Integrated IR-MAD and OBIA for supervised change detection: The case study of Polifitos Dam in Greece

Ch. Z. Pasiakou*[1], M. D. Tsakiri - Strati[2], S. Siachalou[3] and G. Doxani[4]

1 PhD Candidate, 2 Professor, 3 PhD Candidate, 4 Dr Engineer
Aristotle University of Thessaloniki, School of Rural & Surveying Engineering,
Department of Cadastre Photogrammetry & Cartography, Greece

Abstract: The environment of inland water bodies (lakes, rivers and reservoirs) plays major role in the economy of a country by sustaining Agriculture, Farming, Water supply, Tourism, Industrial development and Energy generation. In addition, it forms an environment with high ecological and aesthetic value, which must be monitored and protected. Simultaneously, all the above types of human activities are the causes of a significant variation in water level of the lakes, the rivers and the reservoirs, as well as the land use variations of the surrounding area. The water management, from antiquity to today, is a major issue as an asset necessary for survival and human service well as other water supplies, which are depletable in relation to geographic space and time. Therefore, securing the sufficient quantities of water is catered for every modern country. The sustainable management of inland water body ecosystems requires specialized knowledge. Remote sensing technology can become a valuable tool for obtaining information on the processes taking in the environment of Inland water bodies. Remote sensing methodologies can manage multispectral and multitemporal image data of the Earth and to provide information on changes of land use and in the aquatic environment in relation to differences in volume, quality and depth of water.

The objective of this study was the change detection of the reservoir water level and the land uses of the surrounding area of the Polifitos Dam, by applying the proposed improvement of unsupervised iteratively reweighted multivariate alteration detection (IR-MAD) method. In particular, this automatic unsupervised change detection technique that is implemented on multispectral bitemporal satellite images was improved by obia classification of the IR-MAD result image, with the change types. Specifically, the iteratively reweighted multivariate alteration detection approach is an automatic unsupervised methodology and the IR-MAD output images represent the different change types. For the handling of meaning of change information and addressing the numerical problems in IR-MAD algorithm, a further processing of IR-MAD components were performed through an object oriented classification scheme. The implementation of this application was based on multispectral images XS of Spot satellite, acquired in 1998 and AVNIR-2 image of satellite Alos, acquired in 2007, which were rectified geometric but, because of IR-MAD methodology which was applied, there was no need for their radiometric correction. The aim of this presentation was the improvement of the IR-MAD automatic unsupervised change detection method, which was implemented on bitemporal satellite imagery, to supervised change detection, and the evaluation of the results by obia post-classification.

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1. Introduction

Humans have built dams and impoundments for various purposes, including flood control, water supply, irrigation, recreation and hydropower. Dams and reservoirs play an important role in the control and management of water resources. Undoubtedly, mitigating floods, securing water supplies, and providing hydropower have benefited human societies in many ways, allowing for improved human health, expanded food production and economic growth. (Lehner et al., 2011). Approximately 70% of the world's rivers are modified by large dams and reservoirs constructed for hydropower generation, seasonal flood control, irrigation, and drinking water (Zhao et al.,2013, Kjaerland, 2007, Kummu and Varis, 2007). Monitoring the status of the water reservoir in the dam is critical because it is an important life support, recreational, commercial and aesthetic resource to humans (Yaseen and Noori, 2013).

Remote sensing is a valuable tool for monitoring, mapping, and inventorying various resources (Zhang et al., 2010, Benjankar et al., 2012) because of its high spatial and temporal resolution and the consistency of information available for regional analysis (Zhao et al.,2013). Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh 1989). Timely and accurate change detection of Earth's surface features provides the foundation for better understanding relationships and interactions between human and natural phenomena to better manage and use resources. In general, change detection involves the application of multi-temporal datasets to quantitatively analyze the temporal effects of the phenomenon (Lu et al. 2004). Land-cover change detection has been a focus of great interest and research for decades. Many applications require change information to identify the magnitude, direction and rate of land-cover change (Lu et al. 2005).

According to recently studies, automatic or not change detection techniques are used for the motoring of the environment of inland water bodies (lakes, rivers and reservoirs). The main idea of the researchers is concentrated on the methodologies for detecting land cover changes was based on the comparison between satellite images taken o different dates. (Zhao et al.,2013, Zhao and Shepherd, 2012, Zhang et al., 2009, Bedini et all, 2008, Owor et al., 2007, Lu et al. 2005, Pereira, 2004 etc)

In this paper, the iteratively re-weighted multivariate alteration detection (IR-MAD) was applied on the images for the detection of changes and an object oriented classification scheme was introduced for the labelling of the changes of interest. For this purpose an object-based classification framework is introduced for the automated monitoring of changes in inland areas from multi-temporal imagery data. The main aim of this research was the improvement of the IR-MAD automatic unsupervised change detection method by obia post-classification.

2. Methodology

Change detection has always been an important application for remote sensing data. It may be defined as the analysis of two or more images of the same area but acquired at different times in order to identify significant changes of or at the earth's surface. Methods analysing difference images and classification-based approaches, such as Iteratively Re-weighted Multivariate Alteration Detection (IR-MAD). All these approaches have in common that they compare corresponding image pixels of different acquisition times. However, due to the increased spatial resolution of remote imaging sensors, the aggregation of similar neighbouring pixels into homogeneous objects has become more and more popular (Listner and Niemeyer, 2011). Significant changes can then explicitly be analysed and interpreted by object-oriented approaches using high-resolution satellite imagery. Analysing satellite image data in an object-oriented way generally gives the possibility to involve specific knowledge in the classification or recognition process (Niemeyer and Canty, 2003). In the present work, the IR-MAD Transformation is implemented and enhanced with a supervised, object-oriented post-classification of change images carried out with the image analysis system eCognition. This unsupervised change detection and classification procedure based on object features is performed for the handling of meaning of change information and addressing the numerical problems in IR-MAD algorithm.

2.1 IR-MAD Transformation

MAD Transformation is a change detection technique between two multispectral images covering the same geographical area acquired at different date. The name chosen for the transformation, multivariate alteration detection (MAD), is due to the application in change detection in remote sensing. The MAD variates are orthogonal (uncorrelated) and invariant under affine transformations each other (Nielsen et all, 1998) and each represents different information. The main idea is that areas with small changes or is appeared with zero or low absolute values and areas with large changes is appeared with large absolute values in the transformed image (Nielsen, 1994).

In order to mask out the change pixels in a bitemporal scene, we first form linear combinations of the intensities for all N channels in the two images, acquired at times t1 and t2. Representing the intensities by the random vectors F and G, respectively, we have

$$U = a^T F = a1F1 + a2F2 + \ldots + aNFN$$
$$V = b^T G = b1G1 + b2G2 + \ldots + bNGN \text{ ,}$$

where a and b are constant vectors. Nielsen et al. suggest determining the transformation coefficients so that the positive correlation between U and V is minimized.

This means that the difference image U–V will show maximum spread in its pixel intensities. Specifically, we seek linear combinations such that

$$Var(U - V) = Var(U) + Var(V) - 2Cov(U, V) \Rightarrow \max \tag{1}$$

subject to the constraints

$$Var(U) = Var(V) = 1 \tag{2}$$

and with $Cov(U, V) > 0$.

Nielsen et al. (1998) refer to the N difference components

$$MADi = D = Ui - Vi = a_i^T F - b_i^T G, \quad \mathrm{i} = 1, \ldots\ldots, \mathrm{N} \tag{3}$$

as the multivariate alteration detection (MAD) components of the combined bitemporal image.

The quantities $a_i^T F$ and $b_i^T G$ are called canonical variates.

The MAD variates are orthogonal (uncorrelated) and invariant under affine transformations each other (Nielsen and Conradsen, 1997). This means that they are not sensitive, for example, to the offsets or gain settings of a measuring device, or to radiometric and atmospheric correction schemes that show a linear relationship with brightness counts. The multivariate alteration detection (MAD) transformation gives an optimal (in the sense of maximal variance) detection of alterations (differences, changes) from one scene to the other in all spectral channels simultaneously. The transformation is invariant to linear scaling. It also provides a statistical analysis and it offers an interpretation of the nature of the alterations.

The MAD transformation can be used iteratively and is called iteratively re-weighted multivariate alteration detection (IR-MAD) transformation. The IR-MAD method is proving to be very successful for multispectral change detection and automatic radiometric normalization applications in remote sensing. (Canty et all, 2004), (Canty and Nielsen, 2005). This method can be used to detect outliers (such as drop-outs) and in a second iteration, it can be used to perform the actual change detection after appropriate action on the outliers. Thus, radiometric normalization of imagery is important for many other applications, such as mosaicking, tracking vegetation indices over time, supervised and unsupervised land cover classification, etc. (Canty and Nielsen, 2008)

2.2 Decision thresholds for IR-MAD components

The decision thresholds for the change pixels could be set in terms of standard deviations about the mean for each MAD component. Regarding automation a probability mixture model was applied to the MAD variates based on a simple EM algorithm to determine automatically the density functions for the change and no-change pixels and thence the optimal decision thresholds for discriminating change and no-change pixels. The mixture-model procedure was proposed by Canty (Canty, 2005, 2007).

It is required to distinguish the change from no-change pixels of MAD components. Since the MAD components are approximately normally distributed about zero and uncorrelated, decision thresholds for change or no change pixels can be set in terms of standard deviations about the mean for each component separately. This can be done arbitrarily, for example by saying that all pixels in a MAD component whose intensities are within ±2σMAD are no-change pixels (Canty, 2005). The following mixture model for a random variable X representing one of the MAD components:

$$p(x) = p(x \mid NC)p(NC) + p(x \mid C-)p(C-) + p(x \mid C+)p(C+)$$

where C+, C− and NC denote positive change, negative change and no change (figure 1).

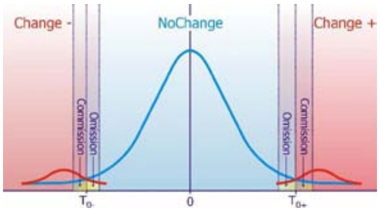


Figure 1: *Probability mixture model for MAD components (Canty, 2005).*

2.3 Object-oriented classification and change detection

Object-based image analysis approaches for the interpretation of aerial and satellite images can be subdivided into approaches that use object-oriented classification rules (Walter, 2005). OBIA comprises two parts: multi-resolution segmentation and context-based classification. Multi-resolution segmentation allows generating image objects on an arbitrary number of scales taking into account criteria of homogeneity in colour and shape. Particularly, it combines segmentation and spatial, spectral and geographic information along with analyst experience with image-objects in order to model geographic entities (Chen et al., 2012, Blaschke and Hay 2001, Hay and Castilla 2008). Image-objects are groups of pixels in the image that represent meaningful objects in the scene. Then, the image objects can then be described and classified by an extensive variety of features that include colour, texture, form, and context properties in several forms (Chen et al., 2012). In addition, classification rules are created by means of decision trees and each object is assigned to the class that fits with the rules or conditions, created as a function of the values of the features. A feature of OBCD is to extract meaningful image-objects by segmenting (two or more) input remote-sensing images, which is consistent with the original notion of using change detection to identify differences in the state of an observed ‘object or phenomenon’ (Singh 1989).

2.4 IR-MAD by Object-oriented classification scheme

The IR-MAD transformation is an effective approach to indicate the changed areas, but, similar to other statistical change detection methods, they do not identify the exact type of change automatically. The implementation of unsupervised (Canty, 2007) or supervised (Niemeyer et al., 2007; Nussbaum and Menz, 2008) classification methods on output images is essential to label the type of changes (Doxani et al., 2010).

In this study, an object-oriented classification approach could improve the results of IR-MAD transformation. Initially, the chessboard segmentation of the IR-MAD variates was applied , by setting the object size equal to a pixel, enabled the use of the thresholds. Two change classes were defined for each MAD component, one class for the decreased grey values (MAD-) and another for the increased ones (MAD+). The visual interpretation of MAD images facilitated the association of MAD classes with the corresponding changes of land cover types. The visual interpretation of MAD images facilitated the association of MAD classes with the corresponding changes of land cover types (Doxani et al., 2010).

3. Study area and data

The study area was the artificial lake wetland Polifitos of Aliakmon River. The artificial lake was created simultaneously with the Polifitos’s dam in 1974 and constructed with a focus on hydropower. The lake is just 5 km from Servia Kozanis of Western Macedonia in Greece and covers an area 74 km^2. Public Power Corporation S.A. is the holder of the lake, which has the right to use water only, while the Ministry of Planning and Environment has the overall responsibility of its management.

The multispectral imagery data of the current study were a XS image (Spot-3) acquired on 3th July 1998 (figure 2a) and a AVNIR-2 image (ALOS) acquired on 19th July 2007 (figure 2b).

The multispectral images must have the same reference system, geographical area, spatial and spectral analysis and the same dimensions: the same number of pixel/line and pixel/column. These conditions apply to all change detection techniques, such as the Algebraic methods, comparing two classified images etc. Towards the application of change detection methods, only the corresponding bands of each image were selected. Thus, the change detection was accomplished based on the spectral information of Green, Red and Nir band.

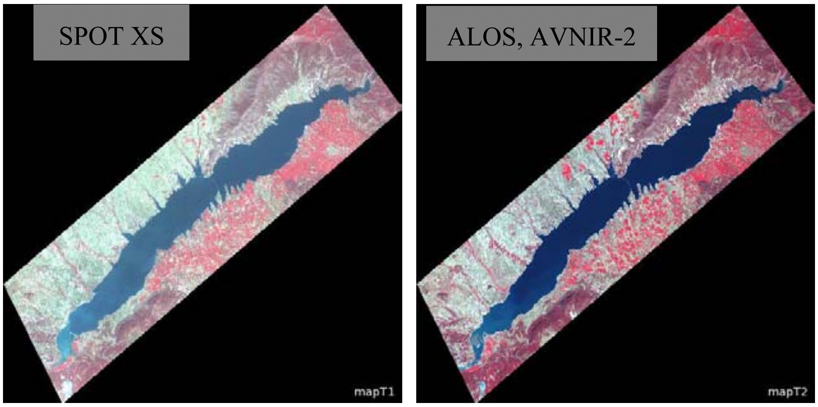


Figure 2: a) The multispectral image (XS) from SPOT-3 High Resolution Visible (HRV), 3/7/1998, spatial resolution 20m, b) The multispectral image AVNIR-2 from ALOS, 19/7/2007, spatial resolution 10m

At the image pre-processing, the satellite sensor images were orthorectified and geometrically corrected to the coordinate system using Greek Geodetic System of Reference (Projection Type: Transverse Mercator, Spheroid name: GRS 1980 and datum: EGSA87). Image-to-image registration is necessary in order to succeed the accurate correspondence of the pixels of the imagery data.

4. Investigations

4.1 Application of MAD Transformation and results

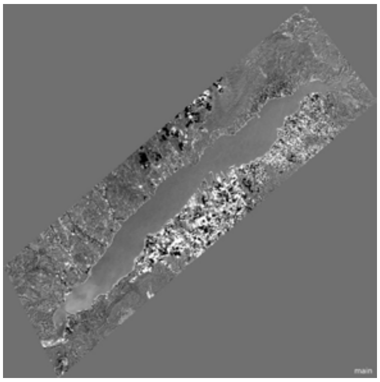
The transformation IR-MAD was applied on multitemporal data of 3/7/1998 and 19/7/2007 and it consisted of the three bands of SPOT XS (R, G, NIR) and the respective bands of ALOS, AVNIR-2. The results of the new MAD components (three components) reflected the differences between the original images.

Below an interpretation was given of the visual and numerical results from the computations of the MAD components. The first iteration was most important and that the correlations increase steadily, corresponding to the gradual exclusion of the change observations from the canonical correlation analysis. Most of the changes took place within 4-5 iterations. (Nielsen and Canty, 2008).

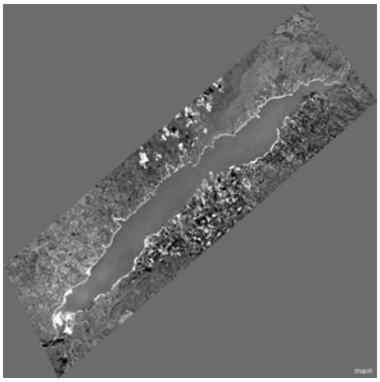
The MAD variates are orthogonal (uncorrelated) and invariant under affine transformations each other (Nielsen and Conradsen, 1997) and they show some differences that are not highlighted in another. Figure 3 shows the IRMAD variates and all three MADs (MAD1, 2 and 3 in red, green and blue). Areas with very high and very low values in MAD1 were the areas of maximal change, and the sign of MAD1 indicates the "direction" of change.

The MAD components can be qualitatively interpreted in two ways:

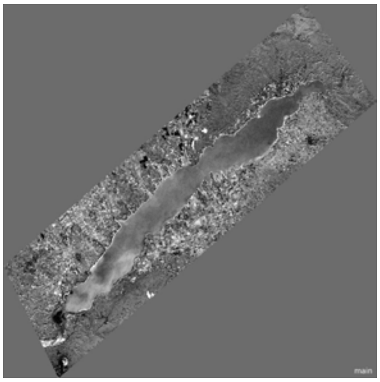
- Visual interpretation, depending on the size and direction of change. Maximum change areas are shown as white (positive changes) and black (negative changes) pixels. Gray areas indicate no change (Nielsen and Canty, 2008).
- The correlations between the original variables and the MAD variates.



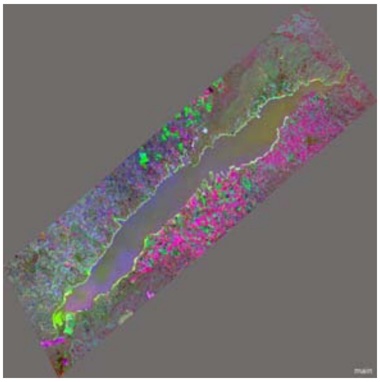
a) IR - MAD 1



b) IR - MAD 2



c) IR - MAD 3



d) IR – MAD (RGB)

Figure 3: *a), b), c) IR - MAD variates of 1998-2007 period, d) IR - MAD 1, 2 and 3 in red, green and blue*

According to visual interpretation, the IR-MAD1 variate gived emphasis on vegetation’s increasing, while IR-MAD2 on vegetation’s decreasing. The IR-MAD3 variate showed more image noise.

The change pixels were again detected by using IR-MAD transformation and the decision thresholds for the change pixels were set by applying the probability mixture model to the MAD variates. Figures 4 shows the resulting MAD variates with automatic threshold, coloured pixels indicate changes while grey pixels represent.

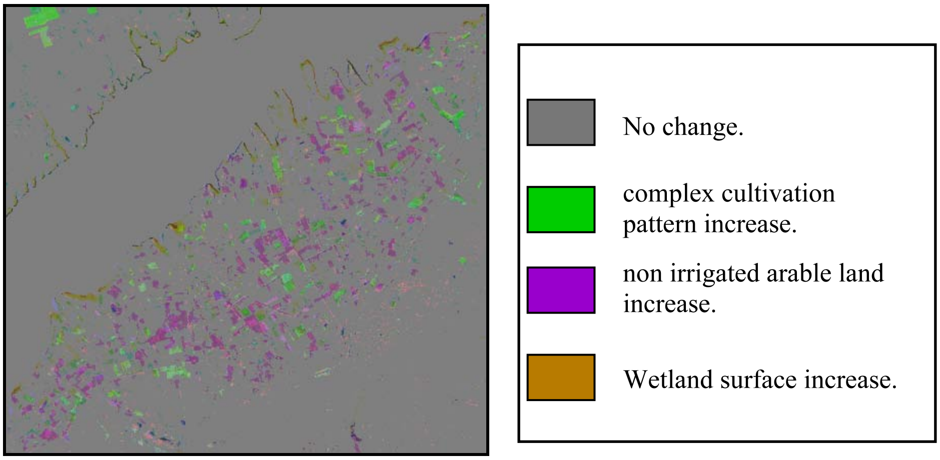


Figure 4: *IR - MAD THRESHOLD variates of 1998-2007 period.*

4.2 Application of IR-MAD by Object-oriented classification scheme and results

After the implementation of IR-MAD transformation, the thresholds for the IR-MAD image was defined automatically by EM algorithm and the change/no-change areas were identified. Below, an object oriented classification scheme was developed through visual interpretation of IR-MAD variates. Specifically the class IR-MAD1+, represented the alterations to non irrigated arable land's increase, the class IR-MAD1-, represented the alterations to complex cultivation pattern's increase and the class IR-MAD2+, represented the alterations to wetland surface increase. The IR-MAD3 variate showed more image noise. Final classification results are given in Figure 5.

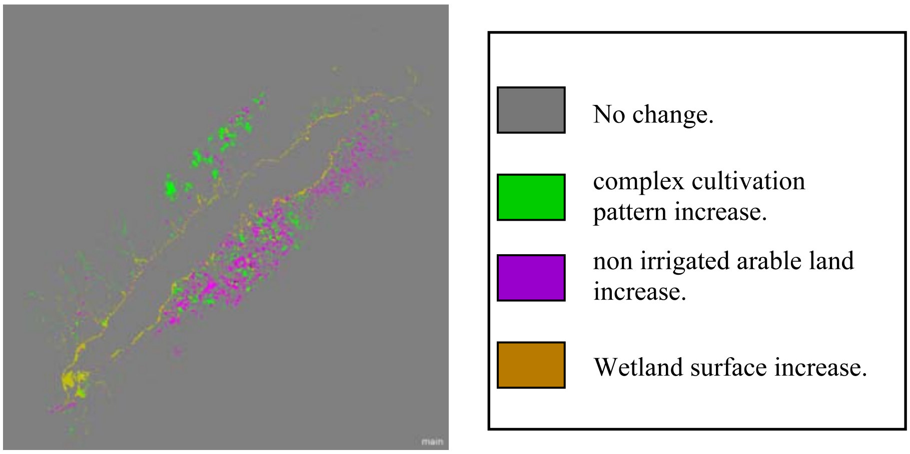


Figure 5: *Classification result for the object-oriented change detection using MAD components.*

Below are some examples of the visual interpretation of the original images, which were taken part in the transformation of IR-MAD and the final image IR-MAD, which shows the differences that emerged with various colours, e.g. to increase and decrease of vegetation in the study area (figures 6,7).

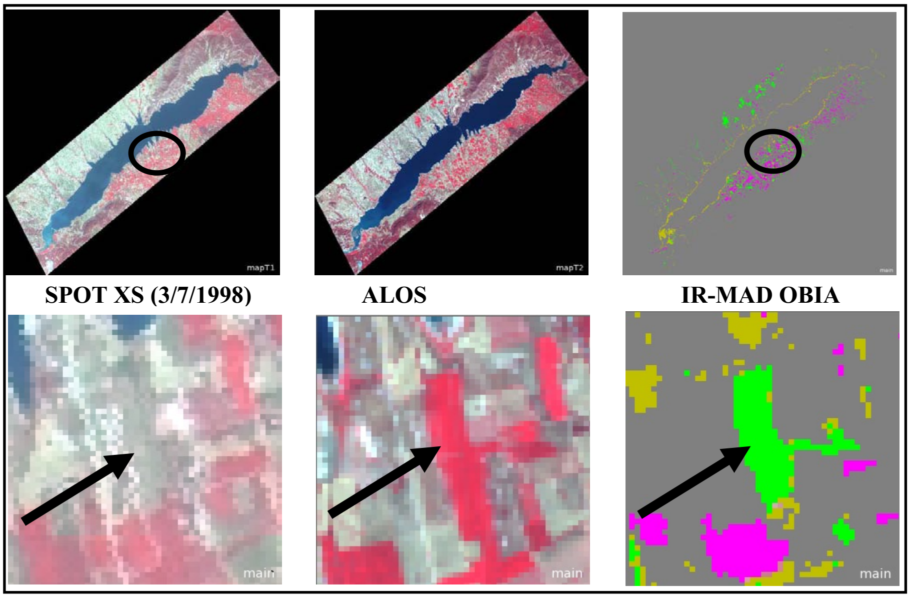


Figure 6: *Change detection, vegetation's increase.*

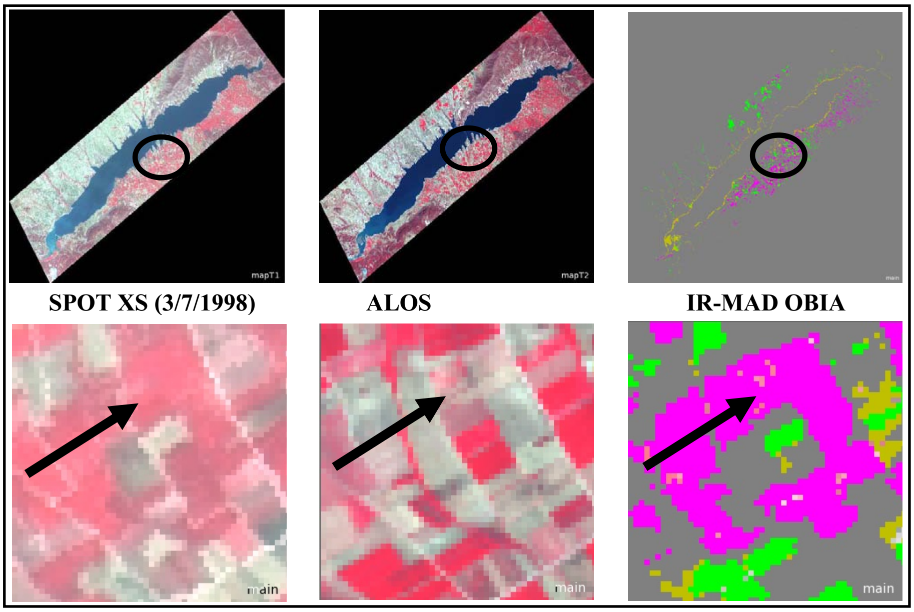


Figure 7: *Change detection, vegetation's decrease.*

4.3 Comparison results of IR-MAD transformation with change detection map of obia post classification

This section evaluates and compares the results of object-oriented change detection using MAD components with the final change detection map by object-oriented post classification, which is the result of the comparison of classified images were acquired at different dates.

For comparison of classified images, the land cover categories were identified and mapped on satellite images, according to the program Corine Land Cover, 2000. The basic classes, which were mapped, were non irrigated arable land, complex cultivation pattern and wetland surface (table 2). The summary statistics of the classification results of the classified images are presented in table 1.

Table 1: *Statistics of the obia post classification results*

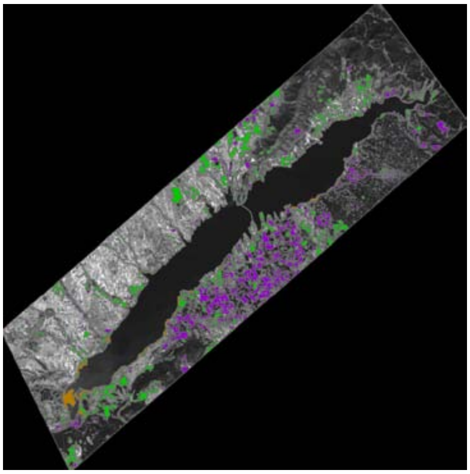
	Overall Accuracy	Kappa coefficient
Spot XS (%)	66.66	0.48
Alos, AVNIR-2 (%)	91.19	0.89

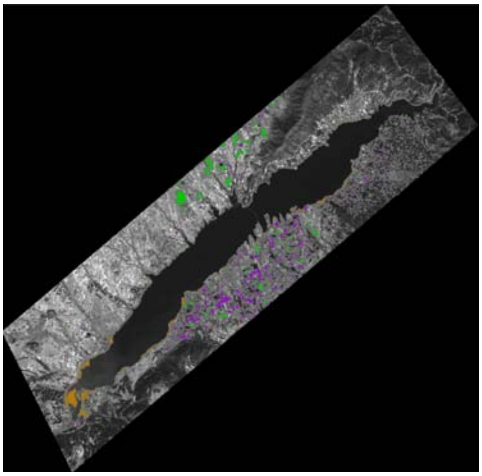
Table 2: *Results of change detection techniques. (Period 1998 to 2007)*

	Comparison of classified images (change detection map)	The transformation IR-MAD by OBIA post-classification
Increase complex cultivation pattern (objects)	1698	1609
Increase non irrigated arable land (objects)	1576	1868
wetland surface increase (objects)	720	3032

Below, rule sets were developed for mapping and monitoring riparian zone land-cover classes within two images and many parameters are used, such as indices (NDVI, LSWI). The final change detection map of obia post classification for the period (1998-2007) shows the changes in the study area (figures 8).

For visual and numerical comparison of the final results of the change detection techniques, the land cover classes, which were common and identify changes, were separated respectively. Changes were shown in different colors. Green pixels represent complex cultivation pattern's increase, while purple pixels represent non irrigated arable land's increase and yellow pixels represent wetland surface increase (table 2).





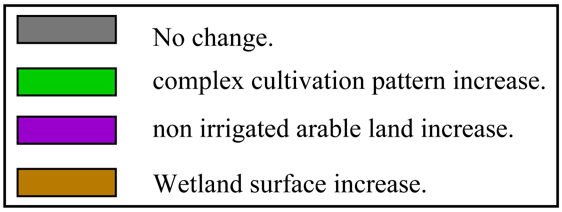


Figure 8: *Change detection map of obia post classification,*

Figure 9: *Object-oriented change detection using MAD components*

The evaluation results of IR-MAD transformation by OBIA post-classification in the case of original data demonstrated that the majority of changes are fully or partly detected. Some objects were classified incorrectly as changed wetland surface, while are change of non irrigated arable land's increase. They are real changes, but their segregation from non irrigated arable land is a difficult task because of the similar spectral and geometric attributes. By visual comparison with the change detection map of classified images, the IR-MAD was given more satisfied results. Some objects in classified image Spot XS were classified incorrectly as complex cultivation pattern instead of non irrigated arable land and as a result the final change detection map detected false changes.

5. Wetland surface increase

A negative position of intervention in nature, by creating artificial lakes, is the change in water levels in lakes, because of the hydropower factories. Specifically, the artificial lake wetland Polifitos began to lose much water, because of waterless in recent years. Results show an increase of the wetland surface and an erosive situation in many parts of artificial lake wetland Polifitos. This could be a natural phenomenon, but it could be observed.

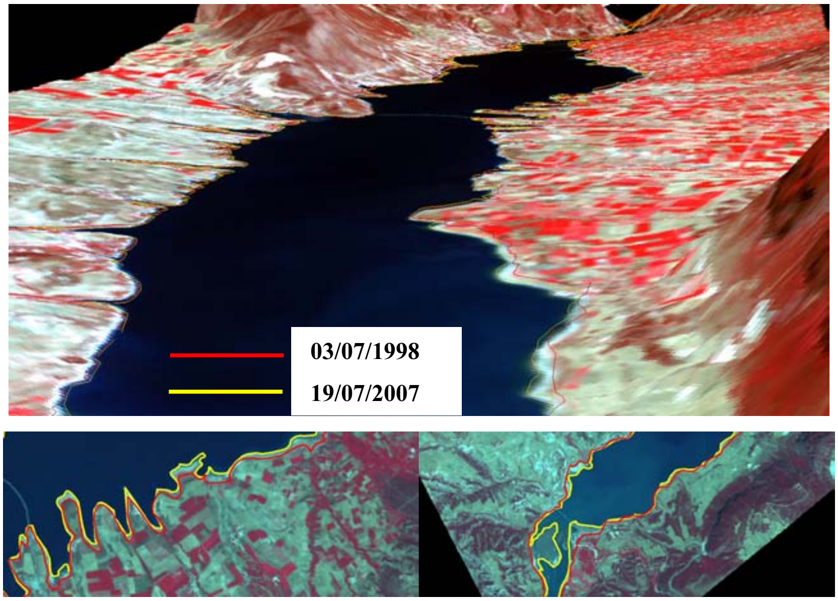


Figure 9: *Representation of lake surface polygons relative to the dataset of images available for the period 1998 to 2007.*

6. Conclusions

The new statistical transformation IR-MAD (Iteratively Re-weighted Multivariate Alteration Detection) has significant potential in remote sensing. This method is an automated processing and is proving to be very successful for multispectral change detection and automatic radiometric normalization applications in remote sensing. (Canty et all, 2004), (Canty and Nielsen, 2005). Therefore, the radiometric normalization of temporal images can be omitted. Thus, the multivariate alteration detection (MAD) transformation gives an optimal detection of alterations (differences, changes) from one scene to the other in all spectral channels simultaneously, while the other methods use their respective bands of the two temporal images per pairs.

The objective of this paper was to implement the proposed improvement of unsupervised iteratively reweighted multivariate alteration detection (IR-MAD) method. A disadvantage is that the MAD transformation detects the changes of study area, but it does not display the nature of the changes and it is demanded visual interpretation of MAD variates. For the handling of meaning of change information and addressing the numerical problems in IR-MAD algorithm, a further processing of IR-MAD components were performed through an object oriented classification scheme. Moreover, the IR-MAD transformation was able to detect the majority of inlands changes with an automated way and numerically issues in the IR-MAD method were addressed.

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