Burned Area Mapping in a Mediterranean Environment Using Time-Series VEGETATION and Simulated PROBA-V Imagery by Employing an Object-Based Change Detection Approach

Pericles Toukiloglou, Ioannis Z. Gitas, Giorgos Mallinis and Thomas Katagis
Aristotle University of Thessaloniki, Faculty of Forestry and Natural Environment, Thessaloniki, Greece;
ptoukiloglou@for.auth.gr, igitas@for.auth.gr, gmallin@for.auth.gr, thkatag@for.auth.gr

Abstract. An object-based changed detection method was developed and assessed for accurately mapping burned areas by employing multi-temporal, PROBA-V and VEGETATION (VGT) NDVI data. Since the PROBA-V sensor is scheduled for launch in the near future, PROBA-V data were substituted with MODIS data. The method was assessed over the 2007 wildfires in the Peloponnese peninsula, Greece. Data captured over the study area were used to form a multi-temporal NDVI image which was then segmented into groups of spectrally similar adjacent pixels (objects). Consequently, the deviation between the multi-temporal NDVI signature of each object and that of an unchanged reference was measured by calculating the Mahalanobis Distance (MD) between them. Assuming that the deviation would be significantly greater for burned areas, objects with the highest MD values were considered burned. Burned area maps were produced based on an area derived MD threshold built on a preexisting knowledge of the percentage of the study area that was burned. PROBA-V data resulted to a kappa value of 0.81 and a burned area user's accuracy of 82.22% while the lower spatial resolution VGT data resulted to lower accuracy (0.73 and 75.54% respectively). Burned area maps were also produced based on MD threshold values derived from the distribution of MD values across the study area that did not require any preexisting knowledge and also resulted in equally accurate maps and PROBA-V out-performing VGT.

Keywords. Fire, burned area mapping, OBIA, object based, Mahalanobis, change detection, time series, VEGETATION, PROBA-V.

1. Introduction

Forest fires are a real threat to natural environments in the countries of Mediterranean Europe given the spectacular increase in the number of fire events observed in recent decades [1]. When a forested area is destroyed by fire, accurate information concerning the location and extent of the burned areas at multiple scales is important to assess economic losses and ecological effects, monitor land use and land cover changes, and model atmospheric and climatic impacts of biomass burning [2].

From national to global scales, several burned area mapping methods have been developed using moderate to low spatial and high temporal resolution remotely sensed data, based mainly on image differencing techniques [3], [4]. This approach, which relies on the high frequency of data acquisition, reduces errors due to spectral confusion with unburned surfaces such as cloud shadows, bare soil and water, allowing observation of burns close to the fire date when the signal has its greatest separability from the surrounding areas [5].

Object-based analysis which has been recently introduced in the field of burned area mapping, has already showed promising results for accurately mapping a burned area on the Mediterranean

coast of Spain using a single post-fire AVHRR image [6]. Deficiencies in pixel based approaches, such as confusions between burned and non-vegetative areas [7], [8] have been minimized by the adoption of objects as the primary unit of classification even using a single post-fire image.

The PROBA-V sensor is scheduled for mid-2013 designed to ensure the continuity of SPOT-VEGETATION (VGT) with spectral responses in accordance with SPOT-VGT. The anticipated PROBA-V sensor will be able to collect data in the red and Near InfraRed (NIR) regions of the spectrum on a near-daily cycle across the globe at a moderate spatial resolution (~300m). Red and NIR spectral bands are particularly useful to discriminate burned areas due to spectral changes resulting from the elimination of healthy green vegetation and charcoal deposition following a fire event [9], [10]. Also, the high temporal resolution of the PROBA-V sensor and the low cost of data acquisition are likely to be well suited in regularly mapping burned areas over large areas at a low cost.

The aim of this study is to develop an object based change detection approach for burned area mapping using moderate spatial resolution, multitemporal data and to assess the merits of using the anticipated PROBA-V data, in comparison to data available from its predecessor VEGETATION sensor.

2. Study area

The study area was the peninsula of Peloponnese located in southern Greece (36°30’-38°30’ N, 21°-23° E). The climate is characterized as typically Mediterranean. The main vegetation types in the area are coniferous and broadleaved forests, shrubs, and olive groves. In August 2007 large wildfires broke out.

3. Data

The proposed methodology is based on temporal NDVI data. However, at the time, such data collected by PROBA-V were not yet available. Thus it was decided to substitute PROBA-V NDVI data with available data of similar characteristics. NDVI data collected by MODIS were considered a good substitute because i) they are collected at a similar spatial resolution (~250m) to PROBA-V (~300m) and ii) a previous study [12] has shown a high correlation between MODIS and VGT NDVI values over the same targets. Considering the similarity between the VGT’s and PROBA-V’s the red and NIR bandwidths, this suggests that a high correlation between MODIS and PROBA-V NDVI values over the same targets is very possible.

The following remotely sensed data were acquired for the time periods 20/7/2006- 10/10/2006 and 20/7/2007- 10/10/2007:

- PROBA-V substitute Data (MODIS): Red and NIR surface reflectance 8-day composites at 250m spatial resolution (MOD09Q1) along with Quality Assurance (QA) information
- VGT Data: Red and NIR surface reflectance 10-day BiDirectional Composite syntheses with 1km spatial resolution along with Status Map (SM) information

In addition to the remotely sensed data the following reference data were also acquired:

- A vector file outlining the perimeter of the 2007 fire based on a visual interpretation of a Disaster Monitoring Constellation (DMC) image with 32m resolution captured in after the fire
- The Corine Land Cover 2000 (CLC2000) map

4. Method

4.1. Introduction

The object-based change detection methodology that was adopted in this study was inspired by the work of Bontemps et al., 2008 [11]. Data captured over the study area were used to form a multi-temporal NDVI image which was then segmented into groups of spectrally similar adjacent pixels (objects). Consequently, the deviation between the multi-temporal NDVI signature of each object and that of an assumed unchanged reference was measured by calculating the Mahalanobis Distance (MD) between them. Assuming that the deviation between the multi-temporal NDVI signature and the unchanged reference would be significantly greater for burned surfaces than other objects, objects with the highest MD values were considered burned.

4.2. Data pre-processing

The acquired remotely sensed data were extracted within the extent of the study area, so that the analysis focuses solely on the place of interest. In order to minimise possible errors caused by NDVI data altered by cloud cover or radiometric noise, these data were identified based on the provided QA (for MODIS) and SM (for VGT) information and masked. Any pixels covered by non-flammable land-cover, such as water bodies, were also identified and masked based on the CLC2000 map. The latter would help reduce possible errors by excluding areas from the analysis that i) could not possibly be burned and ii) could have significantly different NDVI temporal profile than that of the unchanged vegetated reference, which could result in false positive change detection results. The NDVI was then calculated based on the masked red and NIR data of the sensors. The pre-process was repeated for each dataset of the two sensors.

4.3. Data compositing

NDVI data were averaged over four composite time periods, two per year to account for intra-annual changes and for two years to account for the inter-annual changes. A compositing period greater than the original compositing period of the PROBA-V substitute data (8-day) and VGT data (10-day) was considered preferable in order to minimize the effects of brief environmental fluctuations (such as cloud cover, rain etc.) and variations in the data reception geometry [3], [5]. On the other hand, sudden changes (as in the case of fires) would be less pronounced (and hence harder to detect) over longer compositing periods, especially if they were to occur near the end of the composing period. Due to these two opposing factors, a compromise had to be made between a not too long and a not too short compositing period.

It was decided to use a 40-day compositing period in order to also accommodate the comparison between the substitute PROBA-V data and the VGT data over the same time period (a 40-day composite can be composed by an integer number of both 10-day (4) and 8-day (5) composites). If the study did not aim to compare the two sensors' performance under the same conditions, a shorter compositing period could be applied.

The four chosen composite periods were:

- 21/7/2006 - 28/8/2006
- 29/8/2006 - 10/10/2006
- 21/7/2007 – 28/7/2007
- 29/7/2007 – 10/10/2007

It was decided to include only one fire-affected composite period (after the 28th of August 2007, when approximately the major fires broke out), as opposed to two (that would most likely

produce better results), in order to test the performance of the method under more challenging and realistic conditions from an operational point of view.

A multi-temporal NDVI image was produced for each sensor by layer-stacking their respective four composite NDVI layers.

4.4. Segmentation

A multi-temporal segmentation was applied, giving equal weight to all the bands of each image. Each image was segmented for a series of scale values and the result of each segmentation was visually assessed (Figure 1). The visual assessment resulted in the scale parameter values displayed in Table 1.

Figure 1: Segmentation results obtained after setting the scale parameter threshold to 10 (left), 30 (middle) and 100 (right) for the PROBA-V (top) and VGT (bottom) sensors. Note that the burned areas are depicted with yellow colours. Under-and over segmentation is evident in the left and right pictures.

Table 1. Scale parameter values used for the segmentation of the PROBA-V and VGT data for each task.

	PROBA-V	VGT
Scale used	40	30
Segments	16287	1814

4.5. Change detection

An NDVI-temporal signature was created for each object (i), in a form of a 1x4 matrix (Si) comprised of the object's average NDVI values over the four compositing periods (A, B, C and D).

$$S_i = \left[NDVI_{iA} NDVI_{iB} NDVI_{iC} NDVI_{iD} \right]$$

Similarly a NDVI-temporal signature was created for what it was considered as an unchanged reference (Su), by using the average NDVI composite values of the majority of objects that were located away from the general known area of the 2007 fire event. Alternatively, if the general area of the fire event was not known, the NDVI-temporal signature of the unchanged reference could

have been derived from the NDVI values of all the objects in the study area, as long as data from the fire affected composite period (4th) were replaced by data captured over the same period during a non-fire affected year.

$$S_u = \left[NDVI_{uA} NDVI_{uB} NDVI_{uC} NDVI_{uD} \right]$$

Differences between the NDVI values of burned and vegetated areas are significantly greater than the differences between the NDVI values of different vegetation covers. Consequently, it was assumed that the deviation between the NDVI-temporal signature of an object and that of the unchanged reference would be greater for burned area objects. This deviation could be measured for each object (i) by calculating the Mahalanobis Distance (MD_i) (Figure 2). The highest MD values were associated with burned areas.

$$MD_i = \sqrt{\left(S_i - S_u\right) S_c^{-1} \left(S_i - S_u\right)'}$$

Where Sc is the 4x4 covariance matrix of the unchanged reference:

$$S_c = \begin{bmatrix} NDVI_{Variance_A} & NDVI_{Covariance_{A\_B}} & NDVI_{Covariance_{A\_C}} & NDVI_{Covariance_{A\_D}} \\ NDVI_{Covariance_{B\_A}} & NDVI_{Variance_B} & NDVI_{Covariance_{B\_C}} & NDVI_{Covariance_{B\_D}} \\ NDVI_{Covariance_{C\_A}} & NDVI_{Covariance_{C\_B}} & NDVI_{Variance_C} & NDVI_{Covariance_{C\_B}} \\ NDVI_{Covariance_{D\_A}} & NDVI_{Covariance_{D\_B}} & NDVI_{Covariance_{D\_C}} & NDVI_{Variance_D} \end{bmatrix}$$

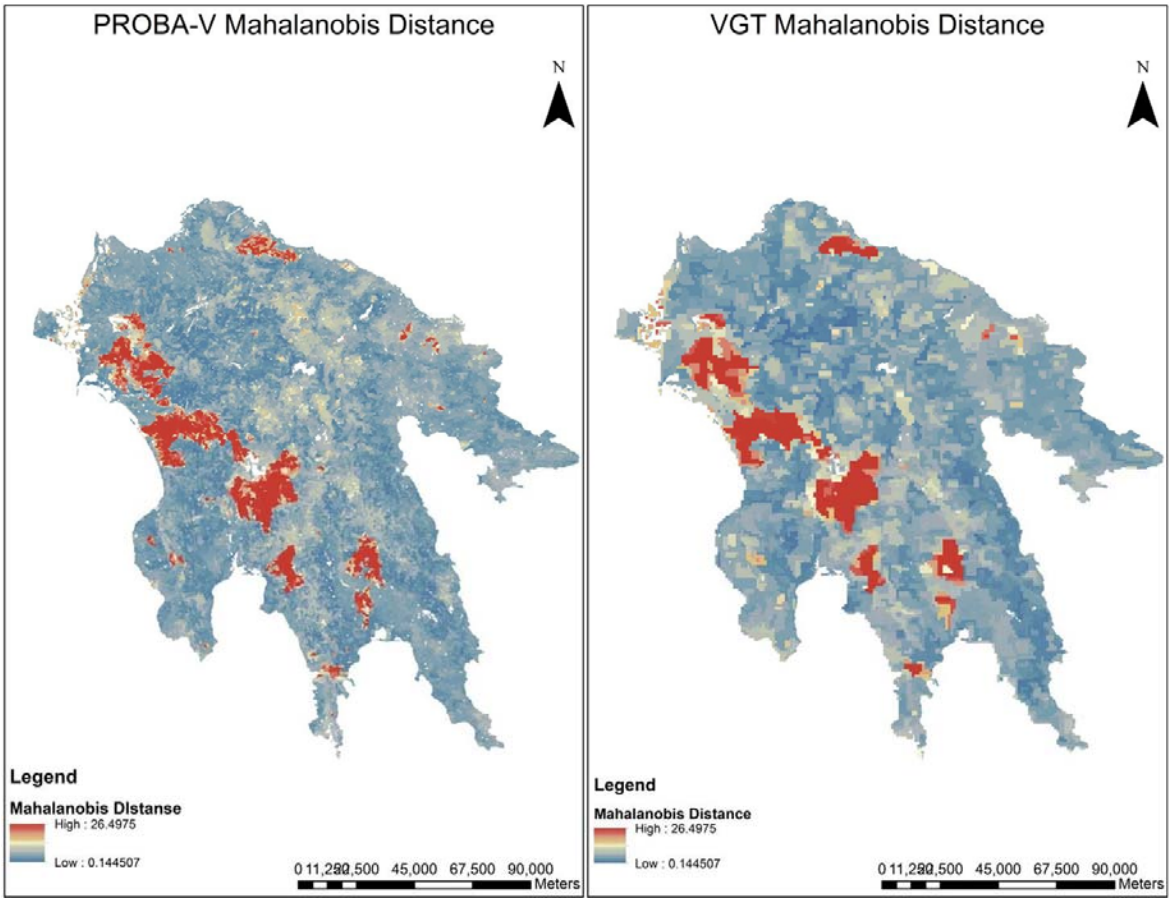

Figure 2: Maps of the calculated MD values using the substitute PROBA-V (left) and VGT (right) datasets.

Burned area/change detection maps could be produced by considering burned/changed any objects with higher MD values than a certain threshold. A series of MD threshold values could be set so that certain X% of the total study area with the highest MD values could be mapped (Figure 3). Hence, the proposed method does not only provide a means mapping burned/changed areas but also a means for measuring the magnitude of the change.

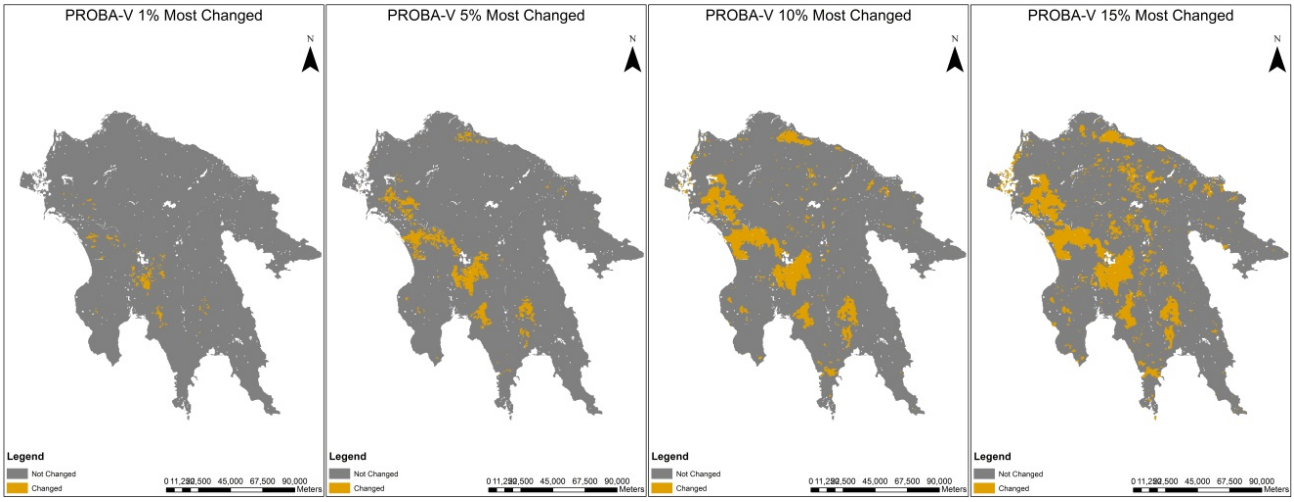

Figure 3: Change detection maps displaying the 1%, 5%, 10% and 15% of the total study area with the highest MD values.

In order to assess the method's performance in accurately mapping burned areas using substitute PROBA-V and VGT data, the resulting maps were validated by comparison to higher spatial resolution reference data, such as the DMC-derived burned area map. However, the proposed method could be set to map a range of different magnitudes of change (by adjusting the MD threshold value), while the reference data did not differentiate between more or less severely burned areas, but depicted a fixed magnitude of change, the percentage of the total study area that was burned (~8.6%). In other worlds, assuming that the burned areas were the most changed areas, the reference data depicted the 8.6% of the total area that changed the most. Therefore, in order to assess the produced maps against reference data, the produced maps had to detect the same magnitude of change; hence, the maps were produced using a MD threshold value that detected the 8.6% of the study area that changed the most.

In the case that the magnitude of change to be detected is unknown then the change detection MD threshold value could be set based either on visual assessment of the corresponding MD histogram or by using a statistical method (e.g. the natural break (Jenks) approach) to split data into changed and unchanged classes.

5. Results

The derived change maps, depicting the 8.6% of the study area which changed the most, were assessed against the reference DMC-derived burned area perimeter vector (Figure 4). Based on a thorough accuracy assessment procedure, it was found out that both PROBA-V and VGT sensors produced satisfactory results (Tables 2 and 3) attaining 96.92% and 95.78% overall classification accuracy respectively. In addition, the user and producer accuracies of the PROBA-V map were also higher than the respective accuracies of the VGT map.

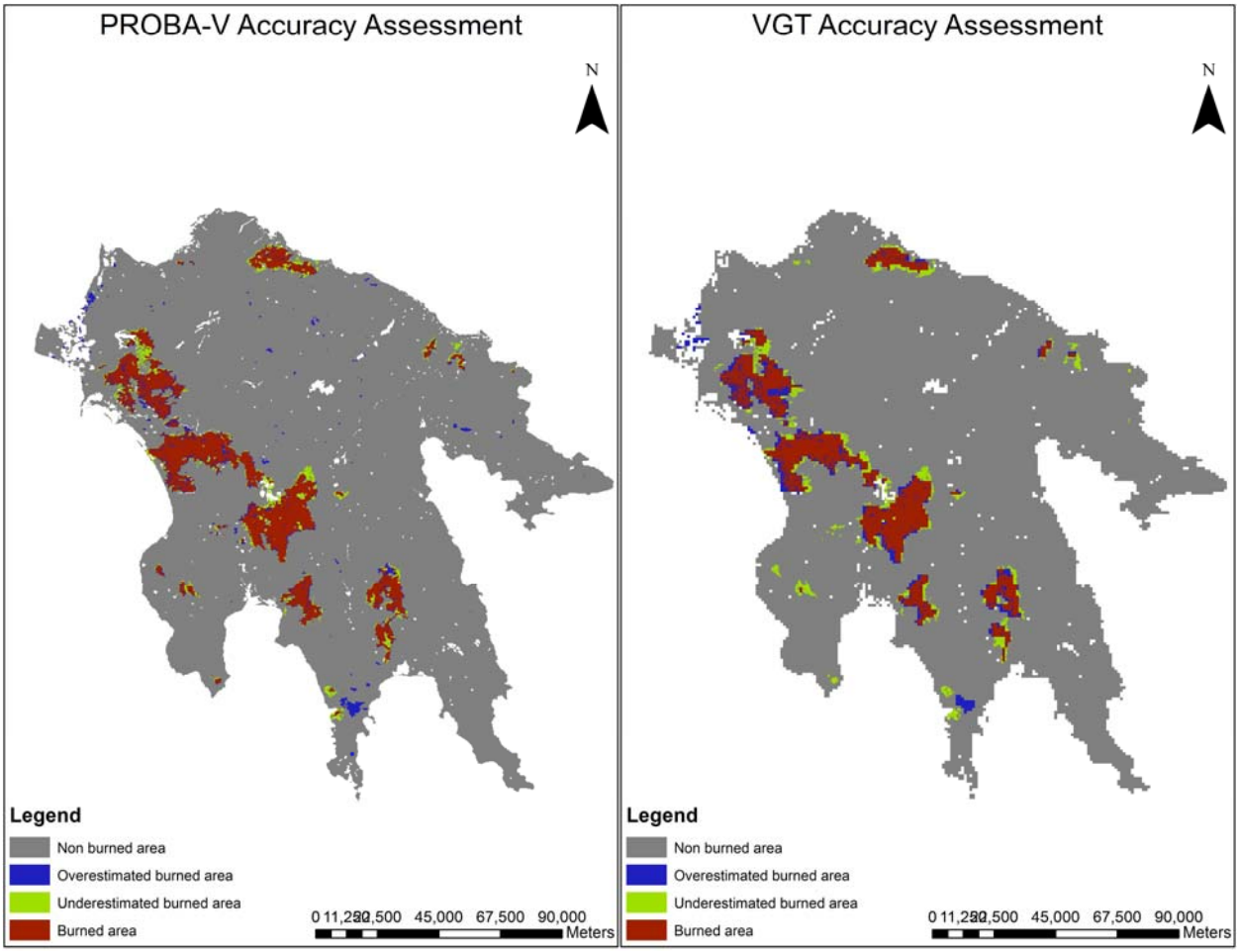

Figure 4: Accuracy assessment maps displaying which burned areas were correctly identified and which were not, when an 8.6% area MD threshold value was applied.

Table 2. Accuracy assessment of the burned area map produced using substitute PROBA-V data and an 8.6% area MD threshold value.

	Reference			
Classified	PROBA-V	Burned (Km^2)	Not burned (Km^2)	Producer Accuracy
	Burned (Km^2)	1446.79	312.58	82.23%
	Not burned (Km^2)	312.83	18231.11	98.31%
	User Accuracy	82.22%	98.31%	
	Overall accuracy: 96.92 % K= 0.81			

Table 3. Accuracy assessment of the burned area map produced using VGT data and an 8.6% area MD threshold value

	Reference			
Classified	VGT	Burned (Km^2)	Not burned (Km^2)	Producer Accuracy
	Burned (Km^2)	1329.16	422.84	75.87%
	Not burned (Km^2)	430.46	18060.24	97.67%
	User Accuracy	75.54%	97.71%	
	Overall accuracy: 95.78 % K= 0.73			

Most misclassification errors were distributed along the border of the reference fire perimeter and corresponding both to commission and omission errors. The existence of such errors is related to landscape fragmentation and the spatial resolution of the imagery. Hence, over the same study area, the number of mixed class objects would increase with the use of lower spatial resolution data. Indeed, in our study, higher classification errors were generated by the use of lower spatial resolution data.

Errors were also detected in small areas located in a distance from the actual fire perimeter on both maps. In these cases, on one hand underestimation errors were mainly caused by the small extent of some burned areas that were not sufficiently large to be detected by the sensors. Once again, such errors were more evident in the classification map produced, based by the use of the lower spatial resolution VGT sensor. On the other hand, overestimation errors were present over the same areas on both of the produced maps; that could be because these areas were either spectrally significantly different than the unchanged reference or because these areas were indeed burned but not included in the reference DMC fire perimeter. The latter was verified by the European Forest Fire Information (EFFIS) 2007 report. The burned area map included in the EFFIS report, shows that some areas that were considered overestimation errors on both the PROBA-V and VGT burned area maps were indeed burned areas (Figure 5). In effect, the actual accuracies of the produced maps were even higher than the assessed.

Maps were also produced using the natural breaks MD threshold value approach in the event that the extent of the burned area was not already known (Figure 6). The assessment of the produced maps also generated satisfactory results (Tables 4 and 5) strengthening the robustness and the reliability of the proposed method which proves prominent even in the case of absence of a priori knowledge about the extent of the change.

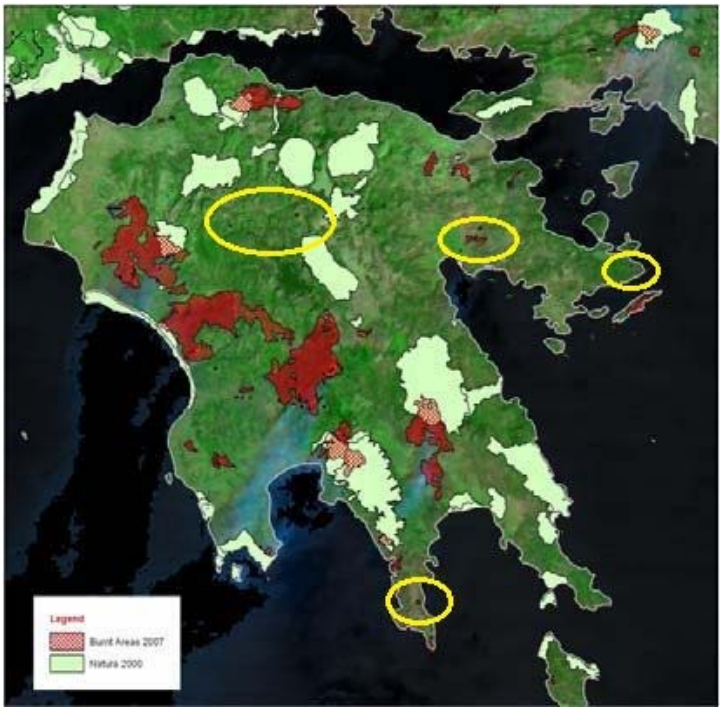

Figure 5: EFFIS 2007 burned area map and identified burned areas not included in the DMC fire perimeter and were consequently falsely considered as burned area overestimation errors.

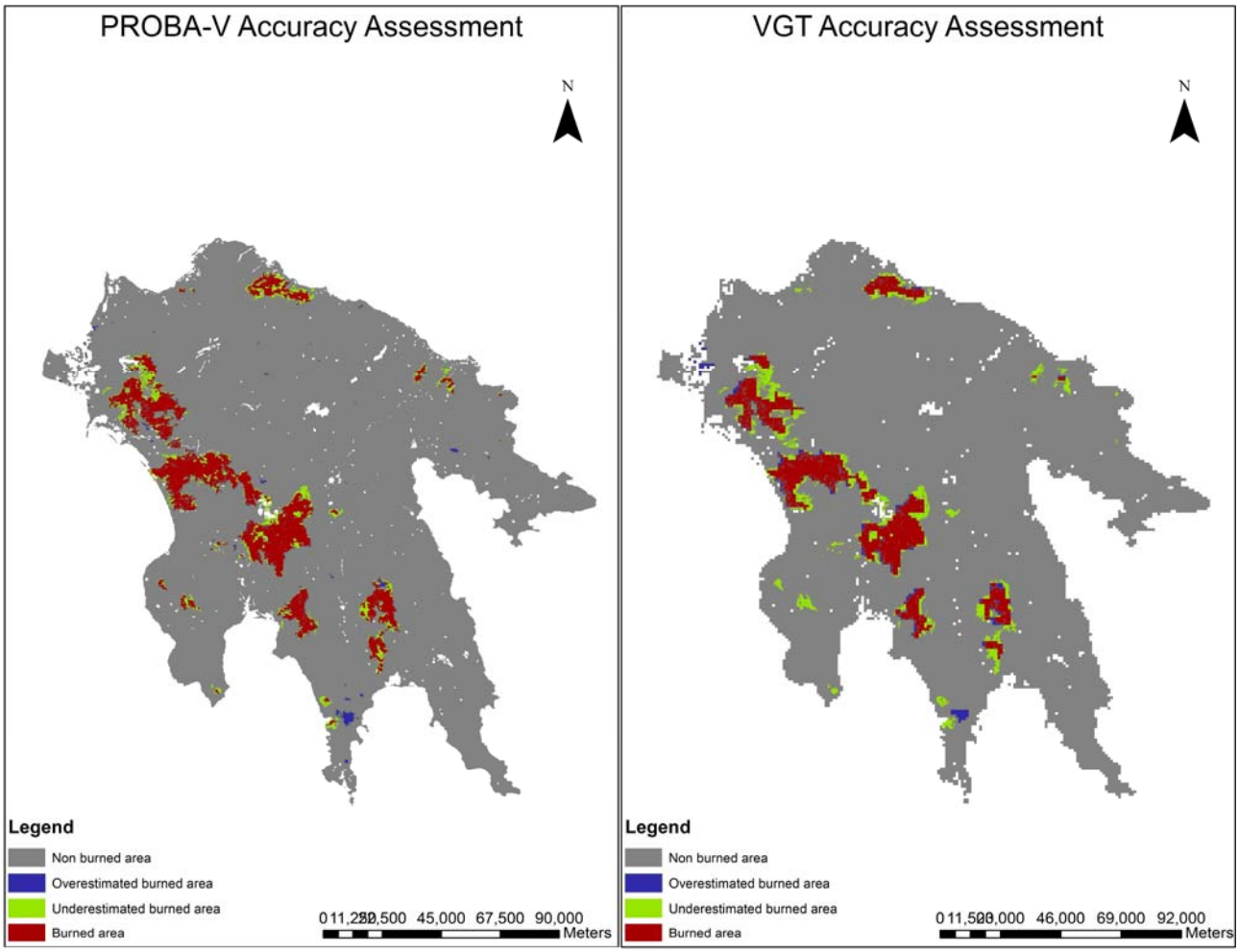

Figure 6: Accuracy assessment maps displaying which burned areas were correctly identified and which were not, when a natural break MD threshold value was applied.

Table 4. Accuracy assessment of the burned area map produced using substitute PROBA-V data and a natural break MD threshold value.

	Reference			
Classified	PROBA-V	Burned (Km^2)	Not burned (Km^2)	Producer Accuracy
	Burned (Km^2)	1332.27	230.17	85.27%
	Not burned (Km^2)	427.36	18313.52	97.72%
	User Accuracy	75.71%	98.76%	
	Overall accuracy: 96.76 % K= 0.78			

Table 5. Accuracy assessment of the burned area map produced using VGT data and a natural break MD threshold Value.

	Reference			
Classified	VGT	Burned (Km^2)	Not burned (Km^2)	Producer Accuracy
	Burned (Km^2)	1157.76	289.24	80.01%
	Not burned (Km^2)	601.86	18193.84	96.80%
	User Accuracy	65.80%	98.44%	
	Overall accuracy: 95.60 % K= 0.70			

6. Conclusions

The developed method can accurately map significant changes, such as fire events, at a range of pre-set change magnitudes. If there is no pre-existing knowledge regarding the extent of the changes that need to be detected, the histogram of the calculated MD values can be used to naturally split the data into changed and unchanged and map them accordingly.

If a library of unchanged NDVI-temporal signatures was produced for different places of interest, then the method could be applied over these places on a regular basis, providing a change detection monitoring product.

The PROBA-V sensor is expected to outperform its predecessor VGT in change detection applications, such as burned areas mapping, mainly due to its improved spatial resolution.

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