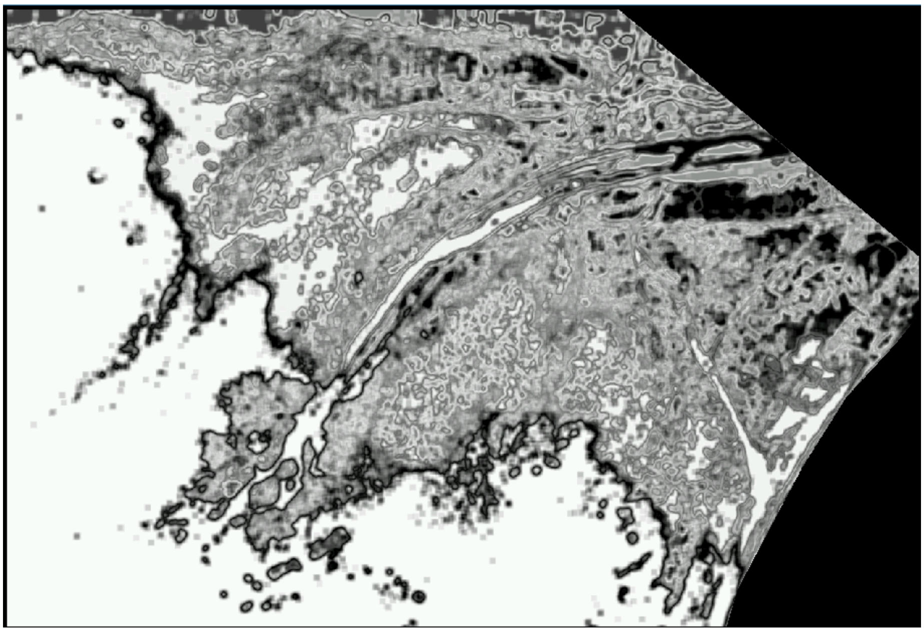

Figure 7: Post classification probability map. White pixels correspond to high probability of successful classification, whilst black to misclassified or no-data.

The final classified image is shown in Figure 6. As already mentioned, the post-classification probability map has to be viewed together with the reclassified image to see for which pixels the kernel reclassification algorithm has given valid results. For our experiment, the corresponding map is shown in Figure 7. Using this information the areas poorly reclassified, with a similarity index less than 0.75 are masked out. The brighter the color the higher the similarity index and thus the confidence level. The map shows that the algorithm has overall performed successfully apart from transitional zones from homogeneous to variable areas as well as along the river (due to the absence of training clusters because of the object size and shape). The average similarity index is 80%, which is indeed very high for such a complex scene.

The classification accuracy was further assessed by means of a confusion matrix (Table 2). The overall accuracy was 71%. The assessment was based on a stratified selection of pixels according to the extent of the class.

OVERALL 71%		Reference Classes					
		G1.112	**C1.3**	**C3.5**	**G1.1xC3.2**	**E5.4**	**Other**
Classified	**G1.112**	14	2	3	3	0	1
	C1.3	2	9	1	0	1	1
	C3.5	2	4	35	0	0	1
	G1.1 x C3.2	1	0	1	9	0	0
	E5.4	0	1	0	1	4	4

Table 2: Confusion matrix for the assessment of kernel based reclassification of IKONOS image

The column 'Other reference class' refers to the cases where the particular class of the pixel was not included in the classification. This was very limited and mainly due to the size of the objects representing the class, for instance along the river, where no training cluster could be defined. The individual class performance was 60%, 64%, 83%, 81% and 40% for G1.112, C1.3, C3.5, G1.1xC3.2 and E5.4, respectively. Since some of these classes vary strongly with season, it is expected that the overall result will be enhanced once an image acquired in late summer or beginning of autumn is included in the analysis. One has to keep in mind, that the classification of the area was performed using a single scene and that some of the classes might have similar spectral signatures in spring.

5. CONCLUSIONS

The present study exploits the potential of applying kernel based reclassification algorithm, originally developed for the urban environment[1] to complex ecosystems. Initial results presented here are very encouraging. Apart from the selection of training clusters (a step inevitable for all supervised classification schemes) the algorithm is automatic and, therefore, does not require particular user expertise. In terms of scale, kernel reclassification is applicable to satellite images with spatial resolution less than 10m, i.e. from 1:10000 down to 1: 5000. Comparing kernel based reclassification algorithm to 'conventional' pixel based classification, such as maximum likelihood, the major advantage of the former lies on the fact that it takes into account the texture together with the spectral information present in the scene. However, one disadvantage of the approach is that the whole process is not entirely autonomous in the sense that a standard satellite image processing tool, such as ERDAS Imagine, should be also used for the initial unsupervised classification and exporting/importing to binary format.

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