# A transferability study of the kernel-based reclassification algorithm for habitat delineation 

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#### Abstract

Wetland mapping using Earth observation (EO) data has proved to be a challenging task for practitioners due to the complexity in the spatial structure and composition, the wide within-class spectral variability and the absence of easily distinguishable boundaries between habitat types. Furthermore, the inherent temporal water instability of these landscapes poses an obstacle to the integration of field data with remote sensing data, which also are not acquired simultaneously at all times.

To cope with these limitations we tested the applicability of the Kernel-based reclassification (KRC) algorithm on very high spatial resolution (VHR) satellite imagery over a wetland. A composite multitemporal (i.e. dual-date) VHR WorldView-2 image consisting of spectral bands and indices derived from two images acquired during flooded and dry water conditions were employed. This dataset stresses the seasonal variations of the habitat in response to environmental changes (i.e. flooding) occurring between the two acquisition dates. Multi-temporal imagery is an important information source for fine mapping of wetlands such are river deltas. A multi-temporal approach could reveal even more specific information during the phenology of these habitats.

The methodology was applied firstly to Axios and then to Aliakmonas river deltas in Northern Greece. The results revealed an overall accuracy of $53 \%$ in the first and more complex site, and $86 \%$ in the second site.


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## Introduction

Wetlands are multiple-value systems covering approximately $4-6 \%$ of the world's terrestrial area with high ecosystem significance. Lately, they became of global concern because of the growing anthropogenic pressure and the sensitivity they demonstrate to climate change. The importance is further underpinned by the fact that the loss of wetlands, and the associated functions and values, through development is often irreversible (Mitsch and Gosselink,

[^0]2000). Furthermore, wetlands sequester and release large volumes of fixed carbon in the biosphere and therefore are potentially an important component in global climate change (Mitsch and Wu, 1995). On a global scale, the loss of biodiversity has initiated a scientific interest in species distribution, the associated environmental drivers and how they operate in different geospatial contexts (Turner et al., 2003), with most of the studies concentrating on temperate regions (Mace et al., 2005).

Efficient management and conservation of natural habitats is increasingly a topic for investigation and concern by several scientific groups during the last years (Spanhove et al., 2012). While the field is prevailed by biological and ecological oriented disciplines, Earth Observation (EO) data are progressively employed for mapping features of interest and indicators (Kerr and Ostrovsky, 2003). This has urged the need for developing methodologies based on remotely sensed data also tailored to wetland characteristics.

Nevertheless, mapping of wetlands based on EO data has proved to be a challenging task for practitioners due to the complexity in
the habitat's spatial structure and composition, the broad withinclass spectral variability and the absence of easily distinguishable boundaries between habitat types. Furthermore, the inherent spatio-temporal variability in the water content of these landscapes poses an obstacle to the integration of field data with EO data, which are not acquired simultaneously at all times. The need to investigate and establish advanced methodologies for mapping habitats based on remotely sensed data is prominent. Those application-specific methodologies combining multiple-source data are an active and vigorous topic of research. Klemas (2013) provides an overview of remote sensing of wetlands based on recent advances on sensor's resolutions, Rebelo et al. (2009) report on several recent initiatives using EO data to foster wetland inventorying and Ozesmi and Bauer (2002) summarize the literature on EO of wetlands.

With the advent of VHR sensors on-board satellites, the discrimination capacity in complex environments increases significantly. For example, WorldView-2 (WV-2), currently one of the satellite sensors with the highest spatial resolution ( 0.46 m and 1.85 m in panchromatic and multispectral bands respectively), is able to record electromagnetic radiation in 8 bands. WV-2 was launched in October 2009 as the successor of Quickbird and WorldView-1 satellites with the enhanced spectral capability of recording data in four additional bands designed for enriching multispectral analysis in vegetation studies. VHR has demonstrated to be a key factor in mapping natural habitats (Corbane et al., 2013) attaining to small wetlands mapping (e.g. Kuria et al., 2014) and small plant communities (e.g. Szantoi et al., 2013), providing information on species level (Turner et al., 2003), and identifying precisely ecosystem characteristics (Salari et al., 2014). However, the processing tools developed for medium resolution images might not provide the most accurate results, especially in cases of high land cover heterogeneity and small patch size (Smith et al., 2002), such as wetland habitats. In this mapping context, Keramitsoglou et al. (2006) applied three advanced pixel window (i.e. kernel) classifiers on VHR multispectral satellite images (IKONOS-2), namely Kernel based spatial Re-Classification (KRC), Radial Basis Function (RBF) Neural Networks (NN) and Support Vector Machines (SVM) and they report overall accuracies between $56 \%$ and $72 \%$ depending on the methodology and its parameterization (kernel size, number of fuzzy sets etc.). Furthermore and adding to the complexity of mapping evaluation, user's and producer's accuracy in wetland related studies can fluctuate significantly depending on the classes' spectral and textural characteristics. For instance Salari et al. (2014) reports accuracy between $60 \%$ and $97 \%$ when mapping land use/land cover in a tropical wetland with WorldView-2 imagery.

Along the development of purposeful algorithms, software tools with familiar interface and limited complexity are needed in order to be useful for ecologists not necessarily skilled in remote sensing science. ANAX (Advanced classification methods for inventorying and mapping protected areas using satellite imagery) is a software platform developed at the Institute for Astronomy, Astrophysics, Space Applications and Remote Sensing (IAASARS) of the National Observatory of Athens (NOA). The software has been specifically designed with the scope of creating a userfriendly interface digitizing polygon sets used for classification and validation purposes, performing unsupervised classification as well as the KRC algorithm. An informative description of ANAX is available at the MS.MONINA Tool Repository website (http://www.ms-monina.eu/tools-catalogue).

This paper focuses on the application of the KRC algorithm on ANAX platform on two neighbouring river deltas for mapping habitat types by evaluating the transferability of the methodology within a typical Mediterranean environment. The objective of this study is to demonstrate the applicability of a classifier which considers spectral and textural image characteristics from multi-temporal data with VHR. We concentrate on specific

Table 1
Habitats of interest that occur in the study areas.

| Code | Description |
| :--- | :--- |
| Natural habitat types of Community Interest (Annex I) |  |
| 1310 | Salicornia and other annuals colonizing mud and sand <br> 1410 <br> 1420 |
| Mediterranean salt meadows (Juncetalia maritimi) |  |
| 6420 | Mediterranean and thermo-Atlantic halophilous scrubs <br> (Sarcocornetea fruticosi) |
| Mediterranean tall humid grasslands of the |  |

habitats (Table 1) of a wetland in Northern Greece covering Axios and Aliakmonas river deltas, and investigate the applicability of the KRC algorithm in mapping their extent.

## Study area

The Axios and Aliakmonas river deltas (Fig. 1) are specially protected areas and sites of conservation interest of the Natura 2000 network (site codes GR12200002 and GR1220010) as well as protected by the Ramsar Convention and included in Greece's national list of Sites of Community Importance (SCI). The river deltas are part of a larger complex National Park (GR1220002) covering $336.76 \mathrm{~km}^{2}$ (source: Natura 2000 Viewer, EEA). Most of the habitats and species are protected under the Habitats Directives (HabDir, Council Directive 92/43/EEC). According to the Axios Loudias Aliakmonas Estuaries Management Authority (Axios - Loudias Aliakmonas National Park, 2013) they encompass more than 370 species including rare and threatened ones as well as one of the most important mixed heron colonies in Greece living in the riparian forest of Axios. It is a valuable habitat for a numerous animals and home to the European ground squirrel (Spermophilus citellus), the European otter (Lutra lutra) and the Hermanns' tortoise (Testudo hermanni), all threatened to extinction. It is home for more than 500 plant species including the rare Sea daffodil (Pancratium maritimum).

Due to their vicinity, Axios and Aliakmonas deltas share common habitat characteristics and main species composition. They are forming a mosaic of brackish lagoons, saline soils, extensive mudflat, saltwater and freshwater, sand dunes, rich vegetation and extensive crops. The prevailing habitat in terms of coverage is the Mediterranean and thermo-Atlantic halophilous scrubs (Sarcocornetea fruticosi), Natura 2000 code 1420 . Of specific interest is the habitat Salicornia and other annuals colonizing mud and sand 1310. The recommended strategic plan (Vareltzidou and Strixner, 2009) considers the surface of these two habitats amongst the indicators for monitoring and assessing the coastal ecosystem structure and its conservation status.

In this study we focus on the deltas as two separate areas of interest and classify the seven main detectable habitats (Table 1) based on two neighbouring satellite images. The nomenclature followed is according to the HabDir (European Council, 1992).

## Materials and methods

In this study we employ dual-date VHR imagery, a habitat delineation map from the European Space Agency's GlobWetland I project and in situ observations.

Two acquisitions of WV-2 multispectral images for each river delta were employed synergistically. The first pair of images was


Fig. 1. Natural colour RGB of the study areas depicting river Deltas Axios (left) and Aliakmonas (right).
acquired on 22 July 2011 during a morning overpass at 09:32 and contains an incomplete number of 4 bands (i.e., Blue, Green, Red and Near Infrared 1). The second overpass of WV-2 was on 9 September 2011 at 09:35 providing data in 8 bands at sensor's full capacity. Both products were delivered orthorectified at level 2A in WGS 1984 (Universal Transverse Mercator, Zone 34N) coordinate system. An investigation of the coefficient of determination ( $R^{2}$, Table 2) between the 8 bands of the September WV-2 image reveals that the correlation between the 4 missing bands of the first acquisition and adjacent bands is above 0.98 .

It is worth discussing at this point on the image acquisition dates and the corresponding seasonality of the summer months July and September during image acquisition. The flowering time of the annual Salicornia europea (1310) spans from May to October (Strid and Tan, 1997). There is a pronounced change in phenology with a change of colour from green to red at late August (Momonoki and Kamimura, 1994). The dominant species of Mediterranean and thermo-Atlantic halophilous scrubs (1420), flower from late July to November (Strid and Tan, 1997). July image corresponds to the start of the flowering time whereas September image captures the final
phenological stage of this particular habitat. Furthermore, Axios Delta is significantly covered by rice fields (Fig. 1), with rice production accounting for the $75 \%$ of total national production (Chamber of Commerce and Industry of Thessaloniki and Gecon Consulting, 2007). Rice fields depend heavily of irrigation and significantly increase the freshwater habitat in the area, especially in summer when they are still flooded and hence postpone the manifestation of the dry period. This affects the water regime of the surrounding area and thus the July image represents the flooded state of the wetland (spring season manifestation) while the September image represents the dry state of the summer.

Complementary to the satellite imagery of the underlying MS.MONINA project, two datasets were provided from the Axios Loudias Aliakmonas Estuaries Management Authority and in close collaboration with the user of this project (i.e. EKBY). The first is a set of field geo-tagged photographs depicting habitat characteristics for each class including orientation and habitat information. The second dataset consists of thematic maps produced in the framework of the new management plan (OMIKRON and ENVECO, 2012) and of the GlobWetland I programme, to support

Table 2
Correlation between the bands of WV-2 image acquired over Axios in September 2011. In bold letters the only four bands present in the image of July.

| Correlation | $\begin{aligned} & \text { Coastal } \\ & 400-450 \mathrm{~nm} \end{aligned}$ | Blue $450-510 \mathrm{~nm}$ | Green $\mathbf{5 1 0 - 5 8 0 n m}$ | Yellow $585-625 \mathrm{~nm}$ | Red <br> 630-690 nm | Red <br> edge | NIR <br> 770-895 nm | NIR2 <br> 860-1040 nm |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  | 705-745 nm |  |  |
| Coastal | 1 | 0.9988 | 0.9822 | 0.9430 | 0.9092 | 0.7512 | 0.6670 | 0.6559 |
| Blue |  | 1 | 0.9881 | 0.9547 | 0.9252 | 0.7637 | 0.6774 | 0.6667 |
| Green |  |  | 1 | 0.9866 | 0.9650 | 0.8450 | 0.7668 | 0.7577 |
| Yellow |  |  |  | 1 | 0.9933 | 0.8920 | 0.8153 | 0.8085 |
| Red |  |  |  |  | 1 | 0.8917 | 0.8126 | 0.8079 |
| Red edge |  |  |  |  |  | 1 | 0.9864 | 0.9847 |
| NIR |  |  |  |  |  |  | 1 | 0.9993 |
| NIR 2 |  |  |  |  |  |  |  | 1 |



Fig. 2. KRC example of a $5 \times 5$ pixel window applied on a $14 \times 10$ pixel image classified into 4 classes (depicted in different colours). Based on the similarity index between $5 \times 5$ window and the training adjacency event matrices, KRC will assign to each pixel the thematic habitat class for which the similarity index is maximum (Keramitsoglou et al., 2006).
inventorying, monitoring and assessing wetland ecosystems and foster the implementation of the Ramsar Convention (Jones et al., 2009). The auxiliary data were delivered in Greek Grid (Geographic Coordinate system GGRS 1987, Projection: Transverse Mercator). For reasons of consistency and interoperability, both satellite images were reprojected to the GGRS 1987 coordinate system.

## Methodology outline

We applied the KRC algorithm to an 8-band composite image from bands and indices derived from the WV-2 images representing the wet and dry conditions of Axios delta (see Table 3) and subsequently on the Aliakmonas delta dataset. The whole process was performed in the ANAX software environment.

KRC was introduced by Barnsley and Barr (1996) in an urban environment related study as an alternative to per-pixel classifiers. It is a two-step approach incorporating spectral and textural analysis of the data. First the image is transformed through unsupervised classification into a single band layer by applying the Iterative Self-Organising Data Analysis Technique Algorithm (ISODATA) developed by Tou and Gonzalez (1974). Subsequently a square kernel scans the values of adjacent pixels and calculates the adjacency event matrix which represents the spatial arrangement and frequency of the labels (Fig. 2). Based on the similarity degree of the adjacency event matrix and the template matrices produced in the training phase, KRC calculates a similarity index $\left(\Delta_{\mathrm{k}}\right)$ based on which the pixels are relabeled (Keramitsoglou et al., 2006). For a more comprehensive explanation of the KRC concept and an application on habitat classification the reader is recommended the papers of Barnsley and Barr (1996) and Keramitsoglou et al. (2006) respectively.

## Composite image

In order to maintain a sound basis for investigating the transferability and applicability of the methodology in two different sites, we replicated the procedure developed, hence the description below refers to both sites.

We first extracted for both study areas several spectral vegetation indices typically used in habitat studies (Ozesmi and Bauer, 2002), namely the Normalized Difference Vegetation Index (NDVI), Greenness, NIR (Near Infrared)/RED, LAI, first Principal Component (PC) and the NDVI difference (dNDVI) between the images before
and after the seasonal change. We identified the best index based on a correlation matrix between the empirical indices and visual interpretation of the information conveyed; we sought for characteristics which highlight the classes of interest. We concluded that the dNDVI was optimal for differentiating the classes and depicting the vegetation vigour, especially at the waterfront area. Furthermore, the bands correlation mentioned earlier was investigated (Table 2) and the individual WV-2 band layers as well as the index selected were visually evaluated for the spectral information content in regard to the habitats of interest. Based on the above, we combined the layers highlighting information on the classes of interest into an 8-band image incorporating both acquisition dates (Table 3). A corresponding image for the Aliakmonas site was compiled and the two products were used as input in the two analogous classifications.

## Selection of training samples

Habitat type identification was mainly based on floristic and phyto-sociological data; several wetland habitats are very difficult to be discriminated based solely on remotely sensed data without making use of additional field observations or measurements. To comply with these specificities and in order to generate a robust training data set, close collaboration with the user (i.e. EKBY) was established. We used the geo-tagged field photographs to identify the area depicted on the Globwetland map product and the satellite image. If an area was consistent on the photograph and the class identifiable, a polygon was drawn on the WV-2 image taking into consideration the coherency of the Globwetland map also. The total area covered by the training polygons of each class was selected proportionally to the area indicated by the Globwetland map product. Considering the complexity of the image, a few classes contain high within-class variability in the original image; for these we selected several representative training polygons representing subclasses in both the ISODATA and the original image. 28 training samples from Axios site representing the main habitat types were selected based on the georeferenced in situ photographs and maps from the Globwetland I project. Several classes exhibited variant spectral characteristics, meaning that the class clusters in the feature space had a very high separability and could not be aggregated into one spectral class. These were split into sub-categories for the classification purpose and merged in the final product. For instance, in the Axios test site, the most representative habitat type is 1420 (Mediterranean and thermo-Atlantic halophilous scrubs (Sarcocornetea fruticosi)), a habitat with significant occurrence at national and European level. It is strongly affected by the anthropogenic use applied in the area (i.e. resource management as is grazing, water management). As a result, the habitat forms a very complex pattern both because of its wide coverage that naturally creates various patterns (i.e., water patches or patches of unvegetated substrates among the vegetated area) and because of the human interventions, mainly along the riverbed where access is possible. Therefore, three subclasses had to be distinguished; (i) the vegetated part on the seasonally flooded area (upwards from the sea and along the riverbed) which was the most degraded part, (ii) the vegetated part on the low reaches of the delta, which was the less degraded part, and (iii) the big spaces of unvegetated salty crust substrate.

## Classification and accuracy assessment

Following the selection of appropriate training samples the KRC algorithm was applied. The first step was the unsupervised classification, based on which the reclassification algorithm will run; therefore this stage is of crucial importance in order to guarantee that the final result will present clear separation

Table 3
Layers of the composite image. The bands selection was based on the depiction of discernible characteristics of the habitats of interest. The NDVI difference was the empirical index which provided the additional information specifically for class 1310.

| Image | Layer | Attribute | Composite <br> image layer |
| :--- | :--- | :--- | :--- |
|  |  |  |  |
| WV-2 July 2011 | Blue band | $450-510 \mathrm{~nm}$ |  |
|  | NIR band | $770-895 \mathrm{~nm}$ | 1 |
|  | PCA | First principal component | $450-510 \mathrm{~nm}$ |
|  | Blue band | $770-895 \mathrm{~nm}$ | 4 |
| WV-2 September 2011 | NIR band | $705-745 \mathrm{~nm}$ | 4 |
|  | Red edge band | First principal component | 5 |
| Combined | PCA | NDVI $_{\text {September }}-$ NDVI $_{\text {July }}$ | 6 |



Fig. 3. Comparison of the raw (original) satellite image, the ISODATA clustering product and the KRC product over Axios delta.
of the classes of interest as well as representation of coherent and homogeneous training samples. In this study we run the ISODATA algorithm with 15 classes. After conducting iterative tests of several kernel sizes for the reclassification algorithm, we decided to use a $13 \times 13$ window size and a threshold value for pair's correlation 0.70 , a combination which provided more solid thematic clusters in the final product and the classes are appropriately large to select training sets. Following the selection of the parameters the KRC is executed. Post-processing included application of $7 \times 7$ majority filter (ERDAS Field Guide 2003) for smoothing the results and exclusion of marginal areas of no interest (agricultural areas). These two processes were performed in ERDAS Imagine 9.2 (Leica Geosystems Geospatial Imaging, LLC). Cartographic production was performed in ArcMAP 10.0 (Environmental Systems Research Institute, Inc.). A pseudocolour representation of the raw satellite image, the ISODATA clustering and the KRC products over Axios delta is presented in Fig. 3.

The same procedure was applied at the Aliakmonas delta site. We kept the classification procedure and thresholds constant so
that we can evaluate the applicability and transferability of the method from the one site to the other on sound basis.

The accuracy assessment was implemented on the basis of the contingency table as proposed by Congalton (1991). The training sites were selected from the composite image assisted by visual interpretation of the GlobWetland I product, as in the training development. Due to the seasonal changes at the area of study, marginal areas were avoided and homogeneous patches, as appear on the satellite image, were selected for delineating the polygons. The cumulative validation sets area and number of samples were equivalent to the respective training sets.

## Results

## Delta of river Axios

The classified image and the corresponding error matrix tables are presented in Fig. 4 and Table 4 respectively. The results of Axios delta revealed an overall accuracy of 53\% and user's accuracy for


Fig. 4. Classification result of the Axios delta.

Table 4
Confusion matrix illustrating the results of KRC classification on Axios delta. Numbers not in percentage denote number of pixels.

| Actual $\downarrow$ | 1310 | 1410 | 1420 | 92D0 | 6420 | 92A0 | Unveg. muddy substr. | Water (river and sea) | Sum | User's accuracy |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1310 | 29,305 | 2897 | 40,915 | 2809 | 10 | 1816 | 8473 | 3704 | 89,929 | 33\% |
| 1410 | 17,083 | 45,138 | 36,550 | 0 | 0 | 0 | 220 | 3385 | 102,376 | 44\% |
| 1420 | 28,406 | 22,501 | 360,419 | 8436 | 38,329 | 4310 | 6045 | 17,751 | 486,197 | 74\% |
| 92D0 | 2799 | 0 | 19,116 | 13,530 | 11,594 | 1240 | 2100 | 8859 | 59,238 | 23\% |
| 6420 | 137 | 0 | 756 | 143 | 21,467 | 118 | 359 | 117 | 23,097 | 93\% |
| 92A0 | 0 | 0 | 75 | 0 | 110 | 324 | 0 | 0 | 509 | 64\% |
| Unveg. muddy substr. | 750 | 0 | 28,767 | 0 | 0 | 0 | 14,322 | 0 | 43,839 | 33\% |
| Water | 22,389 | 17,784 | 1 | 1763 |  | 518 | 0 | 135,165 | 177,620 | 76\% |
| Sum | 277,075 | 88,781 | 486,972 | 26,802 | 71,703 | 8442 | 43,224 | 169,120 |  |  |
| Producer's accuracy | 11\% | 51\% | 74\% | 50\% | 30\% | 4\% | 33\% | 80\% |  |  |
| Overall accuracy: 53\% Cohen's kappa $=0.40$ |  |  |  |  |  |  |  |  |  |  |



Fig. 5. Classification result of the Aliakmonas delta.


Fig. 6. (a) The absolute area for Axios (dark grey) and Aliakmonas (light grey); and (b) the proportion of habitat and land cover types. Inner circle is for Axios and the outer for Aliakmonas.
the classes 1310,1410 and 1420 of the littoral zone $33 \%, 44 \%$ and $74 \%$ respectively. It is worth noting that the aim of this study is to focus on the aforementioned specific classes of interest. The main reason of the poor overall accuracy lays in the fact that some habitats such as 1310 and especially 92A0 (Salix alba and Populus alba galleries) are not abundant and training polygons are difficult to be selected adequately to apply a classifier which derives textural characteristics from the image. For instance 92A0 covers only a very small area of the image and the class unvegetated muddy substrate is mainly thin slivers attached to the class 1310. Hence producer's accuracy is very low ( $4 \%$ and $33 \%$ respectively) which lowers the overall accuracy; this is indicative of the fact that a few of the actual 92A0 patches are classified correctly as such.

Class 1310 (Salicornia and other annuals colonizing mud and sand) shows a low user's accuracy (i.e. 33\%). We reckon that this is attributed to the fact of selecting a large kernel size for maintaining solid classes over space, which is not in favour of classes appearing as slivers between homogeneous classes and covering relatively small areas from the image (Figs. 4 and 6). Similar accuracy is found also in the 'Unvegetated muddy substrate' class of similar spatial characteristics. It is, however, worth noting that a sub-class of 1310 (Salicornia and other annuals colonizing mud and sand) is highlighted in the dNDVI index, probably because of the muddy form that this class can take. Nevertheless, the detection of small vegetation organisms in a mixed environment (mud and sand) can be easily confused, depending on the kernel size of the KRC, with other classes.

## Delta of river Aliakmonas

The respective map product and error matrix for Aliakmonas delta are presented in Fig. 5 and Table 5. The accuracy for the classes
following the same methodology as in Axios habitat was 82\%, 94\% and $89 \%$ respectively, while the overall accuracy was $86 \%$. All in all, KRC performs very well in this test area.

Two classes from the former test site were not included in the Aliakmonas case. First, the 'Unvegetated muddy substrate' class was not found in this delta. Secondly, due to the elongated geometry of the habitat 72A0 it was not possible to acquire a sufficient training sample in the Aliakmonas delta. This constraint is associated with the prerequisite of the kernel based reclassification algorithm which requires training samples at least equal to the kernel. Finally, when taking training samples from the only pure area of 72A0 in the image, the result was confusing and the overall accuracy was significantly decreased. Therefore we proceeded to ignore these two habitats in the classification and any remaining areas with 72 A 0 presence are considered misclassified.

A comparison between ANAX classification and the reference map of GlobWetland I project reveals that areas of habitats 1410 and 1310 are not always properly distinguished. Furthermore, it is important to remark that according to the reference map there are indicated areas of mixed habitats 1410 and 1310 , which means that some patches contain both habitats, a class which we have not considered in our classification scheme. Therefore, error between these two classes is a direct consequence of not considering mixed classes in the classification scheme. Additionally, it is anticipated that these two classes are intertwined and differentiation with sharp boundaries might not be feasible. In particular, 1410 (Mediterranean salt meadows (Juncetalia maritimi), occur in less wet areas, where only for a very short period there is some inundation or there is not at all and normally in higher positions, whilst 1310 (Salicornia and other annuals colonizing mud and sand) occur in periodically inundated areas. A separate classification of the 1310

Table 5
Confusion matrix illustrating the results of the KRC algorithm on Aliakmonas delta. Numbers not in percentage denote pixels.

| Actual $\downarrow$ | 1310 | 1410 | 1420 | 92D0 | 92A0 | Water (river and sea) | Sum | User's accuracy |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1310 | 14,175 | 3191 | 0 | 0 | 0 | 0 | 17,366 | 81.63\% |
| 1410 | 1439 | 21,795 | 0 | 0 | 0 | 0 | 23,234 | 93.81\% |
| 1420 | 496 | 0 | 18,883 | 1644 | 100 | 0 | 21,123 | 89.40\% |
| 92D0 | 0 | 0 | 1360 | 8345 | 2640 | 0 | 12,345 | 67.60\% |
| 92A0 | 0 | 0 | 61 | 2727 | 5505 | 0 | 8293 | 66.38\% |
| Water | 2366 | 100 | 78 | 157 | 68 | 34,969 | 37,738 | 92.66\% |
| Sum | 18,476 | 25,086 | 20,382 | 12,873 | 8313 | 34,969 |  |  |
| Producer's accuracy | 76.72\% | 86.88\% | 92.65\% | 64.83\% | 66.22\% | 100.00\% |  |  |
| Overall accuracy: 86\% |  |  |  |  |  |  |  |  |
| Cohen's kappa $=0.83$ |  |  |  |  |  |  |  |  |

habitat based on the seasonal differences could probably give a more accurate product for the specific habitat due to its dynamic temporal nature, while 1410 habitat might be differentiated from 1310 based on water content information from one image. This stresses the dependence of some of the classes on the inundation level, a change which can be tracked only with multi-temporal data.

In conclusion, the methodology developed performs satisfactorily when transferred to the neighbouring site. It appears that ANAX classifies quite well 1420 and 1410 with users and producers' accuracies ranging from $87 \%$ to $94 \%$. However, 1410 and 1310 may be confused, and pixels composed of these two habitats may appear erroneously.

## Discussion

Wetland habitat types are mixed, and each one may appear with various spectral signatures; this is due to complexity in their spatial structure and in their composition. For instance, different species can be present in different locations of the same habitat type and water presence can also vary seasonally and depend on the micro-relief. To address these specificities it is advisable that an image analyst is trained to photo interpret the image and collects additional ground truth data in order to decide, in collaboration with the user, on the appropriate subclasses that each habitat type should be further analyzed. At the stage of the classification, the most critical factor is the selection of training sets before and after the summer of the same year, when flooding is dissimilar. This approach offers the possibility to detect seasonal variations of wetland environment and is highlighted in this application with the inclusion of the dNDVI index in the image composite. By constructing a composite image based on dual imagery, ad-hoc information in wetland specific studies is made accessible.

The sub-analysis adopted for large classes (e.g. 1420) with different phenology increases the processing time, but allows further spatial analysis in a GIS system which would be very useful in monitoring conservation status; for instance certain spatial indicators could be measured that help to translate the ratios of depredated and non-depredated areas, the density of vegetated areas or the density of unvegetated areas. These results suggest that the KRC algorithm applied to dual date WV-2 satellite imagery covering seasonal flooding, can support monitoring of Mediterranean wetlands to an extend depending on the environmental complexity. The KRC algorithm incorporates spectral and textural information analysis and is a robust classifier when applied to spatially VHR imagery for complex problems as in this wetland. The classifier performs better in the river delta comprising of fewer classes than in an adjacent river delta with more complex habitat structure, indicating that the applicability of the method depends highly on the complexity of the scene. Key information for wetland mapping is provided by the seasonal changes of the habitats, which can be identified from images acquired at the low and high water level.

## Conclusions

This paper reports on the outcome of the kernel-based reclassification algorithm (KRC) applied to the Axios and the neighbouring Aliakmonas deltas using ANAX, a software platform able to perform training, classification and accuracy assessment. The applicability and transferability of the algorithm have been evaluated. On the more complex Axios delta, we obtained an overall accuracy of $53 \%$ and user's accuracy for the three main classes of the littoral zone $33 \%, 44 \%$ and $74 \%$ for the classes 1310,1410 and 1420 , respectively. On the Aliakmonas delta, a simpler classification problem consisting of seven classes only, we obtained an overall accuracy of $86 \%$, and accuracy of $82 \%, 94 \%$ and $89 \%$ for the three main classes 1310 , 1410 and 1420 , respectively.

The results of this study corroborate the results from previous studies (e.g., Keramitsoglou et al., 2005). In the earlier work KRC was applied to IKONOS 10 m spatial resolution single date imagery of Lake Kerkini. The present work has shown progress by using dualdate WV 1.85 m spatial resolution imagery with enhanced spectral information and a new user-friendly software environment for the classification of highly complex wetlands. This study further suggests that dual-date imagery can provide accurate information in wetland habitat mapping in the framework of Natura 2000 monitoring schemes. A multi-temporal approach could reveal more specific information during the phenology of these habitats.

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## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jag.2014.11.002.

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