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EVALUATION OF SPECTRAL INDICES EFFICIENCY IN BURNED AREA MAPPING USING OBJECT-BASED IMAGE ANALYSIS

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Abstract. *Forest fires are an integral part of Mediterranean ecosystems and a key factor in forest fire management. Accurate information regarding the spatial extent of burned areas is essential for the quantification of the environmental impact of forest fires while at long term such information could be used in improving existing forest fire management plans. The aim of this study was to evaluate the efficiency of several spectral indices in burned area mapping using object-based image analysis (OBIA) and medium (Landsat5 TM - 30m) and very high (IKONOS pan-sharpened - 1m) resolution satellite imagery. In the case of the pan-sharpened IKONOS the Soil Adjusted Vegetation Index (SAVI), the modified Soil Adjusted Vegetation Index (mSAVI2) and the Normalized Difference Vegetation Index (NDVI) were used, while in the case of Landsat 5 TM the Char Soil Index (CSI) and the Normalized Burn Index (NBR) were additionally employed. The multiresolution segmentation algorithm was selected and applied to all layers generated from the computation of the aforementioned spectral indices. Training samples were defined based on the multispectral pansharpened IKONOS image and used in the classification process in all different cases. Results were statistically and spatially compared with the official burned area perimeter provided by the National Forest Service.*

Keywords: *IKONOS, NDVI, CSI, forest fires, Mediterranean ecosystems.*

Introduction

Forest fires are an integral part of Mediterranean ecosystems and a key factor in forest fire management. Until the year 2000 the number of forest fires had increased, not only in the Mediterranean basin, but also in the rest of Europe (Schmuck et al. 2011). Even though the number of fire events have decreased the last decade (Füssel and Jol 2012), the phenomenon of climate change is expected to cause a significant increase in the frequency and severity of fires (Kalabokidis et al. 2015), leading to further damage of the already degraded Mediterranean ecosystems.

The effectiveness of forest fire management is highly dependent on precise and current spatial information related to the fire-affected areas (Gitas et al. 2004). In particular, the information provided by detailed and current burned area maps contributes to the quantification of the environmental impact of forest fires, land use and land cover changes monitoring while at long term such information could be used in improving existing forest fire management plans (Chuvieco and Congalton 1988).

Satellite remote sensing constitutes a practical and cost-effective tool for burned area mapping (White et al. 1996). Satellite sensors are a valuable means for the production of accurate burned area maps since they provide broad areal coverage along with the high spatial and temporal resolution (Giglio et al. 2009, Polychronaki and Gitas 2012).

Optical satellite data have been extensively used for decades in the detection and mapping of burned areas (Chuvieco and Congalton 1989, Giglio et al. 2009, Polychronaki and Gitas 2012). This mapping is usually based on satellite data of medium and very high resolution, such as Landsat and IKONOS imagery (White et al. 1996, Roy et al. 2002, Epting et al. 2005).

Moreover, a variety of remote sensing analysis techniques are being employed in burned area mapping such as Maximum Likelihood classification (Razali and Nurud 2012), Support Vector Machines (Alonso-Benito et al. 2013), Unsupervised classifications (Van Wagtendonk and Root 2003) and Object-Based Image Analysis (OBIA) (Alonso-Benito et al. 2016). OBIA provides increased accuracy and detail in classification in comparison with conventional pixel-based analysis. Within this paradigm, rather than treating the image as a collection of pixels to be classified based on their individual spectral properties, the image pixels can be initially grouped into segments. The production of these groups is a process called segmentation and it is the first and most important step in OBIA (Baatz 2000). Segmentation aims at dividing the image into continuous groups of spectrally homogeneous objects that ideally represent real objects of interest in the study area (Jasani et al. 2009). The object segments can then be classified according to spectral and other criteria, such as shape, size and relationship to neighbor objects (Blaschke 2010).

Furthermore, spectral indices are also extensively employed by remote sensing experts in many different scientific fields. (Huete 1988, Chuvieco et al. 2002). Regarding burned area mapping, spectral indices have given a great advantage to the scientific community by enhancing the differences between burned and unburned pixels and, consequently, improving the accuracy of the final cartographic products (Cao et al. 2009). Some of the most widely used burned area related spectral indices include the Normalized Difference Vegetation Index (NDVI) (Rouse Jr et al. 1974), the Soil Adjusted Vegetation Index (SAVI) (Huete 1988), the Modified Soil Adjusted Vegetation Index 2 (mSAVI2) (Qi et al. 1994), the Global Environmental Monitoring Index (GEMI) (Pinty and Verstraete 1992), the Burned Area Index (BAI) (Martín 1998) and the Normalized Burn Index (NBR) (Key and Benson 1999).

The aim of the present study was to evaluate the efficiency of spectral indices in burned area mapping using OBIA and medium (Landsat 5 TM) and very high (IKONOS pansharpened) resolution satellite imagery. The specific objectives of this study were:

- The selection and calculation of spectral indices commonly used for burned area mapping based on the spectral availability of medium resolution (Landsat5 TM) and very high resolution data (IKONOS pan-sharpened).
- The employment of OBIA on Landsat 5 TM and IKONOS images for burned area mapping using the calculated indices.
- The comparison of the results with the official burned area perimeter provided by the forest service.
- The evaluation of the efficiency of each index in burned area mapping.

Study area and dataset description

The study area is Mount Parnitha. Mount Parnitha is located in the southern part of Greece, north of Athens. Parnitha is a national park and also part of the NATURA 2000 network. In 2007, a forest fire destroyed 36,000 acres of land, from which 21,800 acres were Greek fir forests, a species endemic to Greece. Many wild life habitats were also destroyed, such as bird nesting areas, and deer habitats (National Forest Service).

Two satellite images were used in this study, namely Landsat-5 TM and IKONOS, acquired several days after the fire. The Landsat image consists of seven spectral bands with spatial resolution of 30 m each, except for the sixth one which has 120 m resolution. The IKONOS image is pan-sharpened and consists of four spectral bands with 1m spatial resolution (Laben and Brower 2000). In addition, the official fire perimeter, provided by the Greek Forest Service, was used for the accuracy assessment of the results.

Methodology

The general steps of the methodology employed in the present study are presented in the following flowchart (Figure 1):

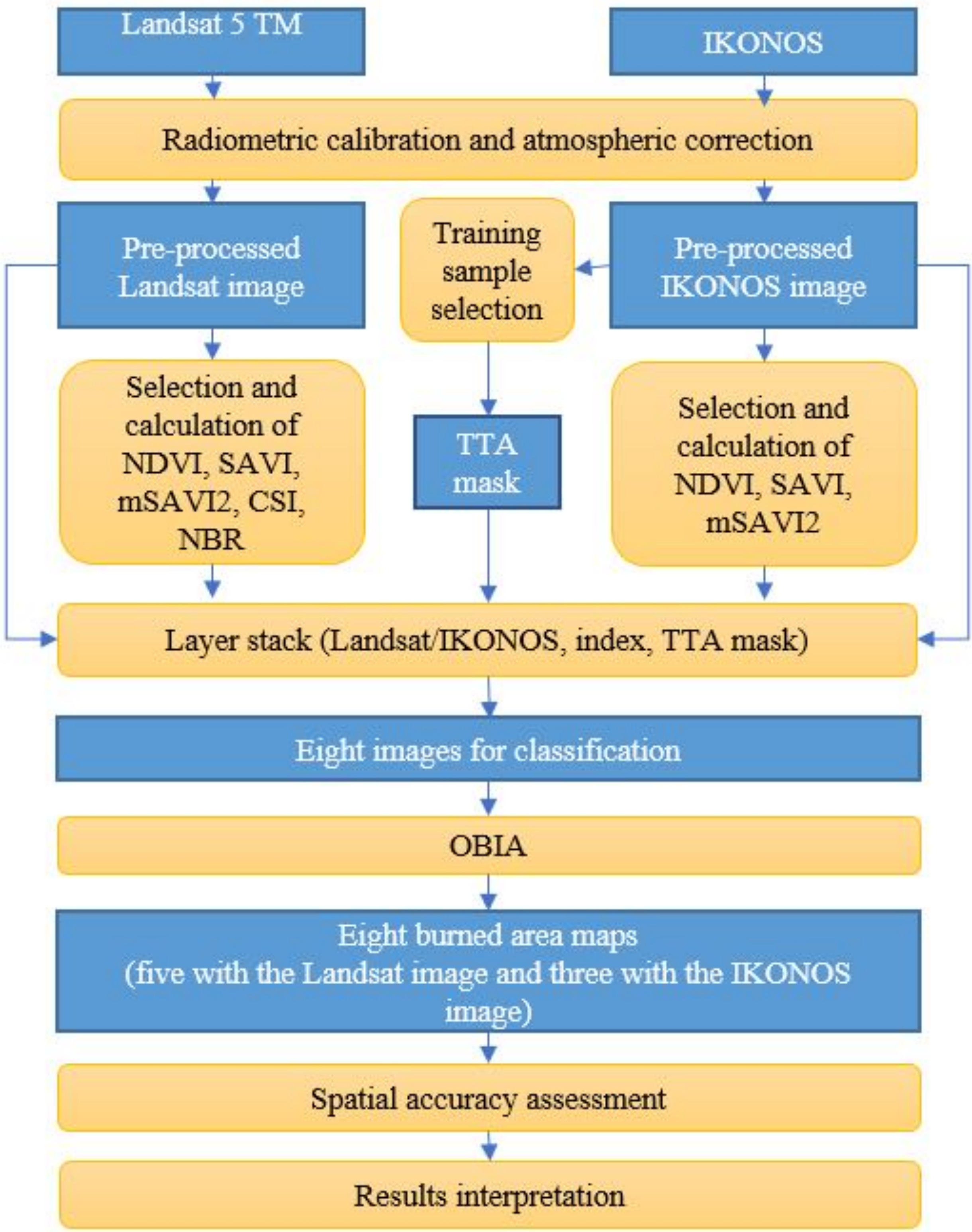

Figure 1. Methodology flowchart

The first step of the methodology included the pre-processing of the satellite data. Pre-processing aims at correcting the sensor and platform-specific radiometric and geometric distortions of data. Radiometric corrections are necessary in case of variations in scene illumination and viewing geometry, atmospheric conditions, and sensor noise and response. The type of the correction may vary depending on the specific sensor and platform used to acquire the data and the conditions during data acquisition (Chander and Markham 2003).

The pre-processing of the IKONOS and Landsat satellite images included radiometric calibration and atmospheric correction. The radiometric calibration was performed through the conversion of the pixel values from digital numbers (DN) to radiance values and, subsequently, to top of atmosphere (TOA) reflectance values. Next, the histogram subtraction method (Jensen 1986, Chavez 1988) was employed in order to atmospherically correct the satellite data.

The indices for this study were selected according to the international literature, their compatibility with various sensors and the amount of data required for them to function (Barati et al. 2011, Harris et al. 2011, Viña et al. 2011). The selected spectral indices are briefly described in the following table (Table 1).

Table 1.

The spectral indices used in the present study for mapping the burned areas

Index name	Equation	Reference	Description
Normalized Difference Vegetation Index:	$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR+RED}}$	(Rouse Jr et al. 1974)	An index designed for vegetation detection (or in our case, the absence of)
Soil Adjusted Vegetation Index:	$\mathrm{SAVI} = \frac{\mathrm{NIR-RED}}{\mathrm{NIR+RED+L}} * (1 + \mathrm{L})$	(Huete 1988)	An index designed for soil color and moisture detection.
Modified Soil Adjusted Vegetation Index 2:	$\mathrm{mSAVI2}= \frac{(2*\mathrm{NIR}-1-\sqrt{(2*\mathrm{NIR}+1)^2 - 8*(\mathrm{NIR}-\mathrm{RED})}}{2}$	(Qi et al. 1994)	A version of SAVI without the “L” constant, which represents vegetation coverage.
Char Soil Index:	$\mathrm{CSI} = \frac{\mathrm{NIR}}{\mathrm{Band5}}$	(Smith et al. 2005)	Performs well in burned area mapping with Landsat TM images.
Normalized Burn Index:	$\mathrm{NBR} = \frac{\mathrm{NIR-Band7}}{\mathrm{NIR+Band7}}$	(Key and Benson 1999)	Similar to NDVI but modified for burned area detection.

NDVI, SAVI, mSAVI2, CSI, NBR were calculated using the Landsat images but only the first three indices were computed for the IKONOS image since it lacks the short-wave infrared (SWIR) spectral bands.

Next, the training samples were selected using the IKONOS pre-processed image considering its very high spatial resolution (1m). Ten samples were selected for each class (burned and unburned). Subsequently, a Test and Training Area (TTA) mask was produced from the samples, which was used to train the classification algorithm in all cases.

Finally, the pre-processed Landsat data, the produced TTA mask and each of the calculated spectral indices (NDVI, SAVI, mSAVI2, CSI, NBR) were combined leading to the creation of five new images (LandsatNDVI, LandsatSAVI, LandsatmSAVI2, LandsatCSI, LandsatNBR), each of which consisted of eight layers (Table 2). The same procedure was performed for the pre-processed IKONOS data and the respective spectral indices (NDVI, SAVI, mSAVI2) resulting in three new images (IKONOSNDVI, IKONOSSAVI, IKONOSmSAVI2), each of which included five layers (Table 2).

Table 2.

Landsat pre-processed image layers, (b) IKONOS pre-processed image layers

Landsat images:

Layers:
Blue band
Green band
Red band
NIR band
SWIR1 band
SWIR2 band
(Index)
TTA mask (Thematic layer)

(a)

IKONOS images:

Layers:
Blue band
Green band
Red band
NIR band
(Index)
TTA mask (Thematic layer)

(b)

In order to classify the burned areas of each generated image, segmentation was initially employed. The classification of the created image objects into the classes "burned" and "unburned" was performed through the application of a supervised classification algorithm, namely the Nearest Neighbor (Gutin et al. 2002), which was trained by the samples contained in the TTA mask.

The Nearest Neighbor classification algorithm was executed using the features of mean values and standard deviation of the spectral bands. Each classification was followed by an enhancement of the resulted cartographic product using user selected thresholds of the Near Infrared (NIR) spectral band and exported as a vector layer for its subsequent accuracy assessment.

Results and discussion

The application of the methodology described in the previous chapters resulted in the eight burned area maps were produced. The specific cartographic products were then evaluated for their spatial accuracy. Hence, the areas misclassified as burned or as unburned were identified and adequate calculations were performed. More specifically, each vector was initially merged with the official perimeter. Then each vector was divided with its corresponding merged vector. The result of this division represented the overall spatial accuracy of each map (Table 3).

Table 3.

Overall spatial accuracy

Indices	**Spatial accuracy**
Landsat$_{SAVI}$	81.22%
Landsat$_{NDVI}$	81.22%
Landsat$_{mSAVI2}$	81.09%
Landsat$_{CSI}$	81.36%
Landsat$_{NBR}$	80.67%
IKONOS$_{NDVI}$	79.11%
IKONOS$_{SAVI}$	79.52%
IKONOS$_{mSAVI2}$	**81.89%**

Generally, the accuracy assessment results showcase that the application of OBIA and the Nearest Neighbor algorithm on images created using spectral indices from medium and very high resolution satellite imagery, yields high spatial accuracy in burned area mapping. More specifically, all the generated cartographic products were highly accurate achieving overall accuracy of approximately 80%. In addition, the highest spatial accuracy (81.89%) was achieved by IKONOS$_{mSAVI2}$. It is also noteworthy that the most and least accurate burned area maps were produced by the classification of the IKONOS$_{mSAVI2}$ and IKONOS$_{NDVI}$ images respectively. Since the IKONOS pan-sharpened image offers very high spatial resolution (1m), it was expected to result in a higher spatial accuracy than the ones of the Landsat bands (30m). However, the difference of the spatial accuracy from the highest scoring index and the lowest scoring index is only 2.78% and in some cases (NDVI and SAVI) the use of the Landsat image led to the production of a more accurate burned area map compared to the IKONOS image ($Landsat_{SAVI}$: 81.22% and $IKONOS_{SAVI}$: 79.52%, $Landsat_{NDVI}$: 81.22% and $IKONOS_{NDVI}$: 79.11%).

It is apparent that in case of using the IKONOS image, the generated burned area maps included significantly more noise compared to the Landsat image despite the enhancement performed to the classification result using user selected thresholds. This suggests that very high spatial resolution might be a disadvantage in burned area mapping unless proper methods are applied to presume upon the specific characteristic of the satellite sensor.

Taking all under consideration, it can be noted that the spatial resolution of the applied satellite images and the applied indices, did not play a key role in the burned area maps' overall spatial accuracy.

Conclusions and future research

In this paper, five spectral indices, namely NDVI, SAVI, mSAVI2, CSI and NBR, were evaluated for their efficiency in burned area mapping using OBIA of Landsat and IKONOS satellite images. The application of all selected indices and satellite images resulted in highly accurate burned area maps using a relatively simple methodology. The conclusions drawn from the present study are the following:

- OBIA, Nearest Neighbor and the spectral indices employed on Landsat 5 TM and IKONOS pan-sharpened images yield high spatial accuracy in burned area mapping.
- The choice of spectral index has little impact in the accuracy of burned area mapping products.
- The application of OBIA and the use of the selected spectral indices led to equal performance of Landsat 5 TM and IKONOS pan-sharpened images in burned area mapping.
- The selection of the appropriate classification method plays a leading role in accurate burned area mapping.

Future research could include the performance evaluation of different spectral indices in mapping fire-affected areas. Moreover, the spectral indices employed in the present study could be applied on other satellite data and the results could be compared with the ones of this work. Finally, it would be of interest to examine other classification techniques in burned area mapping by employing the satellite data and spectral indices used in the present study.

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ОЦЕНКА ЭФФЕКТИВНОСТИ ИСПОЛЬЗОВАНИЯ СПЕКТРАЛЬНЫХ ИНДЕКСОВ ДЛЯ ОПРЕДЕЛЕНИЯ СГОРЕВШИХ УЧАСТКОВ С ИСПОЛЬЗОВАНИЕМ ОБЪЕКТНО-ОРИЕНТИРОВАННОГО АНАЛИЗА ИЗОБРАЖЕНИЙ

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Аннотация: *Лесные пожары являются неотъемлемой частью Средиземноморских экосистем и ключевым фактором в управлении лесным хозяйством. Для количественной оценки воздействия лесных пожаров на окружающую среду необходима точная информация о пространственной протяженности сожженных районов, в то время как в долгосрочной перспективе такая информация может быть использована для улучшения существующих планов управления лесными пожарами. Цель представленного исследования – оценка эффективность нескольких спектральных показателей при картировании сожженных областей с использованием объектно-ориентированного анализа изображений (OBIA) и среды (Landsat5 TM – 30 м) и очень высоких (IKONOS - 1 м) спутниковых снимков разрешения. В случае IKONOS использовался модифицированный индекс mSAVI2 и индекс NDVI, тогда как в случае Landsat 5 TM индекс (CSI) и нормализованный индекс (NBR). Алгоритм сегментации мультирезоляции был выбран и применен ко всем слоям, генерируемым при вычислении вышеупомянутых спектральных индексов. Образцы для обучения были определены на основе мультиспектрального изображения IKONOS и использовались в процессе классификации. Результаты были статистически и сопоставлены с официальным периметром обгоревшего района, предоставленным Национальной лесной службой.*

Ключевые слова: *IKONOS, NDVI, CSI, лесные пожары, средиземноморские экосистемы.*

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