

## Aberystwyth University

### *Assessing the influence of atmospheric and topographic correction and inclusion of SWIR bands in burned scars detection from high-resolution EO imagery*

Abbi Said, Yahia; Petropoulos, George; Srivastava, Prashant K.

*Published in:*  
Natural Hazards

*DOI:*  
[10.1007/s11069-015-1792-9](https://doi.org/10.1007/s11069-015-1792-9)

*Publication date:*  
2015

*Citation for published version (APA):*

Abbi Said, Y., Petropoulos, G., & Srivastava, P. K. (2015). Assessing the influence of atmospheric and topographic correction and inclusion of SWIR bands in burned scars detection from high-resolution EO imagery: A case study using ASTER. *Natural Hazards*, 78(3), 1609-1628. <https://doi.org/10.1007/s11069-015-1792-9>

#### **General rights**

Copyright and moral rights for the publications made accessible in the Aberystwyth Research Portal (the Institutional Repository) are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the Aberystwyth Research Portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the Aberystwyth Research Portal

#### **Take down policy**

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

tel: +44 1970 62 2400  
email: [is@aber.ac.uk](mailto:is@aber.ac.uk)

# Assessing the Influence of Atmospheric, Topographic Correction and SWIR bands Inclusion in Burnt Scars Detection from High Resolution EO Imagery: A Case Study Using ASTER

Yahia Abbi Said<sup>1</sup>, George P. Petropoulos<sup>2,\*</sup>, Prashant K. Srivastava<sup>3,4</sup>

<sup>1</sup>*Mediterranean Agronomic Institute of Chania, Chania 73100, Crete, Greece*

<sup>2</sup>*Department of Geography & Earth Sciences, University of Aberystwyth, SY23 2DB, United Kingdom*

<sup>3</sup>*Earth System Science Interdisciplinary Center, University of Maryland, Maryland, USA*

<sup>4</sup>*NASA Goddard Space Flight Center, Greenbelt, Maryland, USA*

\* Correspondence to: [george.petropoulos@aber.ac.uk](mailto:george.petropoulos@aber.ac.uk), Tel: +44-0-1970-621861

---

## Abstract

In the present study the effect of atmospheric and topographic correction to the burnt area delineation from EO imagery in conditions characteristic of a Mediterranean environment is explored. Furthermore, the potential added-value of the inclusion of the shortwave infrared (SWIR) bands in improving the retrievals of burned area cartography is investigated. In particular the capability of ASTER imagery when combined with the Maximum Likelihood (ML) and the Support Vector Machines (SVMs) classification techniques has been examined herein. As a case study a Mediterranean site on which a fire event occurred in Greece during 2007, for which post-fire ASTER imagery has been available is used. The combination of topographic correction (orthorectification) with the inclusion of the SWIR bands returned the most accurate results in burnt area detection. SVMs showed the highest accuracy, showing the most promising potential in delineating the burned areas. The most accurate results for burnt scar mapping were obtained from the combined use of SVMs with an orthorectified image and SWIR spectral bands, at least this appeared to be the case in our study site.

Our results offer a very important contribution to the understanding of the capability of high resolution imagery such as that from ASTER in burnt area estimation. Also, corroborate the usefulness particularly of the topographic correction as an image processing step to be incorporated in modeling schemes for delineating burnt areas from such data. Findings provide potentially very useful information towards the development of EO-based techniques that aim to operationally provide services related to the estimation of burnt area. This is of considerable scientific and practical value to the wider scientific and users' community given the continuation of free access today to observations from space from high resolution sensors globally.

**Keywords:** *burnt area mapping, ASTER, topography, atmospheric correction, remote sensing, wildfires, Greece*

## 1. Introduction

Wildfires are a powerful management tool in some ecosystems, used long term or short term to change the landscape and floristic components of ecosystems (Salvador *et al.*, 2005). Yet, they are also considered as of the most widespread disturbances of Earth's natural system. Those are affecting the land component of the Earth system by causing dramatic changes to land cover distribution and land surface processes dynamics at a variety of spatial and temporal scales of natural ecosystems (Koutsias *et al.*, 2011; Petropoulos *et al.*, 2012b; Cawson *et al.*, 2013). Moreover, they deteriorate habitat, diminishing biodiversity (Cao *et al.*, 2009), plant reproduction (Johnstone *et al.*, 2004) and nutrients cycling (Cao *et al.*, 2009). Wildfires also affect the Earth's land surface energy and water cycle, decreasing evapotranspiration and increasing surface albedo, surface runoff, erosion and sediment production (Pérez-Cabello *et al.*, 2006), resulting to triggering also phenomena such as floods and desertification. Thus, it is understandable why being able to acquire information on fire events has been underlined as a topic of key importance and priority for future attention by both scientists and policy makers (Boustras and Boukas, 2013; Kontoes *et al.*, 2013).

Being able to obtain accurate as well as rapid mapping of burnt areas in particular after a fire suppression, is of key importance in decision making, as it can be used effectively in establishing rehabilitation and restoration policies in the affected areas and also assisting to avoid post-fire hazards and long-term degradation (Vafeidis & Drake, 2005; Giglio *et al.*, 2009). Acquiring information on burnt area on a consistent monitoring basis can also provide important information on land cover changes related to ecology and biodiversity at different observational scales, which can significantly assist in understanding post-fire recovery of affected areas (Li *et al.*, 2004). An accurate cartography of the area burnt is important as the latter is also one of the key inputs in modelling the atmospheric and climatic impacts of biomass burning, and in estimating the total atmospheric emissions from it (Kasischke and French, 1995; Cao *et al.*, 2009; Giglio *et al.*, 2009; Petropoulos *et al.*, 2010b).

Earth Observation (EO) technology has demonstrated promising potential in the mapping and analysis of wildfires (Ahern *et al.*, 2001; Chuvieco *et al.*, 2008). A major goal in satellite remote sensing of fire is to derive globally accurate measurements of the spatial and temporal distribution of burning (Fuller, 2000). Key advantages of EO technology include its ability to provide timely and often inexpensively spectral information at a variable spatial resolution from local, to regional and global scale (Patel *et al.*, 2013). Particularly the integration of EO datasets with Geographic Information Systems (GIS) spatial analysis techniques provides an excellent framework for data capture, storage, synthesis and analysis of acquired spatial data related to wildfire analysis, including burnt area mapping. Different types of EO data have been exploited for more than 20 years now in performing various fire analysis investigations, including ones focusing on mapping the extent of burnt areas (Knorr *et al.*, 2011; Petropoulos *et al.*, 2010b). As a result, various related operational products have also been developed, currently distributed no-cost and at a wide range of spatial resolutions as regional or continental scale products (Schroeder *et al.*, 2008).

Satellite image classification consists perhaps the most widely used image analysis approach employed in deriving information on the pattern and the spatial distribution of burnt areas, particularly so from high to very high resolution EO datasets (Levin *et al.*, 2012; Hope *et*

1 al., 2012, Huesca et al. 2013; ). Numerous classification techniques have been proposed and  
2 explored for this purpose (for a review see Lu and Weng, 2007). Maximum Likelihood (ML,  
3 Foody *et al.*, 1992) is a supervised pixel-based, parametric classification approach extensively  
4 used in deriving burnt area estimates from different sensors (Turner *et al.*, 1994). Support Vector  
5 Machines (SVMs, Vapnik *et al.*, 1997) is a relatively new machine learning-based non-  
6 parametric classifier. Its use so far has shown a promising potential in mapping changes to land  
7 cover from natural hazards including obtaining burnt areas cartography (Petropoulos *et al.*,  
8 2011). Yet, despite their promising potential and their relative advantages over parametric  
9 classifiers (such as ML), their use still is being ill-explored in burnt area related studies in  
10 comparison to other classification approaches. Thus evidently, a comparative study of the  
11 performances of the different classifiers would be an interesting task to be performed. Indeed,  
12 performing studies assessing the performance of diverse, widely-used classifiers is an important  
13 step towards increasing the accuracy with which information on land use/cover and burnt areas  
14 can be derived from space (Lu and Weng, 2007). This is particularly interesting as well and in  
15 the development of algorithms suitable potentially for satellite sensors recently launched, such as  
16 Landsat 8, or due to be launched, such as the Sentinels 2 mission.

17 A review of the relevant literature also suggests that selection of the suitable classifier as  
18 well as of the appropriate spectral bands, original or derived, is crucial for improved  
19 classification accuracies, and consequently burnt area estimates (Stroppiana *et al.*, 2003;  
20 Petropoulos *et al.*, 2012c). Yet, aspects related to the inclusion of certain image processing steps  
21 such as of the atmospheric and topographic correction or of the shortwave infrared (SWIR)  
22 bands where available to our knowledge seem to have so far been ill-addressed (Bastarrika *et al.*,  
23 2011; Gitas and Devereux, 2006; Van Wagendonk *et al.*, 2004). This despite the significance of  
24 obtaining more accurately estimates of burnt areas, which might be of key importance to  
25 particular users. Also, given that burnt area estimates derived from high resolution EO imagery  
26 are often used as reference in validating burnt area operational products which are distributed  
27 globally (Justice *et al.*, 2002; Roy and Boschetti, 2009; Simon *et al.*, 2004; Tsela *et al.*, 2014), it  
28 is understandable that this in turn could potentially help also in deriving more objectively  
29 information about the accuracy of currently distributed relevant operational products. Last but  
30 not least, if such studies were performed in regions like the Mediterranean basin can be very  
31 significant, given the high occurrence of fires in those areas and their relevance to other  
32 phenomena also taking place in those areas including land degradation and desertification  
33 (Castillejo-González *et al.*, 2009).

34 Based on this context, this study aims at examining the effect of atmospheric and  
35 topographic correction image processing steps as key steps to be included to modelling the  
36 retrievals of burnt area mapping from Advanced Spaceborne Thermal Emission and Reflection  
37 Radiometer (ASTER) operationally distributed products globally when the latter is combined  
38 with the ML and the SVMs techniques. In addition, the potential added-value of the (SWIR)  
39 bands inclusion in improving burned area cartography from the acquired ASTER data is also  
40 explored. As a case study is selected a typical Mediterranean site in Greece, for which ASTER  
41 imagery acquired shortly after the fire suppression was available.

42

## 43 **2. Study Area**

1 Mt. Parnitha was selected the study site to satisfy the objectives of this work. It is located  
2 approximately 30 km north of the capital of Greece, Athens (Figure 1). The area covers  
3 approximately 200 km<sup>2</sup> of land with an altitude ranging from 200-1,400 m above sea level  
4 (a.s.l.). The region is covered mainly by Greek Fir (*Abies cephalonica*) and Aleppo Pine (*Pinus*  
5 *halepensis*) forests on the slopes beneath 1,000 m altitude, grasses and shrubs dominate above  
6 1,000m, and under 300m farmlands dominate to the north with suburban housing to the east.  
7 The climate is continental, characterized by cold winters and warmer summers. Summer  
8 temperatures do not usually exceed 18°C, while in winter temperatures are frequently around  
9 0°C, with an annual average of 11°C (Ganatsas *et al.*, 2012). Average rainfall in the area is 822  
10 mm (at 1,000 m elevation), with approximately 70 rainy days per year.

11 In the summer of 2007, Greece was hit by the most devastating large fires in its recent  
12 history. Specifically on June 27<sup>th</sup>, 2007, a fire erupted in an area approximately 15 km west of  
13 the core of mount Parnitha National Park. On the next day, fanned by a medium strength west  
14 wind, it entered the forested western slopes and canyons of the mountain and spread to the  
15 summit leaving only charred trees. Its main run stopped when it reached sparse vegetation on  
16 the east slope of the mountain in the morning of June 29<sup>th</sup>. Fought by aerial fire-fighting support,  
17 it was controlled three days later (July 1<sup>st</sup>, 2007).

18

19 [ **Figure 1** Location of our study area (shown in the red box) ]

20

### 21 3. Datasets

22 Multispectral imagery from the ASTER sensor acquired shortly after the fire suppression  
23 (acquisition date: July 20<sup>th</sup>, 2007) was the primary data source to satisfy the objectives of our  
24 study. ASTER is a satellite radiometer onboard the Terra polar orbiting platform, launched end  
25 of 1999. The sensor is capable of acquiring data at 15 spectral bands across the visible (VIS) to  
26 thermal infrared (TIR) parts of electromagnetic radiation spectrum at a spatial resolution varying  
27 from 15 to 90m. ASTER has numerous unique design features that make it in many respects  
28 rather superior to other similar instruments. These include increased multispectral coverage,  
29 higher spatial resolution in certain of the spectral bands, and a stereoscopic capability. These  
30 make the sensor an important tool particularly to conduct applications related to modelling land  
31 surface studies where heterogeneity and topography variations are important, including natural  
32 hazards such burnt area mapping Detailed information on the ASTER product can be found on  
33 the National Aeronautics and Space Administration (NASA) Jet Propulsion Laboratory website  
34 (<http://asterweb.jpl.nasa.gov/documents.asp>).

35 For this study, three operationally distributed products of the same post-fire image were  
36 obtained from the ASTER distribution centre in Japan. Those consisted of the registered radiance  
37 at the sensor (ASTL1B), the Surface Radiance (AST09) and the on-Demand Orthorectified  
38 (AST14OTH) image product. The ASTL1B is the registered radiance at the sensor product on  
39 which are co-registered the spectral bands from all the spectral channels of the sensor, and is  
40 radiometrically and geometrically corrected. It has been derived from the Level-1A data on  
41 which have been applied the radiometric calibration and geometric correction coefficients. Also,  
42 both intra-telescope and inter-telescope registration correction for all the bands has been  
43 performed relative to the reference band for each sub-system (i.e. Bands 2, 6, and 11)

1 (<http://asterweb.jpl.nasa.gov/documents.asp>). The AST1B dataset is provided in a single multi-  
2 file packaged either in .hdf or .geotiff format or at a Universal Transverse Mercator (UTM)  
3 projection. The AST09 product contains the atmospherically corrected VNIR and SWIR bands  
4 data. It is derived from the ASTER Level-1B image. Atmospheric correction involves deriving a  
5 relationship between the surface radiance/reflectance and the top of the atmosphere (TOA)  
6 radiance from information on the scattering and absorbing characteristics of the atmosphere. The  
7 product is provided in either .hdf or .geotiff format and at UTM projection. The AST14OTH  
8 product contains imagery transformed from a perspective projection to an orthogonal one. It is  
9 terrain-corrected and provides radiometrically calibrated radiance. It is computed using as inputs  
10 the ASTER L1A product, georeferencing information from the ASTER instrument's and Terra  
11 platform's ephemeris and attitude data and an ASTER-derived digital elevation model (DEM).  
12 The product includes fifteen orthorectified Level-1B calibrated radiance images, one per band  
13 and at a UTM projection in .geotiff format at original spatial resolution provided in the Level 1A  
14 product. More details on the different ASTER products can be found in Abrams *et al.*, (2002). In  
15 addition to the ASTER image products, a vector layer (shapefile format) of the burnt area was  
16 used, which was derived from manual digitisation of the burnt area based on direct photo-  
17 interpretation of the visible/near infrared bands (15 m) of the AST14OTH product. For all the  
18 different products included in our analysis the radiance image product was used to ensure  
19 consistency and comparability in our analysis. This dataset of the three ASTER image products  
20 formed the reference dataset used in our study against which the burnt area estimates from the  
21 different techniques were compared to, as described later on (section 4.3).

22

## 23 **4. Methodology**

24 An overview of the methodology followed in extracting the burnt area from the post-fire  
25 ASTER image products is illustrated in Figure 2. The remainder of this section provides an  
26 overview of the main pre-processing steps implemented. All pre-processing and geospatial  
27 analysis of the spatial datasets were carried out using ENVI (v. 5.0, ITT Visual Solutions),  
28 eCognition (v8) and ArcGIS (v. 10.1, ESRI) image analysis software platforms.

29 [ **Figure 2** *Overall methodology implemented in our study* ]

30

### 31 **4.1 Pre-processing**

32 The pre-processing of the ASTER images entailed a series of steps, depending on the  
33 product type (Figure 2). As ASTER spatial resolution varies from the VNIR (15m) to SWIR  
34 (30m), image resampling of the three VNIR ASTER bands was performed to match the spatial  
35 resolution of the SWIR bands, where appropriate. Image to image co-registration between the  
36 ASTER images and also the DEM was then performed to spatially co-register all data layers  
37 using the AST14OTH orthorectified image were used as a base image. A set of approximately  
38 30 Ground Control Points (GCPs) randomly selected points clearly distinguishable on both the  
39 base and each of the other image products were used to perform the datasets co-registration.  
40 Image warping was performed by applying the nearest neighbour method, allowing a co-  
41 registration of all the images into a common UTM 34N projection under a WGS84 ellipsoid. To

1 check the co-registration accuracy, the coordinates of ~10 additional GCPs not previously  
2 included in the transformation were determined from the base image used. Results showed a  
3 positional accuracy within the sensor pixel range (i.e. < 30 m), which was considered  
4 satisfactory. Next, all the datasets were clipped to a smaller area covering an area that included  
5 the burn scar and sufficient ample land outside its perimeter.

## 7 **4.2 Burnt Area Delineation**

8 Burnt area was delineated from each of the ASTER pre-processed datasets using the ML  
9 and SVMs classifiers. The remainder of this section is focused in providing a brief explanation  
10 of the principles underlying the operation of each approach, including a description of the steps  
11 taken in extracting the burnt area from the ASTER pre-processed image from each technique.

### 13 **4.2.1 Maximum Likelihood (ML)**

14 ML implementation was performed using ENVI, following three main steps. First, a  
15 classification scheme was formulated, which consisted of the following classes: burned area,  
16 agricultural areas, urban fabric/bare soil areas, forests, and scrubland/vegetation areas. Decision  
17 to use those specific classes was assisted by our familiarity with the study area from previous  
18 work conducted in the same region (Petropoulos *et al.*, 2011; Petropoulos *et al.*, 2010b).  
19 Subsequently, training pixels were carefully selected from the AST14OTH image. The training  
20 sites were carefully determined based on the homogenous nature of pixels with respect to tone,  
21 texture, association, etc., within a similar class. Their selection was guided by photo-  
22 interpretation of a near concurrent to the ASTER Google Earth very high resolution imagery.  
23 Approximately 270 pixels of each class were identified as training data. For the selected training  
24 pixels it was examined their statistical separability in ENVI, by computing both the Jeffries-  
25 Matusita and the Transformed Divergence separability indices in (ENVI User Guide, 2008). A  
26 separability index for all class pairs was higher than 1.71 in all cases examined was reported  
27 which was considered as satisfactory. Then, the selected training points were used to  
28 parameterise the ML classifier and implement it in each of the ASTER products. A single  
29 threshold value for all classes in the classification was set up, using probability threshold value  
30 equal to zero, meaning that no pixels lower than this value are classified and also using as a data  
31 scale factor one. This deemed to be appropriate based on trial and errors performed using  
32 different parameterisation and then using the classification accuracy as measure to identify most  
33 suitable parameterisation. This is an approach employed often in optimisation of classifiers  
34 parameterisation (Petropoulos *et al.*, 2012a; Volpi *et al.*, 2013).

### 36 **4.2.2 Support Vector Machines**

37 SVMs are a non-linear and non-parametric large margin supervised classification scheme  
38 developed on the basis of Vapnik's structural risk minimisation principle (Vapnik, 1995) with no  
39 priori information on the underlying data distribution (Foody and Mathur, 2004). SVMs  
40 separates the samples of different classes by finding the separating hyperplane or decision  
41 surface related to maximal margin minimizing the hinge loss function (Boser, 1992) and  
42 maximizing the distance between the hyperplane and the nearest positive and negative training

1 example, called the margin. The aim of these hyperplane is to provide the best separation  
2 between the two classes in a multidimensional feature space reducing the generalization error  
3 which is inversely proportional to the margin. The higher dimensional kernel space is implicitly  
4 performed by applying a kernel function. The non-linear kernel functions such as Gaussian,  
5 RBF, polynomial in SVMs implicitly work linearly in a higher dimensional space, corresponding  
6 to a non-linear solution in the input space, where the data naturally resides. The use of the kernel  
7 function essentially allows the data points to be classified to spread in a way that allows the  
8 fitting of a linear hyperplane (Singh *et al.*, 2013). SVMs also introduce a cost parameter C to  
9 quantify the penalty of misclassification errors in order to handle non-separable classification  
10 problems.

11 Herein, SVMs was implemented in ENVI to each of the pre-processed ASTER images  
12 using the same set of training points selected in the ML classifier implementation. This allowed  
13 ensuring consistency and comparability in the burnt results obtained from the different  
14 classifiers. The RBF kernel was used for performing the pair-wise SVMs classification which is  
15 well tested by many researchers and has also already been shown good classification results  
16 (Petropoulos *et al.*, 2011; Srivastava *et al.*, 2012). The RBF kernel was parameterised based on  
17 performing a number of trials of parameters combinations and then using classification accuracy  
18 as a measure of quality. Such an approach has also been adopted in the past in analogous studies  
19 of SVMs implementation as well (Park and Sandberg, 1991; Petropoulos *et al.*, 2012b; Singh *et al.*,  
20 2013). The  $\gamma$  parameter was set to a value equal to the inverse of the number of the spectral  
21 bands of the imagery used each time SVMs was implemented. The penalty parameter, which  
22 controls the trade-off between allowing training errors and forcing rigid margins, was set in each  
23 SVMs equal to its maximum value (i.e. 100), indicating that we were interested to create the  
24 most accurate possible model. The pyramid parameter was set to a value of zero, since each  
25 image we wished to be processed at full resolution. Finally, a classification probability threshold  
26 of zero was also used, which meant that all image pixels forced to be classified into one of the  
27 classes of the classification scheme.

28

### 29 **4.3 Accuracy Assessment**

30 An evaluation of the classification accuracy of the thematic maps produced from the  
31 ASTER imagery, including the burnt area class, was performed by computing the error matrix  
32 statistics. In particular, the overall accuracy (OA), user's (UA), producer's (PA) accuracy and the  
33 Kappa ( $K_c$ ) statistics were derived (Congalton and Green, 1999). For this purpose, an additional  
34 set of approximately 60 representative pixels for each class included in our classification scheme  
35 were also selected. Validation points were generally selected in homogeneous regions and away  
36 from the locations where the training points had been collected, ensuring non-overlap of pixels  
37 between the training data and validation sites. To ensure consistency in our comparisons, the  
38 same set of validation points were used in evaluating the accuracy of all the thematic maps  
39 produced from the implementation of the different classifiers to the different ASTER products.

40 In addition to the error matrix, the burnt area estimates from the different techniques were  
41 compared each against our reference burnt area which was derived from direct photo-  
42 interpretation of the ASTOTH image product, following Kontoes *et al.* (2009). In this approach,  
43 accuracy of the burnt area detection is expressed in terms of detected area efficiency (DAE),



1 skipped area rate (SBA, omission error) and false area rate (FBA, commission error). These  
2 accuracy figures are computed as follows:

$$3 \quad \text{Detected Area Efficiency} = \frac{DBA}{DBA + SBA} \quad , \quad (8)$$

$$4 \quad \text{Skipped Area Rate} = \frac{SBA}{DBA + SBA} \quad , \quad (9)$$

$$5 \quad \text{False Area Rate} = \frac{FBA}{DBA + FBA} \quad , \quad (10)$$

6  
7 In the above equations, DBA is the Detected Burnt Area (i.e. the common area between  
8 the generated burn scar polygon and the reference in-situ polygon), FBA is the False Burnt Area  
9 (i.e. the area included in the generated burn scar polygon but not in the reference in-situ  
10 polygon) and SBA is Skipped Burnt Area (the area included in the reference in-situ polygon but  
11 not in the generated burn scar polygon). As from the error matrix approach statistical parameters  
12 are computed on the basis of “reference” points which selected directly from the image, the  
13 Kontoes et al. (2009) method provides a complimentary view of the detection accuracy of the  
14 burnt area estimate regionally. This is because it allows the entire predicted burnt area estimate  
15 to be evaluated regionally against another “spatial reference”, i.e. a dataset that represents the  
16 whole burnt area and not only by using selected points from that (or other) dataset. Use of their  
17 method has already been demonstrated not only in validation studies of burnt areas from  
18 different algorithms, but also of relevant operationally distributed products (Kontoes *et al.*, 2009;  
19 Petropoulos et al. 2012). In order to enable overlay and facilitate efficiency in the burnt area  
20 comparisons using the Kontoes et al. (2009) approach, each burnt area estimate from each  
21 ASTER product was extracted from the corresponding classification maps and was then exported  
22 as shapefile (.shp) to match the format of the “reference” burnt area derived from digitisation  
23 earlier during the pre-processing step. The evaluation of the accuracy of the burnt area detection  
24 by this approach was performed in ArcGIS software platform (ESRI Inc., v. 9.3.1). As a  
25 reference burnt area estimate, it was used a vector polygon generated through direct digitizing of  
26 the burned area from the ASTOTH image.

27

## 28 **5. Results**

### 29 **5.1 Classification accuracy**

30 Some of the land use land cover thematic maps produced from the implementation of the  
31 different classifiers to the three ASTER products are illustrated in Figure 3, with the burned area  
32 class shown in red. All the associated accuracy statistics to these maps derived from the error  
33 matrix computation are also summarised in Tables 1 and 2.

34 For the case of the ML classifier implementation on the ASTER image products, OA was  
35 always higher than 93% with a slight improvement when including the SWIR spectral bands to  
36 the orthorectified and the raw (L1b) ASTER image. The atmospheric correction and  
37 orthorectification applied to the ASTER raw image improved the OA from 95.38% to 97.53%

1 and 95.98% respectively when the shortwave bands were included. As seen in Table 1, the  
2 values of the Kc and the OA were always greater than 0.92. According to Table 1, the “burned  
3 area” class was generally well discriminated from the other classes using the ML classifier  
4 reporting constantly a very high PA and UA. In fact, all the PA and UA of this class were  
5 superior to 95%. However, the scrubland class always reported the lowest accuracy from all the  
6 classes in all cases of classification. Also, the highest improvement of the UA and PA of the  
7 “burned area” class was obtained in the case of the ASTER orthorectified and raw image when  
8 including all the ASTER visible near-infrared and shortwave spectral bands to the classification.  
9 As shown in Table 1 the ASTER atmospherically corrected image has shown the best result in  
10 terms of PA (100%) and UA (100%) of the burned area class in both cases of inclusion and  
11 exclusion of the SWIR bands. Also can be observed the orthorectification of the ASTER image  
12 improved only the PA of the “burned area” class passing from 95.31% to 100%. Elsewhere,  
13 when only the VNIR spectral bands were included, the PA and UA of “forest” and “bare soil”  
14 classes were improved in both cases of atmospheric correction and orthorectification, whereas in  
15 the case of SWIR band inclusion, only the atmospheric correction was reported to improve the  
16 PA and UA of the classification except for the UA of the “agriculture” class which decreased  
17 slightly from 100% to 98.28%.

18  
19 [ **Figure 3** *Thematic maps from the ML classifier implementation to the ASTER raw image (a),*  
20 *the atmospherically corrected image (b) and the orthorectified image (c), using only the VNIR*  
21 *spectral bands (left) and the VNIR and SWIR spectral bands (right). ]*

22  
23 In terms of the SVMs performance (Table 1), only the atmospheric correction of the  
24 ASTER raw image reported improvement in the OA of the classification from 94.15% to 96.92%  
25 and 98.87% to 99.01% when including to the SVMs classification only the VNIR and all the  
26 VNIR and SWIR spectral bands respectively. In this case, Kc has shown the same trend and was  
27 always greater than 0.9 with significant improvement for the raw image passing from 0.92 to  
28 0.98, followed by the atmospherically corrected image from 0.96 to 0.98 when all the SWIR and  
29 VNIR bands were included. Both OA and Kc have been improved by the inclusion of the SWIR  
30 bands to the classification process in all the scenarios studied, providing more accurate results  
31 than what was recorded for the ML classifier (Table 1). In general, high PA and UA were  
32 reported for all classes with a slight improvement of the “burned area” UA when including only  
33 the visible near-infrared bands to the ASTER orthorectified image (Table 1). Also, the PA and  
34 UA of the burned area class obtained in all the cases of the ASTER images were 100% when  
35 including the SWIR bands, meaning that all the collected validation points were found to belong  
36 to the same burned class and all the classified points as burned area can be expected to be burned  
37 area when a field survey is performed. Concerning the rest of the classes, except the PA of the  
38 forest class which improved from 98.38% to 100%, all the PA and UA accuracies of the classes  
39 decreased in the case of the orthorectified ASTER image. However, the results seem to suggest  
40 that neither the orthorectification nor the atmospheric correction improved the PA and UA  
41 accuracy of all the classes.

42

1 [ **Figure 4** Surface accuracy assessment maps from the ML classifier implementation to the  
2 ASTER raw image (a), the atmospherically corrected image (b) and the orthorectified image (c),  
3 using only the VNIR spectral bands (left) and the VNIR and SWIR spectral bands (right) ]

4 [ **Table 1** Classification accuracy assessment results from the implementation of the different  
5 classifiers ]

## 6 7 8 **5.2 Spatial agreement of burned area estimates**

9 The principal findings from the implementation of the Kontoes *et al.* (2009) accuracy  
10 assessment method from the implementation of ML classifier to the different ASTER image  
11 products are presented in Table 2. An initial inspection of the results makes apparent that the  
12 ASTER orthorectified image showed the best result compared with the two other images in  
13 terms of common burned area in cases of both exclusion and inclusion of the ASTER SWIR  
14 spectral bands (41.85 and 42.41 km<sup>2</sup> respectively). This result (Table 2) was followed by the  
15 atmospherically corrected image which has shown an improvement of the common burned area  
16 finding in both scenarios as well (40.96 and 40.64 km<sup>2</sup> respectively). Both orthorectification and  
17 atmospheric correction have demonstrated to decrease the false and skipped burned area (Table  
18 2); the inclusion of all VNIR and SWIR ASTER bands to the SVMs implementation also  
19 decreased in the case of the atmospherically corrected image. Moreover, the false burned area  
20 was always smaller than the skipped in all cases of comparisons (Table 2). It is also interesting to  
21 note that the smallest absolute difference between the burned area retrieval and the validation  
22 dataset is observed in the case of the ASTER orthorectified image (5.95 km<sup>2</sup>) when all the visible  
23 and SWIR ASTER bands are included in the classification. The above result was followed by the  
24 same image when only the ASTER visible spectral bands are included. These findings (Table 2)  
25 represent 12.3% and 13.5% respectively of the validation polygon used in the current study.  
26 Most of the skipped burned area is located along the borders of the extreme South-West and East  
27 side of Mt Parnitha region. The most accurate result in terms of absolute difference from the  
28 reference polygon is shown by the ASTER orthorectified image when SWIR bands were included  
29 (Figure 4).

30 The burnt area comparisons from the SVMs implementation to the ASTER products are  
31 illustrated in Figure 5 and the associated accuracy statistics are summarised in Table 2. An initial  
32 visual inspection of these maps also here shows a significant difference in terms of skipped and  
33 false burned area in some cases of scenarios implemented such as the inclusion of the ASTER  
34 SWIR bands to the SVMs developed model. As can be observed, the ASTER orthorectified  
35 image presented the closest prediction compared with the two other products in terms of  
36 common burned area in both cases of exclusion and inclusion of SWIR spectral bands (43.58 and  
37 43.81 km<sup>2</sup> respectively). The ASTER atmospherically corrected image has also shown an  
38 improvement in the common burned area finding but only in the case of exclusion of SWIR  
39 bands (43.52 km<sup>2</sup>). In terms of false and skipped burned area, the false burned area was always  
40 smaller than the skipped, and the orthorectified image achieved better improvement than the  
41 atmospherically corrected image (Table 2). Lastly, it is also interesting to note that the smallest  
42 absolute difference between the derived fire perimeter and the validation polygon is observed in  
43 the case of the orthorectified image (4.55 km<sup>2</sup>) in the case of ASTER SWIR bands inclusion. The  
44 given area represented 9.4% of the reference validation polygon used in the present investigation

1 (Figure 6). This result is followed by those obtained from the atmospherically corrected (3.97  
2 and 44.39 km<sup>2</sup>) and raw (4.05 and 44.31 km<sup>2</sup>) ASTER images. More recently, in an independent  
3 study Mondal et al. (2012) performed a comparative study of SVMs and ML applied to identify  
4 the accurate method for land use classification and they also reported in their study that accuracy  
5 was comparatively better in the SVMs method than the ML method.

6  
7 [ **Table 2** *Surface accuracy assessment of the burnt area derived from the classifiers*  
8 *implemented to our ASTER products* ]  
9

10 [ **Figure 5** *Thematic maps from the SVM classifier implementation to the ASTER raw*  
11 *image (a), the atmospherically corrected image (b) and the orthorectified image (c), using only*  
12 *the VNIR spectral bands (left) and the VNIR and SWIR spectral bands (right)* ]  
13

14 [ **Figure 6** *Surface accuracy assessment maps from the SVM classifier implementation to the*  
15 *ASTER raw image (a), the atmospherically corrected image (b) and the orthorectified image (c),*  
16 *using only the VNIR spectral bands (left) and the VNIR and SWIR spectral bands (right)* ]  
17

## 18 **6. Discussion**

19 Considering the error matrix of the accuracy assessment, the atmospherically corrected  
20 image showed evidently the best result in terms of OA and Kc in both ML and SVMs classifiers  
21 implementation. On the other hand, the general statistics (OA & Kc) produced from the SVMs  
22 classifier performance clearly outperformed those of the ML method with lowest performance in  
23 terms of OA, Kc, PA and UA. In fact, the inclusion of the three remaining SWIR ASTER bands  
24 to the classification process reported an improvement in the OA (between 1 and 4%) and Kc in  
25 all the three tested methods. The result can be explained by the fact that one of the direct  
26 consequences of fire is the loss of water by plant tissues (Busch and Smith, 1993). Therefore,  
27 this physiological change is easily detectable in the SWIR region of the ASTER sensor (1.6 -  
28 2.43  $\mu\text{m}$ ) and of benefit for distinguishing between the healthy or unburned and burned  
29 vegetation. Furthermore, in a study over a site in Greece, Koutsias *et al.*, (2012) reported an  
30 increase in reflectance of burned surfaces observed in the middle-infrared region (2.08 - 2.35  $\mu\text{m}$   
31 or band 7) of the Landsat TM sensor which corresponds to ASTER 5, 6, 7 and 8 bands because  
32 of the water content. The improving incidence of ASTER SWIR band inclusion to the  
33 classification process was also reported in another study by Petropoulos *et al.*, (2012c), in which  
34 the authors concluded that the benefit from Advanced Land Imager (ALI) sensor use in burned  
35 area extraction appears to be partially due to its higher number of spectral SWIR bands.

36 Findings presented herein are also in close agreement to those reported by others who  
37 have explored the use of either the ML or the SVMs classifier in burn scar extraction from  
38 multispectral imagery. For example, Petropoulos et al. (2010a) combined ASTER and Landsat  
39 TM data respectively with the SVMs in mapping the extent of the burned area of the same fire  
40 event. The results presented herein outperformed the performance of the Artificial Neural  
41 Network (ANN) and Spectral Angle Mapper (SAM) classifiers when combined with the Landsat  
42 imagery reported to that study by the authors. More recently, Mallinis and Koutsias (2012) tested

1 the combination of ASTER data considering all the bands in the classification process of the ML  
2 for mapping fire scars in the Mt Parnitha 2007 fire. Results presented herein were comparable to  
3 the results from these authors for the ML implementation; yet even more accurate in the case of  
4 the atmospherically corrected image (97.53% of OA and 0.97 of Kc). Also, a close agreement  
5 has been reported herein with the results reported by Palandjian *et al.*, (2009), who assessed the  
6 post-fire impact in the Kassandra peninsula, Greece, using LANDSAT TM imagery and the ML  
7 classifier. In addition, many authors have reported some confusion occurring between the  
8 spectral signature of recently burned area and the shaded surfaces resulting from slope  
9 illumination and high topography variation, as is the case in many Mediterranean landscapes  
10 Pollet and Omi, 2002; Veraverbeke *et al.*, 2010).

11 Koutsias *et al.*, (2012) conducted a study of the spectral signature of burned surfaces over  
12 the Mt Parnitha region and concluded that there was a strong decrease in the reflectance of  
13 burned surfaces observed in the near-infrared region (0.78-0.90  $\mu\text{m}$ ). As a general remark, a  
14 great spatial discontinuity of fire over the study area has been reported by all methods which  
15 mean small patches of unburned areas within the perimeter due to the topography and/or the  
16 vegetation response after fire. Additionally, a poor image co-registration could be at the origin of  
17 a spatial agreement problem when using the surface accuracy assessment method for evaluating  
18 the burned area. The origin of differences in terms of spatial distribution of burned area could be  
19 closely related to the land cover types of the study area and/or to the terrain structure. These two  
20 elements are the most important determining factors of burn severity in the Mediterranean  
21 region.

22

## 23 **7. Conclusions**

24 In the present study, the use of high resolution EO imagery was explored for mapping  
25 burnt scars from space using the Maximum Likelihood (ML), and Support Vector Machines  
26 (SVMs) image processing algorithms. In particular, this study was focused on investigating the  
27 potential added value of atmospheric correction, topographic correction and SWIR bands  
28 inclusion to the modelling of burnt area detection from space using these specific techniques  
29 using the techniques implemented in the ASTER global operational products. As a case study a  
30 fire event in a characteristic Mediterranean site was used for which post-fire ASTER imagery  
31 was available.

32 All the techniques used procured satisfactory results and provided clear evidence that the  
33 introduced methods offer advanced burned area mapping in terms of effectiveness and cost,  
34 compared to conventional field surveys. The SVMs classifier exorted the best result in terms of  
35 overall accuracy, kappa coefficient and UA and PA of the “burned area” class. This at least  
36 appeared to be the case in this study. The ML was less accurate than SVMs, perhaps due to the  
37 high heterogeneity of vegetation on Mt Parnitha with respect to the fire behavioural spatial  
38 variability patterns which were difficult to be modelled adequately by either method.

39 The atmospheric correction applied to the ASTER raw image proved to bring a slight  
40 improvement. A more noticeable increase was exorted by the orthorectified image in both cases  
41 of inclusion and exclusion of ASTER SWIR bands to the ML classifier. This means that the  
42 orthorectification step could be a necessary step to be included to any processing if the extent of  
43 burned area is to be mapped and there is high topography of the terrain. The inclusion of the

1 ASTER SWIR bands to the three ASTER image products also significantly improved the overall  
2 accuracy of classification. The combination of orthorectification and inclusion of SWIR bands to  
3 the ASTER raw image seems to be an essential step prior to any method implementation procedure  
4 to accurately develop models in obtaining accurately burn area cartography from EO data.

5 The research indicates that an adaptive management are very much required in allowing  
6 fire and post fire hazard reduction projects to become successful. The final results of this study  
7 indicate the key steps that should be included in a methodology for burnt area mapping which  
8 would be potentially very beneficial for forest management and conservation officials. The same  
9 time, provides potentially very useful information towards the development of EO-based  
10 techniques that aim to operationally provide services related to the estimation of burnt area. This  
11 is of considerable scientific and practical value to the wider scientific and users' community,  
12 given the continuation of free access to resolution EO data from space globally.

## 13 14 **Acknowledgments**

15 George Petropoulos wishes to thank the Greek Scholarships Foundation (IKY) for the  
16 financial support provided to support the implementation of this study. Authors would also like  
17 to thank the anonymous reviewers for their comments which assisted to improving the  
18 manuscript.

## 19 20 **References**

- 21 Abrams, M., Hook, S., Ramachandran, B., and Center, E. D.: ASTER User Handbook\* Version  
22 2, Jet Propulsion Laboratory, 4800, 2002.
- 23 Abrams, M. D. and Hulbert, L. C.: Effect of topographic position and fire on species  
24 composition in tallgrass prairie in northeast Kansas, *American Midland Naturalist*, 442-445,  
25 1987.
- 26 Ahern, F. J., Goldammer, J. J. G., and Justice, C. O.: Global and regional vegetation fire  
27 monitoring from space: planning a coordinated international effort, Kugler Publications, 2001.
- 28 Banerjee, R. and Srivastava, P. K.: Reconstruction of contested landscape: Detecting land cover  
29 transformation hosting cultural heritage sites from Central India using remote sensing, *Land*  
30 *Use Policy*, 34, 193-203, 2013.
- 31 Bastarrika, A., Chuvieco, E., and Martín, M. P.: Mapping burned areas from Landsat TM/ETM+  
32 data with a two-phase algorithm: Balancing omission and commission errors, *Remote Sensing*  
33 *of Environment*, 115, 1003-1012, 2011.
- 34 Boustras, G. and Boukas, N.: Forest fires' impact on tourism development: a comparative study  
35 of Greece and Cyprus, *Management of Environmental Quality: An International Journal*, 24,  
36 498-511, 2013.
- 37 Busch, D. E. and Smith, S. D.: Effects of fire on water and salinity relations of riparian woody  
38 taxa, *Oecologia*, 94, 186-194, 1993.
- 39 Cao, X., Chen, J., Matsushita, B., Imura, H., and Wang, L.: An automatic method for burn scar  
40 mapping using support vector machines, *International Journal of Remote Sensing*, 30, 577-  
41 594, 2009.

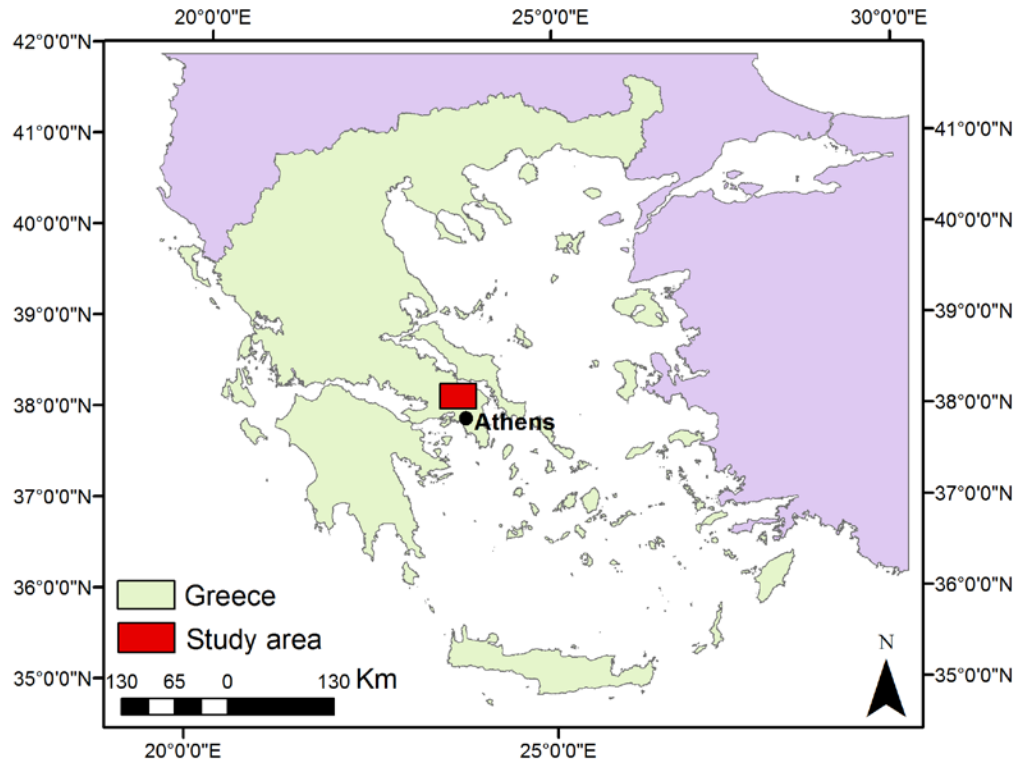
- 1 Castillejo-González, I. L., López-Granados, F., García-Ferrer, A., Peña-Barragán, J. M., Jurado-  
2 Expósito, M., de la Orden, M. S., and González-Audicana, M.: Object-and pixel-based  
3 analysis for mapping crops and their agro-environmental associated measures using  
4 QuickBird imagery, *Computers and Electronics in Agriculture*, 68, 207-215, 2009.
- 5 Cawson, J. G., Sheridan, G. J., Smith, H. G., and Lane, P. N. J.: Effects of fire severity and burn  
6 patchiness on hillslope-scale surface runoff, erosion and hydrologic connectivity in a  
7 prescribed burn, *Forest Ecology and Management*, 310, 219-233, 2013
- 8 Chuvieco, E., Giglio, L., and Justice, C.: Global characterization of fire activity: toward defining  
9 fire regimes from Earth observation data, *Global change biology*, 14, 1488-1502, 2008.
- 10 Congalton, R. G.: Accuracy assessment and validation of remotely sensed and other spatial  
11 information, *International Journal of Wildland Fire*, 10, 321-328, 2001.
- 12 ENVI User Guide: ENVI on-line software user's manual, ITT Visual Information Solutions,  
13 2008.
- 14 Foody, G. M., Campbell, N., Trodd, N., and Wood, T.: Derivation and applications of  
15 probabilistic measures of class membership from the maximum-likelihood classification,  
16 *Photogrammetric Engineering and Remote Sensing*, 58, 1335-1341, 1992.
- 17 Foody, G. M. and Mathur, A.: Toward intelligent training of supervised image classifications:  
18 directing training data acquisition for SVM classification, *Remote Sensing of Environment*,  
19 93, 107-117, 2004.
- 20 Fuller, D. O.: Satellite remote sensing of biomass burning with optical and thermal sensors,  
21 *Progress in Physical Geography*, 24, 543-561, 2000.
- 22 Ganatsas, P., Daskalakou, E., and Paitaridou, D.: First results on early post-fire succession in an  
23 *Abies cephalonica* forest (Parnitha National Park, Greece), *iForest-Biogeosciences and*  
24 *Forestry*, 5, 6, 2012.
- 25 Giglio, L., Randerson, J., van der Werf, G., Kasibhatla, P., Collatz, G., Morton, D., and DeFries,  
26 R.: Assessing variability and long-term trends in burned area by merging multiple satellite fire  
27 products, *Biogeosciences Discussions*, 6, 2009.
- 28 Gitas, I. and Devereux, B.: The role of topographic correction in mapping recently burned  
29 Mediterranean forest areas from LANDSAT TM images, *International Journal of Remote*  
30 *Sensing*, 27, 41-54, 2006.
- 31 Hope, A., Albers, N., and Bart, R.: Characterizing post-fire recovery of fynbos vegetation in the  
32 Western Cape Region of South Africa using MODIS data, *International Journal of Remote*  
33 *Sensing*, 33(4), 979-999, 2012.
- 34 Huesca, M., Merino-de-Miguel, S., González-Alonso, F., Martínez, S., Miguel Cuevas, J., and  
35 Calle, A.: Using AHS hyper-spectral images to study forest vegetation recovery after a fire,  
36 *International Journal of Remote Sensing*, 34(11), 4025-4048, 2013.
- 37 Justice, C., Giglio, L., Korontzi, S., Owens, J., Morisette, J., Roy, D., Descloitres, J., Alleaume,  
38 S., Petitcolin, F., and Kaufman, Y.: The MODIS fire products, *Remote Sensing of*  
39 *Environment*, 83, 244-262, 2002.
- 40 Kasischke, E. S. and French, N. H.: Locating and estimating the areal extent of wildfires in  
41 Alaskan boreal forests using multiple-season AVHRR NDVI composite data, *Remote Sensing*  
42 *of Environment*, 51, 263-275, 1995.
- 43 Knorr, W., Pytharoulis, I., Petropoulos, G. P., and Gobron, N.: Combined use of weather  
44 forecasting and satellite remote sensing information for fire risk, fire and fire impact  
45 monitoring, *Computational Ecology and Software*, 1, 112-120, 2011.

- 1 Kontoes, C., Keramitsoglou, I., Papoutsis, I., Sifakis, N. I., and Xofis, P.: National scale  
2 operational mapping of burnt areas as a tool for the better understanding of contemporary  
3 wildfire patterns and regimes, *Sensors*, 13, 11146-11166, 2013.
- 4 Kontoes, C., Poilve, H., Florsch, G., Keramitsoglou, I., and Paralikidis, S.: A comparative  
5 analysis of a fixed thresholding vs. a classification tree approach for operational burn scar  
6 detection and mapping, *International Journal of Applied Earth Observation and*  
7 *Geoinformation*, 11, 299-316, 2009.
- 8 Koutsias, N., Arianoutsou, M., Kallimanis, A. S., Mallinis, G., Halley, J. M., and Dimopoulos,  
9 P.: Where did the fires burn in Peloponnisos, Greece the summer of 2007? Evidence for a  
10 synergy of fuel and weather, *Agricultural and Forest Meteorology*, 156, 41-53, 2012.
- 11 Koutsias, N., Karteris, M., and Chuvico, E.: The use of intensity-hue-saturation transformation  
12 of Landsat-5 Thematic Mapper data for burned land mapping, *Photogrammetric Engineering*  
13 *and Remote Sensing*, 66, 829-840, 2000.
- 14 Koutsias, N., Martínez-Fernández, J., and Allgöwer, B.: Do factors causing wildfires vary in  
15 space? Evidence from geographically weighted regression, *GIScience & Remote Sensing*, 47,  
16 221-240, 2010.
- 17 Levin, N., Levental, S., and Morag, H.: The effect of wildfires on vegetation cover and dune  
18 activity in Australia's desert dunes: a multisensor analysis, *International Journal of Wildland*  
19 *Fire*, 21(4), 459-475, 2012.
- 20 Li, R. R., Kaufman, Y. J., Hao, W. M., Salmon, J. M., & Gao, B. C. (2004). A technique for  
21 detecting burn scars using MODIS data. *Geoscience and Remote Sensing, IEEE Transactions*  
22 *on*, 42(6), 1300-1308.
- 23 Lu, D. and Weng, Q.: A survey of image classification methods and techniques for improving  
24 classification performance, *International Journal of Remote Sensing*, 28, 823-870, 2007.
- 25 Mallinis, G., & Koutsias, N.: Comparing ten classification methods for burned area mapping in a  
26 Mediterranean environment using Landsat TM satellite data. *International Journal of Remote*  
27 *Sensing*, 33(14), 4408-4433, 2012.
- 28 Mondal, A., Kundu, S., Chandniha, S. K., Shukla, R., & Mishra, P. K.: Comparison of Support  
29 Vector Machine and Maximum Likelihood Classification Technique using Satellite Imagery,  
30 2012.
- 31 NASA Jet Propulsion Laboratory, 2004. *ASTER Documents*. [online] Available at:  
32 <http://asterweb.jpl.nasa.gov/documents.asp> [Accessed 5 June 2014].
- 33 Palandjian, D., Gitas, I. Z., and Wright, R.: Burned area mapping and post-fire impact  
34 assessment in the Kassandra peninsula (Greece) using Landsat TM and Quickbird data,  
35 *Geocarto International*, 24, 193-205, 2009.
- 36 Park, J. and Sandberg, I. W.: Universal approximation using radial-basis-function networks,  
37 *Neural computation*, 3, 246-257, 1991.
- 38 Patel, D., Gajjar, C., and Srivastava, P.: Prioritization of Malesari mini-watersheds through  
39 morphometric analysis: a remote sensing and GIS perspective, *Environmental Earth Sciences*,  
40 69, 2643-2656, 2013.
- 41 Pérez-Cabello, F., de La Riva Fernández, J., Montorio Llovería, R., and García-Martín, A.:  
42 Mapping erosion-sensitive areas after wildfires using fieldwork, remote sensing, and  
43 geographic information systems techniques on a regional scale, *Journal of Geophysical*  
44 *Research: Biogeosciences* (2005–2012), 111, 2006.



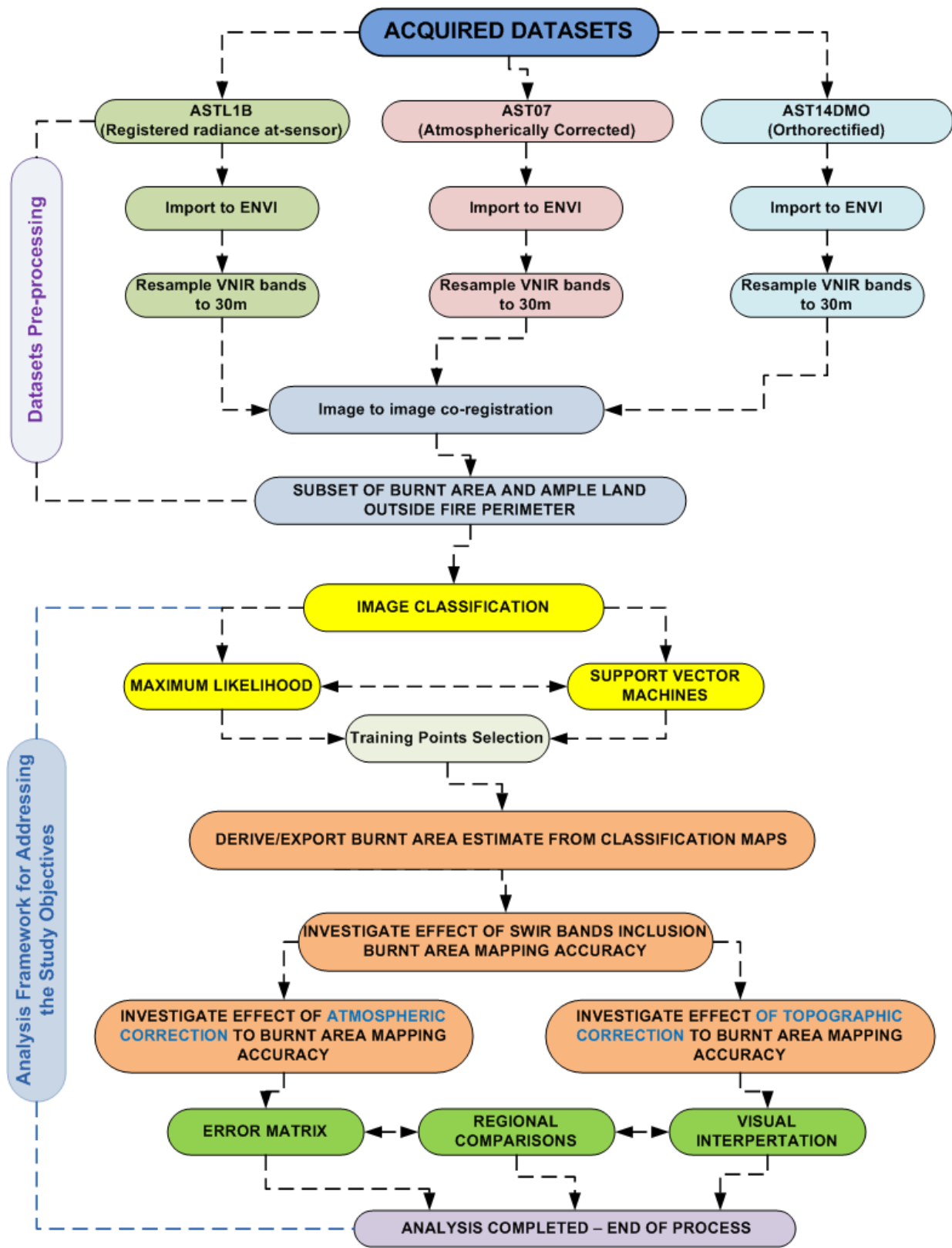
- 1 Petropoulos, G., Knorr, W., Scholze, M., Boschetti, L., and Karantounias, G.: Combining  
2 ASTER multispectral imagery analysis and support vector machines for rapid and cost-  
3 effective post-fire assessment: a case study from the Greek wildland fires of 2007, *Natural*  
4 *Hazards and Earth System Science*, 10, 305-317, 2010a.
- 5 Petropoulos, G. P., Arvanitis, K., and Sigrimis, N.: Hyperion hyperspectral imagery analysis  
6 combined with machine learning classifiers for land use/cover mapping, *Expert systems with*  
7 *Applications*, 39, 3800-3809, 2012a.
- 8 Petropoulos, G. P., Kalaitzidis, C., and Prasad Vadrevu, K.: Support vector machines and object-  
9 based classification for obtaining land-use/cover cartography from Hyperion hyperspectral  
10 imagery, *Computers & Geosciences*, 41, 99-107, 2012b.
- 11 Petropoulos, G. P., Kontoes, C., and Keramitsoglou, I.: Burnt area delineation from a uni-  
12 temporal perspective based on Landsat TM imagery classification using Support Vector  
13 Machines, *International Journal of Applied Earth Observation and Geoinformation*, 13, 70-80,  
14 2011.
- 15 Petropoulos, G. P., Vadrevu, K. P., Xanthopoulos, G., Karantounias, G., and Scholze, M.: A  
16 comparison of spectral angle mapper and artificial neural network classifiers combined with  
17 Landsat TM imagery analysis for obtaining burnt area mapping, *Sensors*, 10, 1967-1985,  
18 2010b.
- 19 Petropoulos, G.P., C. C. Kontoes & Keramitsoglou (2012c): Land cover mapping with  
20 emphasis to burnt area delineation using co-orbital ALI and Landsat TM imagery.  
21 *International Journal of Applied Earth Observation and Geoinformation*, 18, 344-355
- 22 Pollet, J. and Omi, P. N.: Effect of thinning and prescribed burning on crown fire severity in  
23 ponderosa pine forests, *International Journal of Wildland Fire*, 11, 1-10, 2002.
- 24 Rothmel, R. C.: A mathematical model for predicting fire spread in wildland fuels, USFS,  
25 1972.
- 26 Roy, D. P. and Boschetti, L.: Southern Africa validation of the MODIS, L3JRC, and GlobCarbon  
27 burned-area products, *Geoscience and Remote Sensing, IEEE Transactions on*, 47, 1032-  
28 1044, 2009.
- 29 Salvador, R., Lloret, F., Pons, X., and Pinol, J.: Does fire occurrence modify the probability of  
30 being burned again? A null hypothesis test from Mediterranean ecosystems in NE Spain,  
31 *Ecological Modelling*, 188, 461-469, 2005.
- 32 Schroeder, W., Ruminski, M., Csiszar, I., Giglio, L., Prins, E., Schmidt, C., and Morissette, J.:  
33 Validation analyses of an operational fire monitoring product: The Hazard Mapping System,  
34 *International Journal of Remote Sensing*, 29, 6059-6066, 2008.
- 35 Simon, M., Plummer, S., Fierens, F., Hoelzemann, J., and Arino, O.: Burnt area detection at  
36 global scale using ATSR-2: The GLOBSCAR products and their qualification, *Journal of*  
37 *Geophysical Research: Atmospheres* (1984–2012), 109, 2004.
- 38 Singh, S., Srivastava, P., Gupta, M., Thakur, J., and Mukherjee, S.: Appraisal of land use/land  
39 cover of mangrove forest ecosystem using support vector machine, *Environmental Earth*  
40 *Sciences*, 1-11, 2013.
- 41 Srivastava, P. K., Han, D., Ramirez, M. R., Bray, M., and Islam, T.: Selection of classification  
42 techniques for land use/land cover change investigation, *Advances in Space Research*, 2012.
- 43 Stroppiana, D., Grégoire, J.-M., and Pereira, J. M.: The use of SPOT VEGETATION data in a  
44 classification tree approach for burnt area mapping in Australian savanna, *International*  
45 *Journal of Remote Sensing*, 24, 2131-2151, 2003.

- 1 Tsela, P., Wessels, K., Botai, J., Archibald, S., Swanepoel, D., Steenkamp, K., and Frost, P.:  
2 Validation of the Two Standard MODIS Satellite Burned-Area Products and an Empirically-  
3 Derived Merged Product in South Africa, *Remote sensing*, 6, 1275-1293, 2014.
- 4 Turner, M. G., Hargrove, W. W., Gardner, R. H., and Romme, W. H.: Effects of fire on  
5 landscape heterogeneity in Yellowstone National Park, Wyoming, *Journal of Vegetation*  
6 *Science*, 5, 731-742, 1994.
- 7 Vafeidis, A. T., and Drake, N. A.: A two-step method for estimating the extent of burnt areas  
8 with the use of coarse-resolution data. *International Journal of Remote Sensing*, 26(11), 2441-  
9 2459, 2005.
- 10 Van Wagtenonk, J. W., Root, R. R., and Key, C. H.: Comparison of AVIRIS and Landsat  
11 ETM+ detection capabilities for burn severity, *Remote Sensing of Environment*, 92, 397-408,  
12 2004.
- 13 Vapnik, V., Golowich, S. E., and Smola, A.: Support vector method for function approximation,  
14 regression estimation, and signal processing, *Advances in neural information processing*  
15 *systems*, 281-287, 1997.
- 16 Veraverbeke, S., Verstraeten, W. W., Lhermitte, S., & Goossens, R.: Illumination effects on the  
17 differenced Normalized Burn Ratio's optimality for assessing fire severity. *International*  
18 *Journal of Applied Earth Observation and Geoinformation*, 12(1), 60-70, 2010.
- 19 Volpi, M., Petropoulos, G. P., and Kanevski, M.: Flooding extent cartography with Landsat TM  
20 imagery and regularized kernel Fisher's discriminant analysis, *Computers & Geosciences*,  
21 2013.
- 22



- 1
- 2
- 3
- 4
- 5

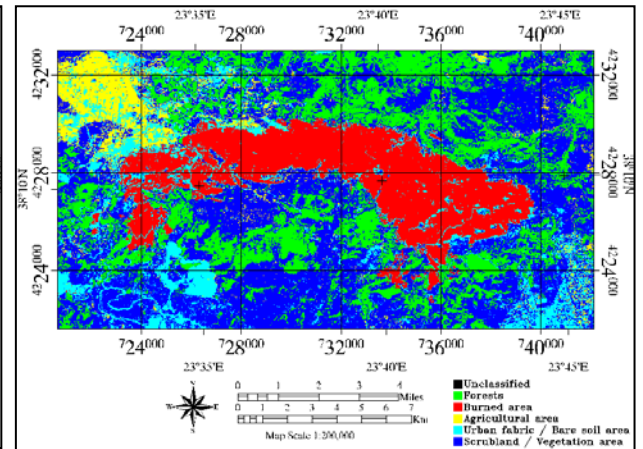
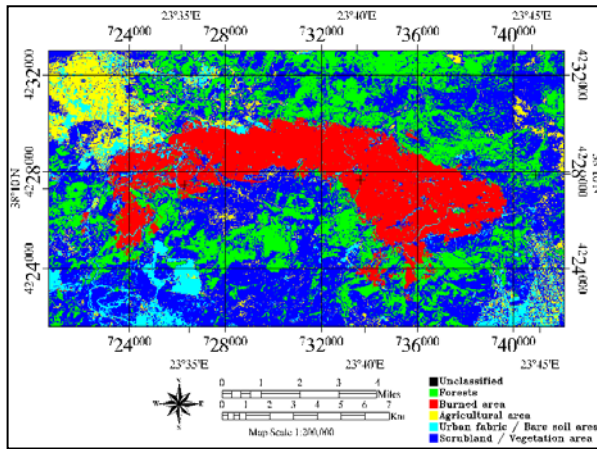
**Figure 1** *Study area location (shown in the red box)*



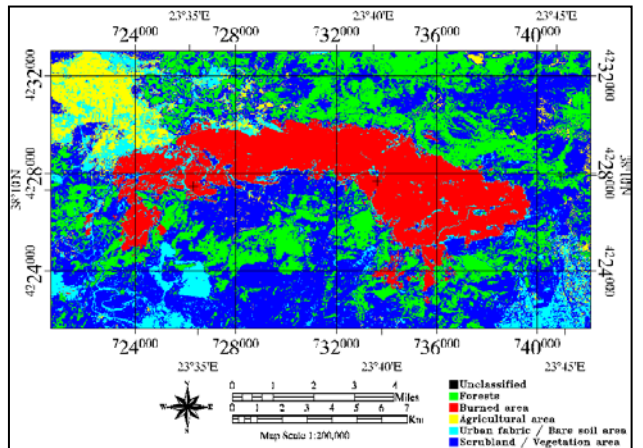
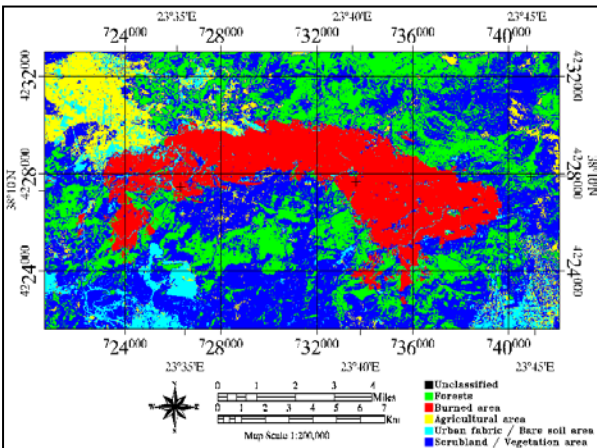
1  
2  
3

Figure 2 Overview of the methodology implemented

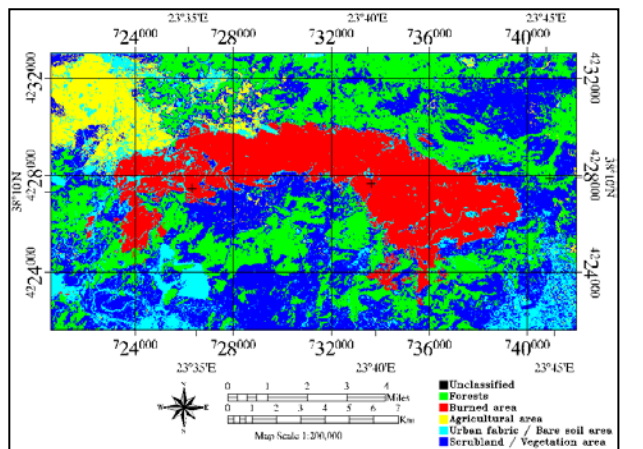
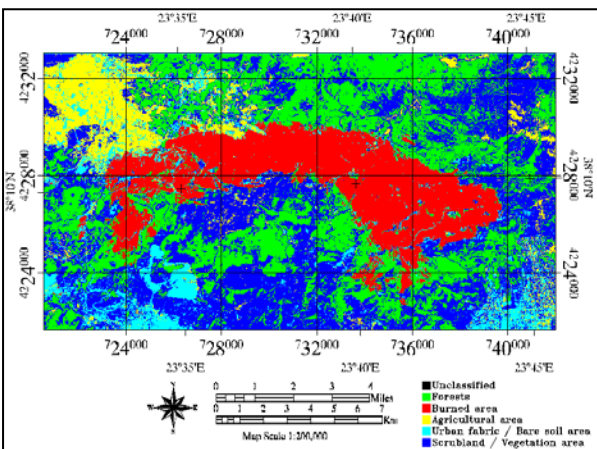
1  
2  
3  
4 (a)



5  
6  
7  
8  
9  
10 (b)



11  
12  
13  
14  
15  
16  
17 (c)

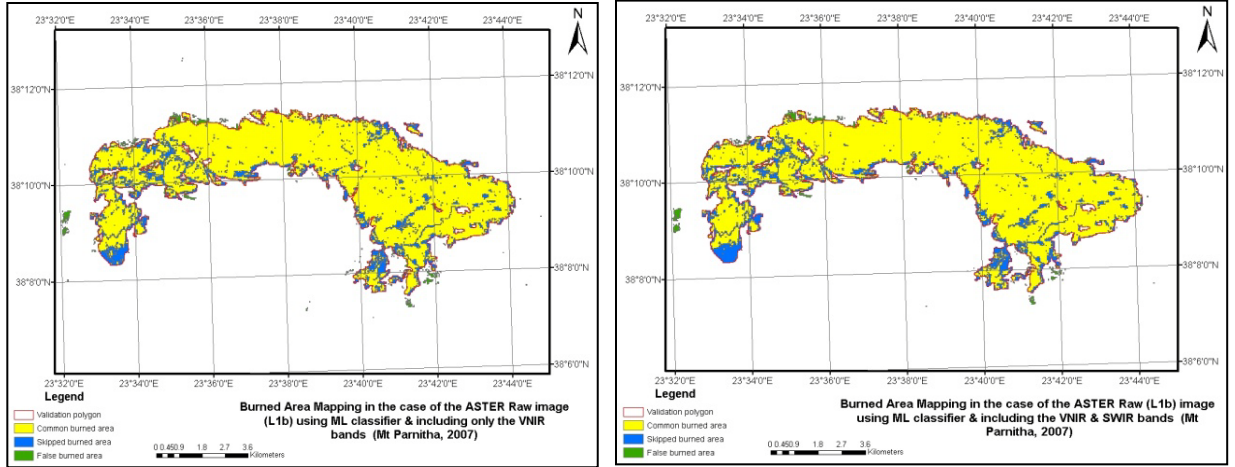


18  
19  
20  
21  
22  
23  
24  
25  
26 **Figure 3** Thematic maps from the ML classifier implementation to the ASTER raw image (a), the  
27 atmospherically corrected image (b) and the orthorectified image (c), using only the VNIR  
28 spectral bands (left) and the VNIR and SWIR spectral bands (right).  
29



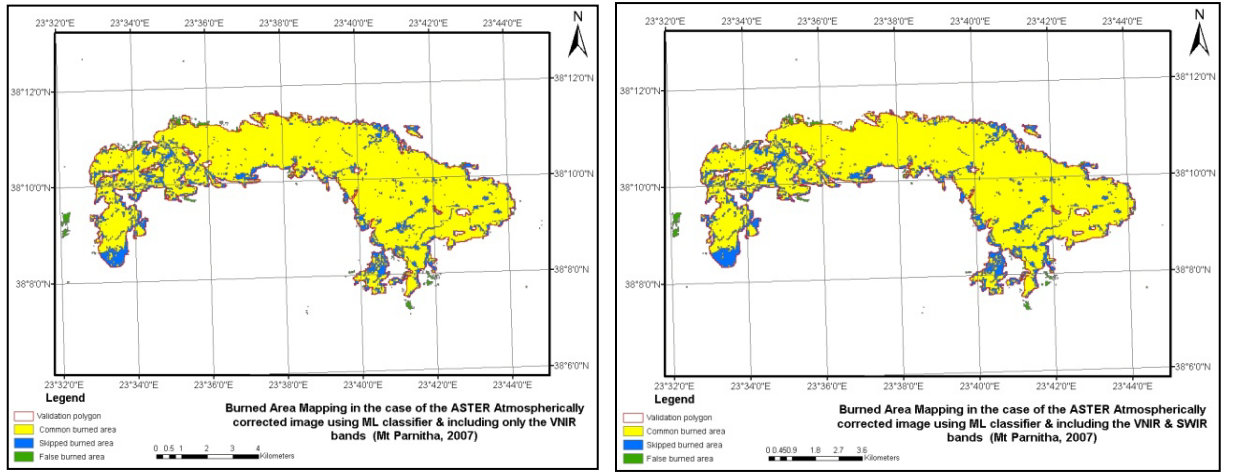
1  
2  
3  
4  
5  
6  
7  
8

(a)



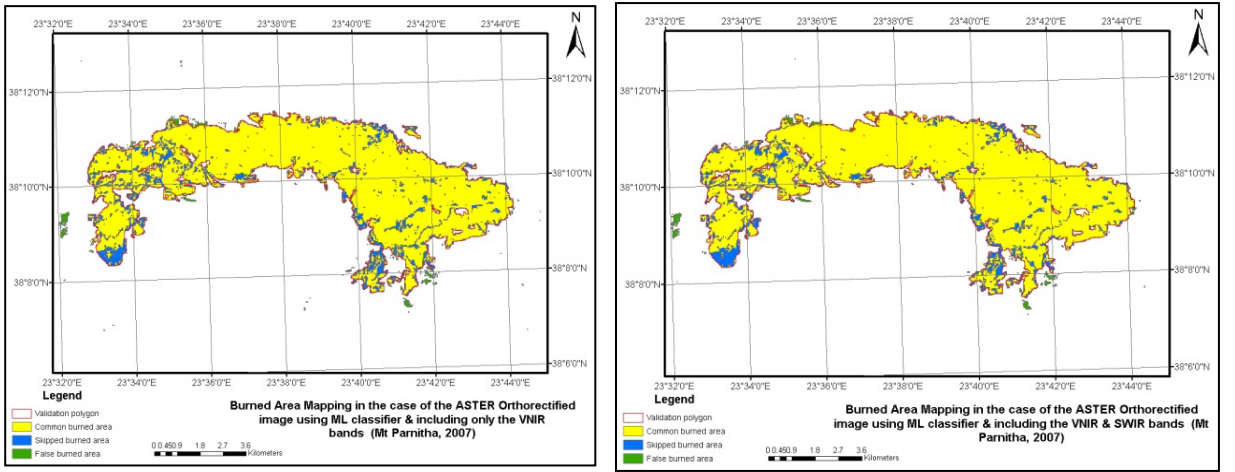
9  
10  
11  
12  
13  
14  
15

(b)

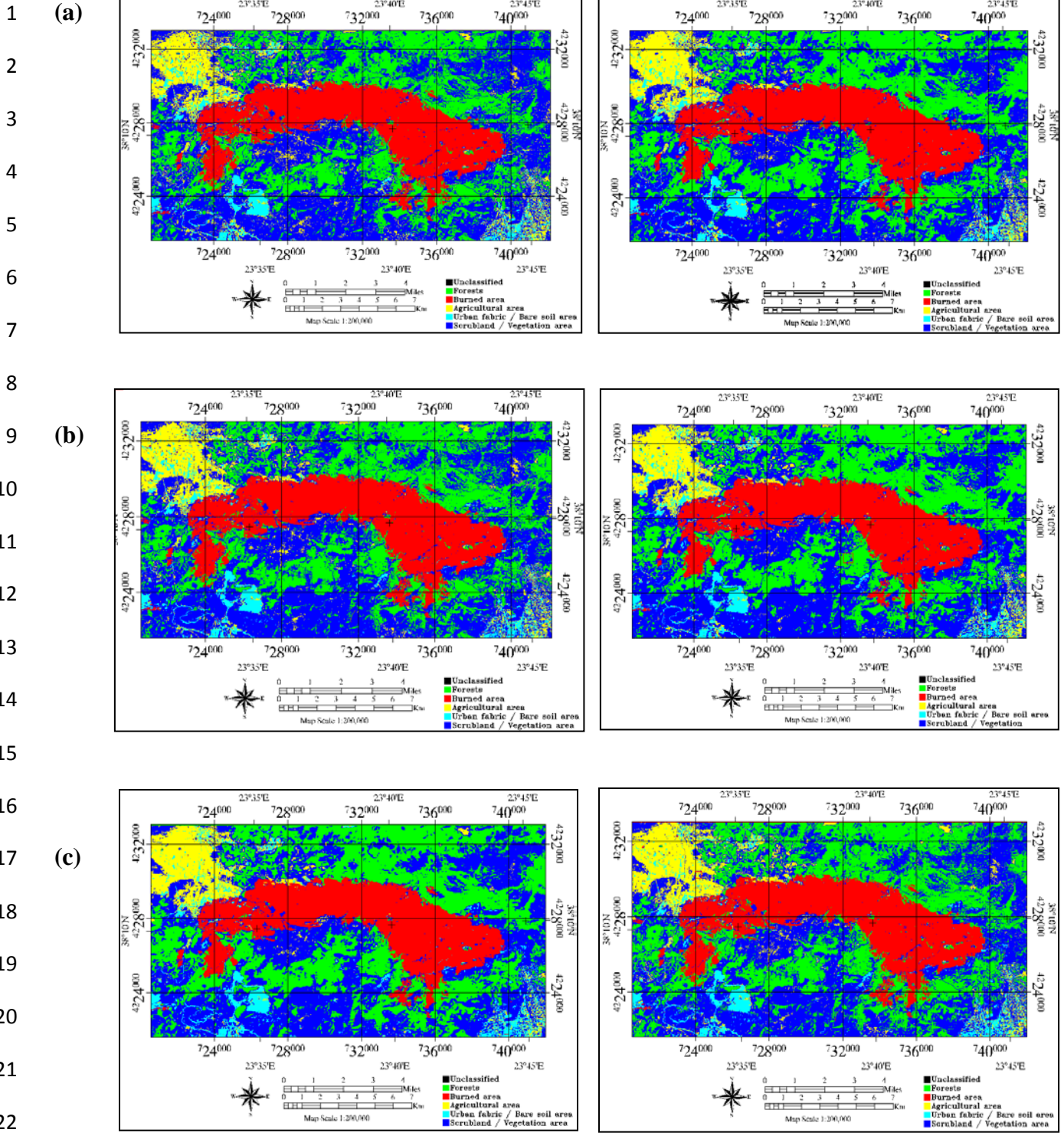


16  
17  
18  
19  
20  
21  
22  
23

(c)

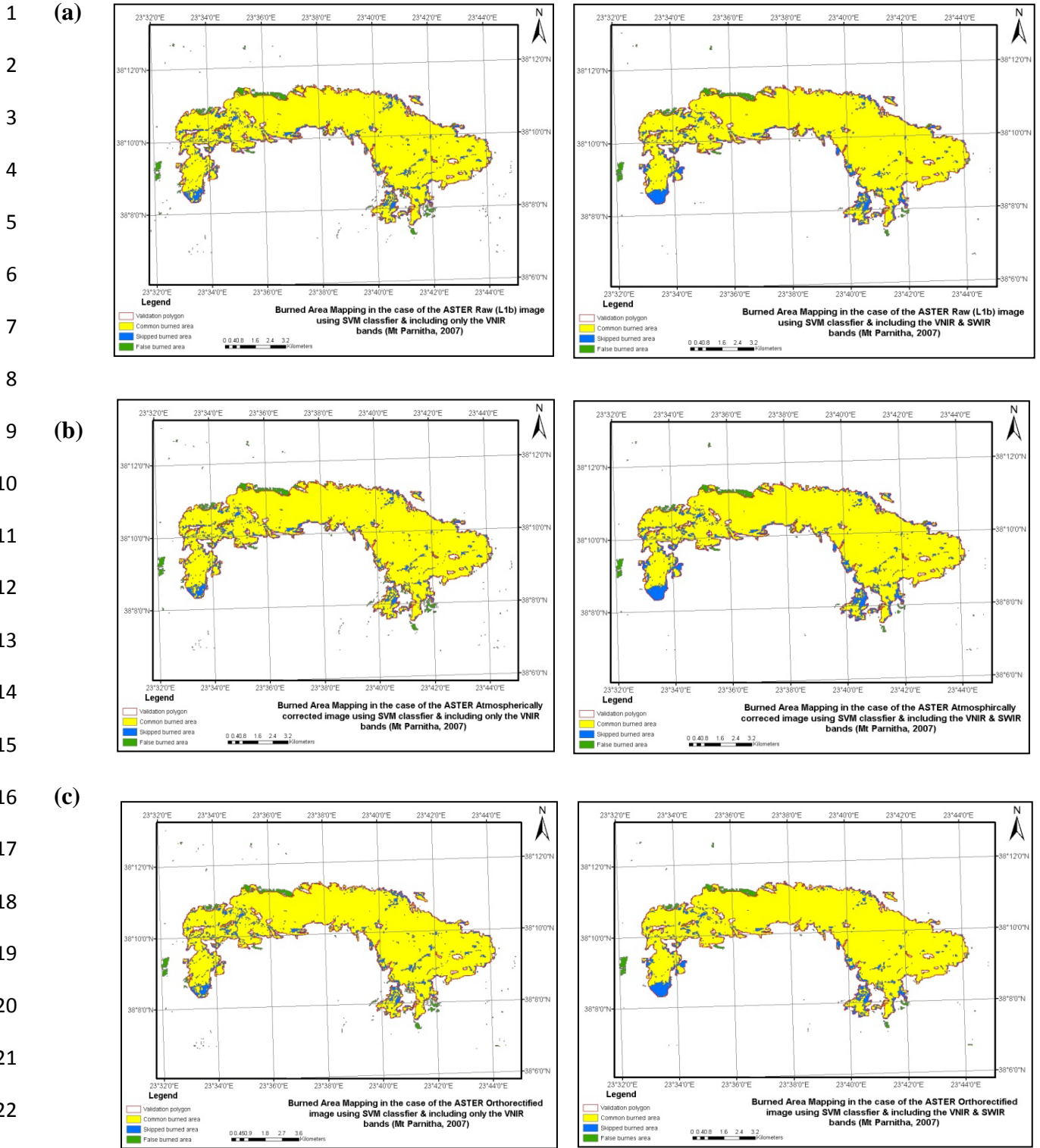


24 **Figure 4** Surface accuracy assessment maps from the ML classifier implementation to the  
25 ASTER raw image (a), the atmospherically corrected image (b) and the orthorectified image (c),  
26 using only the VNIR spectral bands (left) and the VNIR and SWIR spectral bands (right)



24 **Figure 5** Thematic maps from the SVM classifier implementation to the ASTER raw image (a),  
 25 the atmospherically corrected image (b) and the orthorectified image (c), using only the VNIR  
 26 spectral bands (left) and the VNIR and SWIR spectral bands (right)





24 **Figure 6** Surface accuracy assessment maps from the SVM classifier implementation to the  
 25 ASTER raw image (a), the atmospherically corrected image (b) and the orthorectified image (c),  
 26 using only the VNIR spectral bands (left) and the VNIR and SWIR spectral bands (right).



1  
2  
3  
4  
5

**Table 1** Classification accuracy assessment results from the different scenarios implemented using a range of ASTER image products

		ML CLASSIFICATION					
Combination of spectral bands	ASTER Product	Raw (L1b)		Atmospherically corrected		Orthorectified	
	Class	Producer's %	User's %	Producer's %	User's %	Producer's %	User's %
VNIR	Forest	97.06	89.19	100	90.67	100	83.95
	Burned area	98.39	95.31	100	100	98.39	100
	Bare soil	94.74	100	100	100	97.37	98.67
	Scrubland	88.71	87.30	88.71	98.21	75.81	94
	Agriculture	91.23	100	98.25	100	96.43	94.74
	<b>OA</b>	<b>94.15</b>			<b>97.53</b>		<b>93.82</b>
	<b>Kappa</b>	<b>0.926</b>			<b>0.969</b>		<b>0.922</b>
VNIR + SWIR	Forest	100	87.18	100	90.67	100	95.77
	Burned area	100	100	100	100	98.39	100
	Bare soil	100	98.70	100	100	98.68	94.94
	Scrubland	82.26	92.73	87.10	100	90.32	93.33
	Agriculture	92.98	100	100	98.28	91.07	96.23
	<b>OA</b>	<b>95.38</b>			<b>97.53</b>		<b>95.98</b>
	<b>Kappa</b>	<b>0.942</b>			<b>0.969</b>		<b>0.949</b>
		SVMs CLASSIFICATION					
Combination of spectral bands	ASTER Product	Raw (L1b)		Atmospherically corrected		Orthorectified	
	Class	Producer's %	User's %	Producer's %	User's %	Producer's %	User's %
VNIR	Forest	100	89.47	100	95.77	100	86.08
	Burned area	100	92.54	100	92.54	100	95.38
	Bare soil	92.11	100	92.11	100	89.47	100
	Scrubland	87.10	96.72	95.16	96.72	77.42	88.89
	Agriculture	91.23	100	98.25	100	96.43	93.10
	<b>OA</b>	<b>94.15</b>			<b>96.92</b>		<b>92.59</b>
	<b>Kappa</b>	<b>0.926</b>			<b>0.961</b>		<b>0.907</b>
VNIR + SWIR	Forest	98.38	98.06	98.06	98.06	100	89.47
	Burned area	100	100	100	100	100	100
	Bare soil	99.60	100	99.20	100	90.79	100
	Scrubland	97.99	96.70	97.99	97.34	93.55	95.08
	Agriculture	98.50	100	100	100	94.64	94.64
	<b>OA</b>	<b>98.87</b>			<b>99.01</b>		<b>95.67</b>
	<b>Kappa</b>	<b>0.986</b>			<b>0.987</b>		<b>0.945</b>

**Table 2** Surface accuracy assessment of the burnt area detection from the scenarios implemented using different ASTER products. L1B-VNIR is the registered radiance at the sensor visible and near infrared bands only, Atmo-VNIR is the atmospherically corrected visible and near infrared bands only, Ortho-VNIR is the Orthorectified visible and near infrared bands only, VNIR+SWIR is used to indicate that all visible, near infrared and shortwave infrared bands have been used.

**ML CLASSIFICATION**

<b>Image code</b>	<b>Total BA (km<sup>2</sup>)</b>	<b>Common BA (km<sup>2</sup>)</b>	<b>False BA (km<sup>2</sup>)</b>	<b>Skipped BA (km<sup>2</sup>)</b>	<b>Detection efficiency rate</b>	<b>Commission error</b>	<b>Omission error</b>
<b>L1B-VNIR</b>	41.66	40.25	1.41	8.1	0.832	0.034	0.168
<b>Atmo-VNIR</b>	42.33	40.96	1.36	7.39	0.847	0.032	0.153
<b>Ortho-VNIR</b>	42.9	41.85	1.04	6.5	0.866	0.024	0.134
<b>L1B-VNIR+SWIR</b>	41.29	40.13	1.15	8.22	0.830	0.028	0.170
<b>Atmo-VNIR+SWIR</b>	41.83	40.64	1.18	7.71	0.841	0.028	0.159
<b>Ortho-VNIR+SWIR</b>	43.36	42.41	0.94	5.94	0.877	0.022	0.123

**SVMs CLASSIFICATION**

<b>Image code</b>	<b>Total BA (km<sup>2</sup>)</b>	<b>Common BA (km<sup>2</sup>)</b>	<b>False BA (km<sup>2</sup>)</b>	<b>Skipped BA (km<sup>2</sup>)</b>	<b>Detection efficiency rate</b>	<b>Commission error</b>	<b>Omission error</b>
<b>L1B-VNIR</b>	45.73	43.1	2.63	5.26	0.891	0.058	0.109
<b>Atmo-VNIR</b>	46.26	43.52	2.73	4.83	0.900	0.059	0.100
<b>Ortho-VNIR</b>	45.66	43.58	2.08	4.77	0.901	0.046	0.099
<b>L1B-VNIR+SWIR</b>	45.01	42.93	2.07	5.42	0.888	0.046	0.112
<b>Atmo-VNIR+SWIR</b>	44.45	42.48	1.96	5.88	0.878	0.044	0.122
<b>Ortho-VNIR+SWIR</b>	45.54	43.81	1.73	4.54	0.906	0.038	0.094