Journal for Nature Conservation 13 (2005) 91—99

Available online at www.sciencedirect.com

Journal for Nature Conservation

www.elsevier.de/jnc

Kernel based re-classification of Earth observation data for fine scale habitat mapping

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Received 21 November 2004; accepted 3 February 2005

KEYWORDS
Ecology;
IKONOS;
Quickbird;
Remote sensing;
VHSR

Summary

State-of-the-art Earth observation systems that provide very high spatial resolution imagery have given ecologists a powerful tool to directly identify species, habitats and other ecological units. At the same time, there is an urgent need for harmonised tools and methods to evaluate status and trends in European habitats. Towards that goal, the current work explores the applicability and transferability of an advanced pixel window classifier applied on very high spatial resolution satellite imagery for fine scale habitat mapping. The algorithm is tested on images of varying spatial resolutions acquired over test sites designated for the NATURA 2000 list located in different biogeographical zones. Algorithm application to Quickbird and IKONOS images gives encouraging results, regarding both the overall accuracies and the level of class hierarchy (habitats) identified.

Introduction

At the World Summit on Sustainable Development, Johannesburg, 2002, the Conference of the Parties of the Convention on Biological Diversity Strategic (CBD) Plan, including the target to achieve, by 2010, a significant reduction in the rate of biodiversity loss at the global, regional, and national level, was endorsed. Under the CBD, European conservation organisations have obligations to ensure the conservation and enhancement of habitats and species in both national and international context. A major approach for achieving this has been the establishment of a system of protected areas providing a statutory protection for sites including Special Areas of

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1617-1381/$ - see front matter © 2005 Elsevier GmbH. All rights reserved.
doi:10.1016/j.jnc.2005.02.004

Conservation established under the EC Habitats Directive and contributing to the NATURA 2000 network.

In Europe, there is an urgent need for harmonised tools and methods to evaluate status and trends in European habitats to achieve the objectives of the European Community biodiversity strategy. One key element would be an accessible Europe-wide geo-referenced inventory of habitat distribution, status and trends, and harmonised habitat and landscape classifications, to deliver policy-relevant information on the status and trends of biodiversity (Young et al., 2004). The lack of consistent and up-to-date information on location, extent and quality of European habitats is a major constraint for the implementation of European conservation strategy (Weiers, Bock, Wissen, & Rossner, 2004). A strong and consistent classification system is an important tool in nature conservation to be able to monitor species and ecological communities of interest that are under threat so that they can be related to a legal framework to ensure their protection. In contrast with the long history of species classification in Europe, the requirement for a classification of habitats has only been identified in recent decades and currently there are numerous national-level classifications in use (e.g. the National Vegetation Classification in the UK; Rodwell, 1992). More harmonised methods at the international level are beginning to be developed (Rodwell et al., 2003; Mucina, Rodwell, Schaminée, & Dierschke, 1993). But in general terms, national-level vegetation classifications use a range of different parameters for classification, so that they are not strictly comparable.

Furthermore, although traditional field-based habitat classification and mapping techniques might be thought to provide high accuracy in local level applications, inter-surveyor error is an issue. For example Cherrill and McClean (1999) found that even when different surveyors used a standard method applied widely within the United Kingdom agreement between pairs of maps averaged only 25.6% of the study site's area. Thus, quality control and quality assurance are important but neglected issues in ecological survey and habitat mapping. Integrating remote sensing data, e.g. air photos, with field survey has been identified as one way to improve precision of field mapping (Cherrill & McClean, 1999).

Remote sensing approaches are finding increasing usage in combination with field-based survey for habitat classification and mapping. Aerial photographs offer the advantages of generally good availability, high quality and resolution and potential regional-scale coverage. Until a decade ago, satellite imagery had been less used for terrestrial habitat classification and mapping because of cost, poor availability (e.g., in regions prone to regular cloud cover) and low resolution. However, as technology advances and availability issues are overcome, there is potential for high spatial resolution satellite imagery to contribute more and more to conservation monitoring (Mehner, Cutler, Fairburn, & Thompson, 2004; Kerr & Ostrovsky, 2003; Turner et al., 2003; Read, Clark, Venticinque, & Moreira, 2003; Mumby & Edwards, 2002; Nagendra & Gadgil, 1999).

The launch and subsequent acquisitions of the IKONOS platform in 1999 have heralded a new era by providing very high spatial resolution images. The IKONOS panchromatic and multispectral bands offer a spatial resolution of 1 and 4 m, respectively. In 2001 Quickbird was launched, fulfilling the remote sensing community requirement for imagery with spatial resolution of less than 1 m (0.70 m in panchromatic mode). At these resolutions, ecologists are able to directly identify certain species (e.g. detection of individual tree crowns) and species assemblages (Turner et al., 2003). To date, however, very few studies have examined the suitability of Quickbird images for mapping land cover types. It is worth mentioning here that with the improvement of spatial resolution, pixel-based classifiers are prone to errors due to between-class spectral confusion and within-class spectral variation for land cover studies (Barnsely & Barr, 1996).

This paper explores the applicability and transferability of an advanced pixel window classifier, namely kernel based re-classification (KRC) algorithm, applied to very high spatial resolution satellite imagery for fine scale habitat mapping. The algorithm is tested on images of varying spatial resolutions (10–0.7 m) acquired over test sites designated for the NATURA 2000 list located in different biogeographical zones.

Methodology

KRC algorithm was originally developed by Barnsely and Barr (1996) for the urban environment. The KRC algorithm used in the present study derives information on habitat classes in two stages. The first step is to transform the original multispectral image into a single channel image using a pixel-based unsupervised classification. This is performed using the Iterative Self-Organising Data Analysis Technique (ISODATA) algorithm (Tou & Gonzalez, 1974). The number of initial classes depends on user's choice but usually six to 12 classes are sufficient. The purpose of the initial classification is to highlight the spectral classes of the image (e.g. water, trees), not the information (thematic) classes such as riparian woodland, which consists of two spectral classes, namely water and trees, in a particular arrangement and frequency of occurance. Unsupervised classification offers a fast and efficient way to achieve this. However, in other studies supervised classification has been used (e.g. Barnsely & Barr, 1996). The KRC is then applied to the initially classified image.

KRC examines labels of adjacent pixels within the square kernel and calculates the so-called adjacency-event matrix, accounting for the spatial arrangement and frequency of the labels. Criterion for pixel re-labelling is the degree of matching between the adjacency event matrix and the Template Matrices produced during training. Thus, the algorithm accounts for texture and spectral components of the information classes. The functionality and performance of the classifier can be found in the original paper of Barnsely and Barr (1996).

The accuracy assessment of KRC product is based on two factors: (a) the mean post-classification probability, which is a measure of the similarity between the cluster centred at each pixel and the training clusters and (b) a confusion matrix using the accuracy assessment functionality of ERDAS Imagine (version 8.6).

The common nomenclature used for this study is the European Nature Information System (EUNIS) (Davies & Moss, 2002). EUNIS was developed by the European Environment Agency (EEA) to facilitate harmonised 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. Therefore, the results from the different resolutions and different test sites can be compared. In addition the level of habitat classification can be assessed in a consistent manner.

The following section describes the application of KRC algorithm to different NATURA 2000 test sites.

Wye Downs national nature reserve, UK

Description of test site

Wye Downs is the most easterly NNR in England and comprises a part of the complex of steep scarp slopes and dry valleys known as the North Downs (latitude: 51°09′N, longitude: 0°58′E). The primary conservation objective is to maintain one of the best remaining examples of chalk downland (calcareous grassland) in Kent, a habitat which has declined markedly in the last 50 years due to modern farming methods. The reserve covers about 100 ha, half of which is mixed deciduous woodland and the remaining half grassland. Due to the close proximity of Kent to the continental European mainland, the calcareous grassland is rich in wild flowers with a pronounced Southern Continental element including 17 species of orchids. The species-rich sward is the product of traditional hill grazing by sheep and cattle, although in recent decades undergrazing has resulted in an increase of coarse grasses and scrub.

Available data

A pan-sharpened product of a panchromatic and a multispectral Quickbird image is used for the application of the method. The image was acquired on 9 December 2002 at 10:31 a.m. The panchromatic band covers a spectral length of 450–900 nm at a spatial resolution of 0.7 m while multispectral image consists of four bands (blue: 450–520 nm; green: 520–600 nm; red: 630–690 nm; near-IR: 760–900 nm) at a spatial resolution of 2.7 m. The two images are merged using a Smoothing Filter-based Modulation Approach (SFIM), (Liu, 2000), and a pan-sharpened product with a spatial resolution of 0.7 m is produced at a subset of the image covering the test site (total size of approximately 1.5 km^2). SFIM is found to be the most appropriate technique for resolution merge of Quickbird data since the four bands of the pan-sharpened product had a correlation with the original multispectral ones of more than 96% in all cases. The pan-sharpened image is geometrically corrected using Land-line data (1:2500) to a spatial accuracy of 1 m. The very high spatial resolution of the image gives a fine working scale of 1:2500.

The date and especially time of image acquisition affects image quality. The acquisition date in December makes the distinction between different broadleaved woodland habitats impossible, due to the absence of foliage. Furthermore, the time of the day (10:31 a.m.) imposed the most crucial problem, as the low sun angle and the sharp relief of the area resulted in extensive shadows on the image. For that reason, the shadowed areas are dealt as a separate class throughout the classification process.

Table 1. EUNIS classes present in Wye Downs test site (UK)

Class code	Class definition	NVC code
E1.2	Perennial calcareous grassland and basic steppes	CG4
E2.11	Unbroken pastures	MG6
G1.A22	British [Fraxinus] [Acer campestre]	W8a
	[Mercurialis perennis] forests	W8f
N/A	Shadowed areas	N/A

Table 2. EUNIS classes present at River Strymon Delta at Lake Kerkini (Greece)

Class code	Class definition
G1.112	Mediterranean tall galleries (key species)
C1.32	Free floating vegetation of eutrophic waterbodies
C1.34	Rooted floating vegetation of eutrophic waterbodies
C3.5	Pioneer and ephemeral vegetation of periodically inundated shores
G1.1	Riparian woodland
E5.4	Moist or wet tall herb and fern fringes and meadows

A set of ground truth data is necessary for training the classifier for the three target classes shown in Table 1, as well as for assessing the final map accuracy. A Phase 2 habitat map composed by English Nature in 1992 (P. Williams, personal communication) following the UK National Vegetation Classification (NVC) nomenclature (Rodwell, 1992) and a field survey in May 2003 were used as ground truth data. Table 1 gives a conversion table from NVC nomenclature to EUNIS.

Selection of training samples

The pan-sharpened image is originally classified into ten classes. Subsequently, the extraction of training clusters is performed, taking into account the ground-truth data. For each class in Table 1, five training samples were selected to depict the representative pixel arrangements. Following the selection of the appropriate training clusters, the KRC is carried out. The kernel size is set at 9×9 pixels, and training clusters at 50×50 pixels. The threshold value for pairs correlation is set at 0.70.

Delta of River Strymon, Greece

Test site description

River Strymon's delta is located at Lake Kerkini, a wetland ecosystem of international importance (Ramsar Convention, NATURA 2000 proposed site, IBA, etc.) located in Northern Greece (latitude: 42°12′N, longitude: 23°09′E). Lake Kerkini is a large artificial freshwater lake created on the site of a former natural swamp, after the construction of a dam across River Strymon in 1932, primarily for flood control. The lake receives a large quantity of sediments from River Strymon. Following siltation by river sediments, which led to a loss of 61% of the lake's storage capacity, and an increase in the surface of irrigated land, it proved necessary to build a new, higher dam and a new dyke to the west in 1982. The purpose of the damming was 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 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. One of the most important ecological features of the area around the delta is the *riparian forest* and now consists mainly of species of wild willow. It is the most important habitat of the wetland not only for birds but also for reptiles, amphibians and fishes. It is the nesting and feeding habitat for many rare bird species as well as spawning grounds for fish species. Table 2 gives the classes present in the study area. Class G1.112 is the riparian forest mentioned above and is a key habitat. Classes C1.32 and C1.34 are considered as one class (C1.3), since their spectral signatures are identical.

Available data

The satellite image used for the present application was acquired on 15 June 2000 by the 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 and 4 m in the panchromatic and multispectral modes, respectively. For the purposes of our study, a sub-scene of multispectral data of about 18 km^2 centred at the delta of River Strymon is used. The four IKONOS-2 multispectral channels are tuned to detect radiation in the visible spectrum (450–530 nm centred in the blue, 520–610 nm centred in the green and 640–720 nm in the red) as well as in the near infrared spectrum (near-IR; 770–880 nm).

For the extraction of the training sets as well as validation of classification results, a habitat classification map of the year 2000, conducted using black and white orthophoto maps (aerial photography, scale: 1:5000; date: 1997; source: Hellenic Army Geographic Service) updated with field work is used.

Selection of training samples

The selection of training samples is carried out by extracting representative sample areas of same size (30×30 pixels) from each EUNIS class of Table 2. It has to be noted that the current version of KRC does not allow variable training cluster size. The training samples for KRC are extracted from the initially classified image. Following the selection of the appropriate training samples, the KRC software is executed. The kernel of 9×9 pixels is chosen in order not to deteriorate the classified image by eliminating objects of smaller size. The threshold value of the similarity index is set to 0.75.

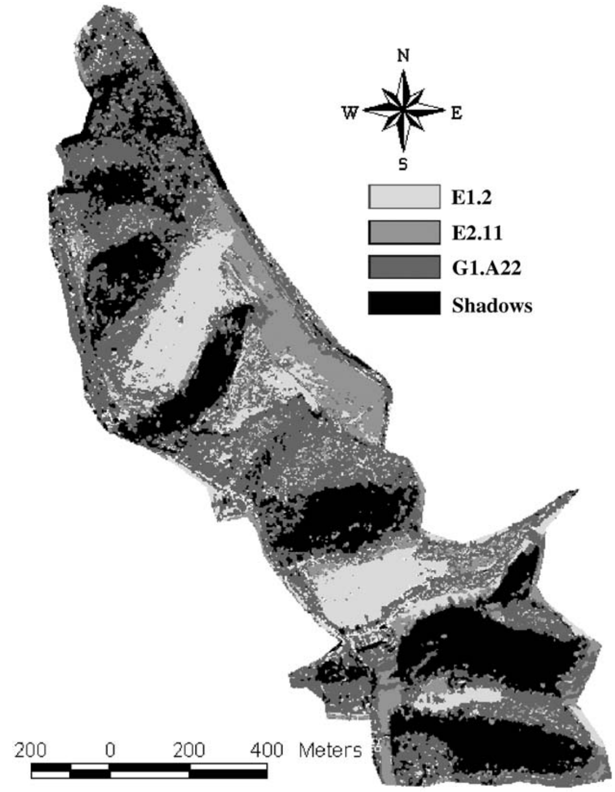

Figure 1. KRC Product in Wye Downs, UK.

Results and discussion

Wye Downs national nature reserve, UK

Map product and accuracy assessment

The classified Quickbird image over Wye Downs is presented in Fig. 1. The resulted classes appear as rather homogenous objects and the salt and pepper effect usually resulting from pixel-based classifiers when applied to VHSR images is reduced significantly. Despite the homogeneity of the classes, detailed information required at a finer working scale, such as scrub encroachment in grasslands, is still preserved. The patchiness shown mainly in class G1.A22 is the result of ground reflection due to the absence of tree foliage – a problem that would have been absent from an image from the active growing period.

In order to assess the accuracy of the produced map, one hundred points were selected across the classified image stratified according to the size of the resulted classes and randomly located within each class. The overall classification accuracy as well as the accuracy in each class are used to evaluate the performance of the method.

The mean post-classification probability, which is the first measure of the method's performance, is 82%, and is encouragingly high. The confusion matrix results are shown in Table 3. The accuracy is indeed high, especially if one takes into account the absence of tree foliage and the rather extensive shadow cover. The latter was a great problem in identifying woodland habitats since the absence of tree foliage caused a fine mosaic of shadows across woodland canopy. KRC performed very well in all identified classes as the users' accuracy of 75%, 83.3%, 77.7% and 89.3% for classes E1.2, E2.11, G1.A22 and Shadows, respectively suggests. The identification of different grassland types has been proven to be a difficult task when the classification relies on spectral information (Fuller, Groom, & Jones, 1994). The fact that KRC performs so well without using any ancillary data, such as soil or geology maps, is remarkable and reveals the potential of the method for mapping Atlantic grasslands.

The same area was also classified using an object-based method (OBM; Bock, Xofis, Rossner, Wissen, & Mitchley, 2005). Both methods performed well reaching a correct classification rate of $>80\%$ and the performance in individual classes was also good in both methods. The OBM had the advantage

Table 3. Error matrix and accuracy measures for the application of Kernel re-classification on Quickbird image*

	Reference classes					
	E1.2	E2.1	G1.A22	Shadows	Producers accuracy (%)	Users accuracy (%)
E1.2	12	2	2	0	80.0	75.0
E2.1	0	10	1	1	55.5	83.3
G1.A22	3	6	35	0	85.3	79.5
Shadows	0	0	3	25	96.1	89.2

of integrating external knowledge which made the classification of shadowed objects possible, whereas with KRC this could not be done. On the other hand, KRC gave a very good result with limited input of external knowledge and was quicker and less labour intensive than OBM. However, OBM can be applied to large areas irrespective of the existence of large homogenous areas (lacking texture), situations in which KRC fails (see below).

Sensitivity to kernel size

The effect of different kernel size on the final classification is assessed in the present study. Two different sizes are applied: kernel size of 9 and 15 pixels. All the other parameters are kept the same, namely class and training clusters and a threshold value for pairs correlation of 0.80. A subset of each of the two classified images is shown in Figs. 2(a) and (b) for kernel size of 9 and 15 pixels, respectively. The two classification products were thematically evaluated and they are discussed on the basis of the suitability of the resulted habitat maps for conservation and monitoring purposes. Large kernel size (15) tends to result in more solid classes, which is particularly obvious at points A, C and D in the two images. This effect can be beneficial in cases such as point D where the patchiness shown in the image does not really reflect the natural vegetation pattern but is rather the result of the reflection from the ground due to the date of image acquisition; mid-December when there is no foliage in the deciduous tree canopy. On the other hand, the solid classes may obscure significant information, as is the case at points A and B in the two images. At point A in Fig. 2(a) (kernel size 9), a large area is shown as covered by either E1.2 or E2.11 (grassland), however in (b) (kernel size 15) the area is shown as G1.A22 (woodland) and according to the ground truth data the former is correct. At point B the classification shown in image (b) (kernel size 15) obscures the invasion of E1.2 calcareous grassland, by G1.A22 woodland, which is of significant importance for the conservation goals of this particular area, maintaining open calcareous grassland with only limited woodland/scrub mosaics.

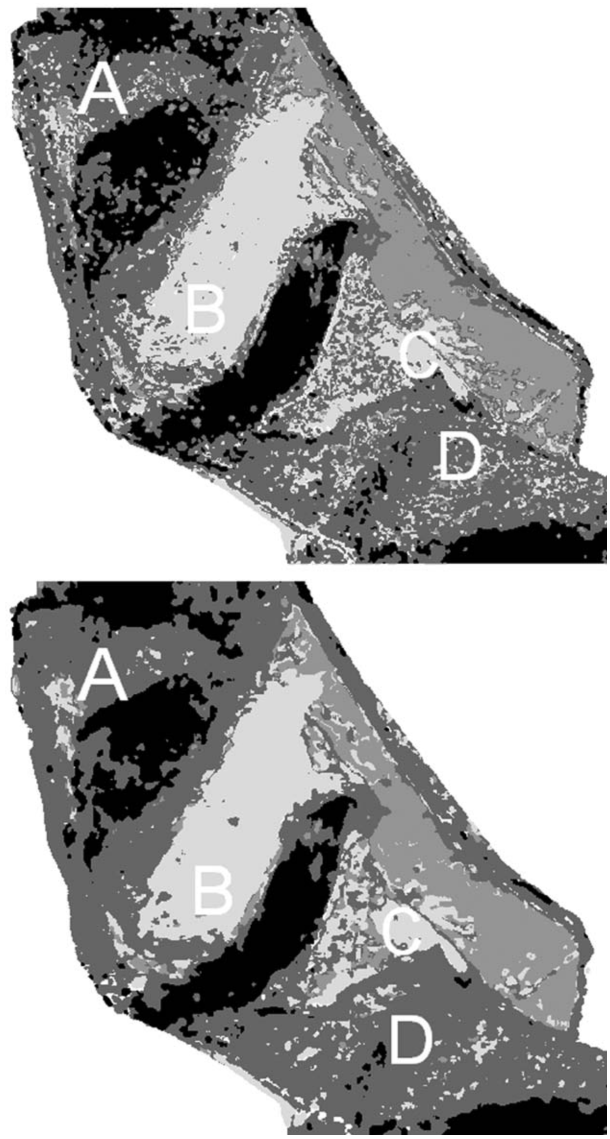

Figure 2. Subsets of the classified image using (a) kernel size 9 and (b) kernel size 15.

For this study a kernel size of 9×9 pixels was selected as the most appropriate one due mainly to the fact that it preserves information related to the invasion and subsequently degradation of the sensitive and important habitat of calcareous grasslands from a biodiversity viewpoint. If, however, the objective is to create a land use map where that level of detail is not needed then a larger kernel size resulting in homogenous classes would be more appropriate.

Delta of River Strymon, Greece

The re-classified image, which is the final product of KRC is shown in Fig. 3. In order to investigate the performance of the kernel classifier in terms of better class discrimination and overall accuracy, the confusion matrix was computed. This was based on stratified random selection of pixels and provides a comparison between the re-classified image and the ground-truth map. The confusion matrix is presented in Table 4. The overall performance is 71%. Comparison between the produced map and the ground-truth data in a pixel-by-pixel fashion gives lower overall accuracy; this is also attributed to the inclusion of transitions from homogeneous to spectrally variable areas (sometimes referred to as 'the boundary effect'; Gong, Marceau, & Howarth, 1992) as well as along the river. The latter is due to the absence of training clusters because of the object size and shape. The column 'Other reference class' of Table 4 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, G1.1 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.

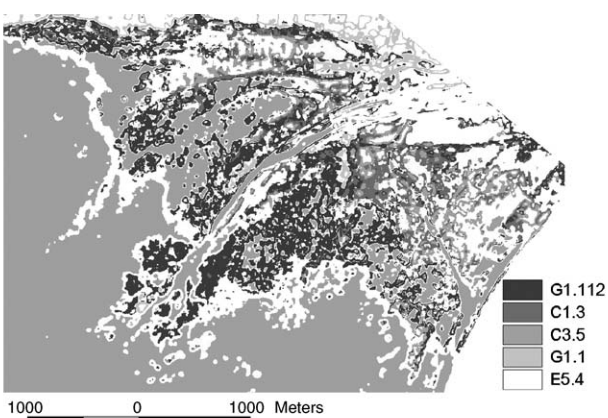

Figure 3. KRC Product for Delta of River Strymon in Lake Kerkini, Greece.

SW Toulouse – a case where KRC did not work

KRC gives valid results when the scene to be mapped contains spectral variation as well as texture. Therefore, very high spatial resolution is required. In order to exploit the limits of the approach, KRC was applied on SPOT data of a test site located in south-west of Toulouse, France. A SPOT-5 image of 29 September 2002 was used. The multispectral image had a spatial resolution of 10 m. After the initial classification was completed, training sets were defined on the classified image. However, the classes are robust and homogeneous. The extraction of appropriate training clusters for the subsequent KRC confirmed the homogeneity of the classes. Therefore, the homogeneity of the area, together with the spatial resolution of the image used (10 m), made KRC not applicable in this case.

Conclusion

This paper studies the applicability of KRC algorithm and its transferability to different spatial

Table 4. Error matrix for the assessment of Kernel based re-classification of IKONOS-2 image*

	Reference classes							
	G1.112	C1.3	C3.5	G1.1	E5.4	Other	Prod Acc (%)	Users Acc (%)
G1.112	14	2	3	3	0	1	73.7	60.9
C1.3	2	9	1	0	1	1	56.2	64.3
C3.5	2	4	35	0	0	1	89.7	83.3
G1.1	1	0	1	9	0	0	69.2	81.8
E5.4	0	1	0	1	4	4	80.0	40

resolutions and biogeographical regions. In particular, the results of KRC application to Quickbird and IKONOS very high spatial resolution images of different test sites are encouraging. The overall accuracies attained are 82% and 71%, respectively, whilst the level of class hierarchy reached ranged from EUNIS level 1 to level 5. However, the algorithm did not work for the French case study using SPOT-5 images due to the coarser resolution as well as the lack of texture in the area. It appears that the finer the spatial resolution the better the performance of the classifier. This highlights the constraint of the algorithm transferability to highly homogeneous regions and/or to the classification of satellite images of spatial resolution less than 10 m.

Different kernel sizes result in different map products. The higher the kernel size the more solid the resulting classes which may sometimes obscure information. The selection of the most appropriate size depends on the aim and future use of the output.

One of the main advantages of the method is that it is automated and therefore not labour intensive. The only stage in which the user intervenes is in the selection of the training set. On the other hand, the user does not have full control of the output product and requires additional image processing software for image display and initial classification steps. Having control on the final output might be a desirable feature in situations where the spectral and texture information is poor, e.g. shadow cover, but it may also lead to significant bias and misclassification error when the information used are either spatially or thematically inaccurate (Bock et al., 2005).

The results from this paper suggest that very high spatial resolution satellite imagery can play an increasing role in mapping and monitoring NATURA 2000 sites in the coming decades. As technology improves remote sensing methods can be cost-effective compared with alternative field survey methods when effectiveness is defined as overall map accuracy (Mumby, Green, Edwards, & Clark, 1999).

Acknowledgements

The authors wish to thank Mrs. Eleni Fitoka (Greek Biotope/Wetland Centre; EKBY) for providing the ground truth data of delta area of River Strymon. We would also like to thank Prof. Michel Gay and Mrs. Anne Jacquin (Ecole Supérieure d'Agriculture de Purpan; ESAP) for testing KRC on SPOT data. This work was funded by the SPIN (Spatial Indicators for European Nature Conservation; project web site: www.spin-project.org) research project supported by the Fifth Framework Programme (Contract No. EVG 1-CT-2000-019).

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