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PRINT

Published in
International Journal of
Applied earth
Observation &
Geoinfomration

Exploring the Potential of Sentinels-1 & 2 of the Copernicus Mission in Support of Rapid and Cost-effective Wildfire Assessment

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Abstract: The present study explores the use of the recently launched Sentinel-1 and -2 data of the Copernicus mission in wildfire mapping with a particular focus on retrieving information on burnt area, burning severity as well as in quantifying changes in soil erosion. As study area, the Sierra del Gata wildfire, occurred in Spain during the summer of 2015 was selected. First, diverse image processing algorithms for burnt area extraction from Sentinel-2 data were evaluated. In the next step, burning severity maps were derived from Sentinel-2 data alone, and the synergy between Sentinel-2 & Sentinel-1 for this purpose was evaluated. Finally, the impact of the wildfire to soil erodibility estimates derived from the Revised Universal Soil Loss Equation (RUSLE) model implemented to the available Sentinel images was explored. In overall, the Support Vector Machines (SVM) classifier obtained the most accurate burned area mapping, with a derived accuracy of 99.38%. An object-based SVM classification using as input both optical and radar data was the most effective approach of delineating burn severity, achieving an overall accuracy of 92.97%. Soil erosion mapping predictions allowed quantifying the impact of wildfire to soil erosion at the studied site, suggesting the method could be potentially of a wider use. Our results contribute to the understanding of wildland fire dynamics in the context of the Mediterranean ecosystem, demonstrating the usefulness of Sentinels and their derived products in wildfire mapping and assessment.

Keywords: Sentinel-1, Sentinel-2, burned area mapping, burning severity, Support Vector Machines, RUSLE, soil erodibility, Mediterranean

1. Introduction

At a global scale, about 350 million hectares of land are annually affected by fire events (van der Werf et al., 2006). Wildland fires play an important role in the evolution, organization and distribution of ecosystems (Knorr et al., 2011; Koutsias et al. 2012; Ireland et al., 2015). They also have negative effects, such as being a threat to the natural environment, wildlife, the economy and putting human life at risk (Kalivas et al., 2013; Tanase et al., 2015; Vhengani et al., 2015). In the Mediterranean region, wildfires are regarded as one

of the most threatening natural disasters to effect property and infrastructure, with wildfires having a long and important presence in the region, intertwined with the area's history. On a regional scale, nearly 90% of all wildland forest fires within the boundaries of the European Union take place in Mediterranean countries (Petropoulos et al., 2011). This translates to approximately 65,000 fires every year, which in turn burn, on average, half a million hectares of forested areas (European Commission, 2010). The damages caused by wildfire events and the potential for more frequent events have led to policy changes to reflect changing attitudes globally. Policies towards wildfires in the European region in particular are driven by the European Union (EU), in particular the establishment of the European Forest Fire Information System (EFFIS, <http://effis.jrc.ec.europa.eu/>). This collaboration has allowed EU member states to have uniform information on forest fires in the Pan-European region (European Commission, 2015); exchanges of information on fire prevention and restoration practices, amongst other activities, are enabled by this collaboration.

One of the issues with an increase in fires occurrence globally and regionally is that there is an accompanying rise in costs to monitor and suppress these events. Therefore, there is a need to understand patterns of fires and develop or further improve cost-efficient techniques of mapping burned areas (Kalivas et al., 2013; Lentile et al., 2006; Said et al., 2015). A number of approaches are available to evaluate the extent and damage of wildfires. Due to the rise in accessible Earth Observation (EO) products, wildfire risk and areas affected can be mapped with relatively low labor-intensive costs over large areas (Vhengani et al., 2015). The use of EO datasets for this purpose has been advocated by many, as when gathering ground fire severity estimates there is considerable effort and labor involved; EO is essential for landscape level assessments of wildland fires (Tanase et al., 2015). Some of the main advantages of using EO data when exploring wildland fires is that large areas can be assessed with relative ease and cost (Cohen & Goward, 2004; Petropoulos et al., 2014), as well as assessing regions that are inaccessible at regular time intervals (Tanase et al., 2015).

The Copernicus is the umbrella name for a number of satellite missions including optical instruments, altimetry systems, radiometers and spectrometers (Borgeaud et al., 2015). Two of the most recent missions within Copernicus are the Sentinel missions, with this project focusing on Sentinel-1 and -2. Each Sentinel is based on a constellation of 2 satellites in the same orbiting pattern, with Sentinel-1 a C-band SAR system (Torres et al., 2012) and Sentinel-2; a multispectral high-resolution optical satellite system (Drusch et al., 2012; Fletcher, 2012; Fernández-Manso et al., 2016; Chatziantoniou et al., 2017). These two systems have only recently come online; Sentinel-1A was launched on 03 April 2014 and -1B on 25 April 2016, with Sentinel-2A launched on 23 June 2015 and 2B planned for launch in 2017 (Fernández-Manso et al., 2016; European Space Agency, 2016). At the time of writing this communication, and to the authors knowledge only a few studies have related Sentinel-2A to wildfires (Fernández-Manso et al., 2016; Mallinis et al., 2017) only one study has been conducted specifically aimed at Sentinel-1 and wildfires (Imperatore et al., 2017).

Information in terms of burn severity in relation to these two missions is to our knowledge limited, with minimal to no research being conducted to explore their suitability in regards to wildfires. Therefore, it is evident that, having outlined the potential of EO data for monitoring wildfires, the new Sentinel-1 and 2 can complement this. Datasets from these constellations are free to use, therefore further reducing costs and enabling a greater understanding of wildfires in the Mediterranean and further afield. It has been observed that vulnerability to soil erosion is indicated immediately after a fire event has taken place (Certini, 2005; Shakesby, 2011). Therefore, the opportunity arises to test Sentinel-1 and 2

products to predict post-wildfire soil erosion rates through the use of the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1997).

The aim of this study was to assess the suitability of the recently launched Sentinel-1 and 2 missions for mapping wildfires, and the potential applications of derived products in the Mediterranean ecosystem. This was initially achieved by using multi-temporal Sentinel-1 and Sentinel-2 datasets obtained pre- and post- wildfire events, to assess the suitability of different methods of deriving burned area maps. Consequently, a burn severity map was produced by using Sentinel-2 datasets and derived products and it was investigated whether the introduction of Sentinel-1 in a synergistic dataset could improve accuracy of burn severity. Finally, the suitability of the Sentinel missions for contributing to post-fire soil erosion vulnerability maps from the RUSLE model was evaluated.

2. Materials and Methods

2.1. Study site

Due to the requirements of co-orbital Sentinel 1 & 2 images imposed in this study, there were few available study sites; Sentinel-2A was only launched on the 23 June 2015, with this being roughly half way into the commonly acknowledged European wildfire season that runs from March until October (European Commission, 2015). Therefore, the study was limited to wildfires that occurred in the latter half of the 2015 season. Information freely available from EFFIS was used to locate a suitable site. Based on that, the wildfire that occurred from the 5th to 10th August 2015 in Sierra de Gata, Caceres (central-western Spain, near the Portuguese border) was chosen to evaluate the study objectives. The study area is shown in Figure 1. The study site is located in a Mediterranean region which is juxtaposed by large mountains that make up part of the Central Iberian system; the area is mountainous with large variations in elevation and aspect (Menéndez et al., 1995). The wildfire chosen in this study lasted for 5.5 days, burning approximately 79.50 km² of scrublands and forest (Fernández-Manso et al., 2016; EFFIS, 2016), making this wildfire the largest by a considerable margin in the Spanish wildfire season of 2015.

2.2. Data sets

Sentinel-1 is the first of the Copernicus mission's operational Sentinel satellites, and comprises of a constellation of two satellites: Sentinel-1A and 1B. They are C-band SAR satellite systems, operating at a center frequency of 5.405 GHz, supporting HH-HV and VV-VH co- and cross-polarization channels (Torres et al., 2012; Hornacek et al., 2012). Within the Sentinel-1 system, the main mode is the Interferometric Wide-swath mode (IW), which allows for a large swath width (250 km) and a high geometric resolution on the ground (5m x 20m) (Torres et al., 2012). Sentinel-2 is a multispectral high-resolution optical satellite system (Drusch et al., 2012; Fletcher, 2012; Fernández-Manso et al., 2016).

One post-fire Sentinel-1 image obtained in this study was an IW scene and had an acquisition date 12 August 2015. The scene orbit number was 7226 and the pass direction was descending. The polarization of the obtained scene was both VV and VH. The imagery of this specific date was chosen due to being the closest available to the fire event, and closest to synchronization with the Sentinel-2 products.

The Sentinel-2 scenes were acquired through the European Space Agency's (ESA) Sci-Hub. Two scenes were acquired, one before the wildfire event and one after the wildfire

event. Due to the relatively short operational period of Sentinel-2 and cloud cover, the range of images was limited. The two images obtained to carry out the bulk of this study were captured on 4 August 2015 and 12 August 2015. These were the closest cloud free dates on either side of the fire event, and allowed for continuity with the radar image captured. To test the suitability of the Sentinel missions for contributing to post-fire soil erosion vulnerability maps through the use of the RUSLE soil erosion index in conjunction with burn severity maps, ancillary datasets were obtained. The first dataset, obtained to perform slope and elevation analysis, was an SRTM 1 ARC-second image. SRTM 1 ARC-second datasets (<https://lta.cr.usgs.gov/SRTM1Arc>) provide global coverage of elevation data with a resolution of 30 meters. Soil maps were obtained from the European Union, alongside meteorological data for the days surrounding the fire. Rainfall erosivity and soil erodibility factors were provided from the Joint Research Centre's (JRC) European Soil Data Centre (ESDAC, <http://eusoils.jrc.ec.europa.eu/resource-type/datasets#>).

Figure 1. Location of study site, Sierra de Gata, within Caceres, Spain. Image acquired from Sentinel -2 on August 4, 2015.

Further to the datasets described above, a reference dataset was required to undertake accuracy assessments. A vector shapefile was provided by EFFIS, so that fire perimeters could be derived from satellite data and visual interpretation. To compliment the EFFIS dataset, further materials were obtained from the Copernicus Emergency Management Service (EMS). This is a service that provides rapid mapping of natural disasters, with products derived from satellite remote sensing and field observations (Kucera, 2016). Numerous products were obtained from the Copernicus EMS, including an EMS-grading map (EMSR132) for the Sierra de Gata wildfire event. The dataset detailed four levels of burn severity: destroyed area, highly damaged area, moderately damaged area, and negligible to slight damaged area. This dataset was derived from Pleiades-1A data (<https://www.satimagingcorp.com/satellite-sensors/pleiades-1/>) (acquired on 15 August 2015) and field plots, with the dataset considered to have an overall accuracy of over 85% (Copernicus EMS, 2016).

2.3. Datasets pre-processing and derived products

A summary of the pre-processing procedures adopted is illustrated in Figure 2. Briefly, the Sentinel-1 Toolbox (S1TBX) within SNAP was used to perform the main steps (Kucera, 2016). The scene was imported in SNAP, and due to the large nature of each swath (~250 km per burst) the first step was to perform 'TOPSAR Split'. Next, a de-burst operation was performed. This involves concatenating the individual bursts of sub-swaths into a single sub-swath, allowing for the rectification and normalization of the scene (Koppel et al., 2015). To ensure the image is properly aligned, before conducting radiometric correction, an orbit file was applied to the scene. Following this step, the scene was radiometrically corrected; digital pixel values were converted to radiometrically calibrated backscatter. This then allowed for a conversion of image intensity values into sigma nought (σ^0), which were derived as recommended by the literature (Stroppianna et al., 2015). SAR images are associated with salt and pepper like texturing (Lillesand et al., 2008), called speckling. To reduce this speckling effect, a Refined Lee filter was applied (Stroppianna et al., 2015). Finally, geometric correction was performed, through the Range-Doppler Terrain Correction. The output for the outlined process was a Sentinel-1 scene for the study area made up of σ^0 backscatter values. The final step applied to the Sentinel-1 scene was a conversion to decibels (dB), again using SNAP. Finally, the Sentinel-1 scene was resampled to 10 m, to allow for an accurate implementation with the Sentinel-2 scene. The resulting VV and VH images calibrated to a decibel measure of backscattering coefficient.

The Sentinel-2 datasets included all available spectral bands (shown in detail in Table 1) apart from the three 60 m bands (Coastal aerosol, water vapor and SWIR-Cirrus). Due to a multi-temporal approach adapted here, it is important to be aware of effects the atmosphere can have on imagery, as false changes could be observed in Sentinel-2 images due to changes in atmospheric constituents (Drusch et al., 2012; Novelli et al., 2016). To perform this, the Semi-Automatic Classification Plugin (SCP) was used (Congedo., 2016). The L1C product is characterised by Top of Atmosphere reflectance values (TOA) (Novelli et al., 2016); however to obtain an L2A product, a Dark Object Subtraction (DOS) was performed to scale the Sentinel-2 bands to surface reflectance (Chavez, 1996). Within the SCP, Sentinel-2 images are first converted to radiance prior to applying DOS (Congedo, 2016). The radiance of dark object was calculated as (Sobrino et al., 2004):

$$L_{D01\%} = 0.01 \cdot |(ESUN_{\lambda} \cdot \cos\theta_s \cdot T_z) + E_{down}| \cdot T_z / (\pi \cdot d^2) \quad (1)$$

ESUN is solar irradiance, in $W/(m^2 \mu m)$. SCP uses the DOS1 technique, the simplest DOS. For the above equation, the assumptions are made with the following values (Congedo, 2016): $T_v = 1$, $T_z = 1$, $E_{down} = 0$. These values are used to calculate path radiance, where path radiance for Sentinel-2 is:

$$L_p = M_L \cdot DN_{min} + A_L - 0.01 \cdot ESUN_{\lambda} \cdot \cos\theta_s / (\pi \cdot d^2) \quad (2)$$

From path radiance, land surface reflectance is calculated. Land surface reflectance is the fraction of incoming solar radiation reflected from the Earth's surface (Feng et al., 2013), and is given by (Congedo, 2016):

$$p = [\pi \cdot (L_{\lambda} - L_p) \cdot d^2] / (ESUN_{\lambda} \cdot \cos\theta_s) \cdot b \quad (3)$$

Figure 2. Methodology work flow for the pre-processing of Sentinel 1.

Table 1. Spectral properties of the Sentinel-2 instrument (adapted from Drusch et al, 2012).

Band number	Band	Central wavelength (nm)	Band (nm)	Ground spatial resolution (m)
1	Coastal aerosol	443	20	60
2	Blue	490	65	10
3	Green	560	35	10
4	Red	665	30	10
5	Red-edge 1	705	15	20
6	Red-edge 2	740	15	20
7	Red-edge 3	783	20	20
8	NIR	842	115	10
8a	NIR narrow	865	20	20
9	Water vapour	945	20	60
10	SWIR - Cirrus	1380	30	60
11	SWIR1	1610	90	20
12	SWIR2	2190	180	20

The scenes selected were cloud free, therefore there was not a requirement to perform cloud masking. Each band was homogenized to 10 m using the nearest neighbor resampling technique, to allow for an accurate comparison between spectral bands.

The approach used to map burned areas and then subsequently quantify the level of burn severity, required several products to be derived from the Sentinel-2 dataset. Each product is listed in Table 2 to summarize the calculations used. The first of these derived products was the Normalized Burn Ratio (NBR), developed in Garcia & Caselles (1991). Values of the NBR dataset range from -1 to +1, where burned areas have negative values (towards -1) and unburned areas have positive values (towards +1). The next burnt area product generated was the Normalized Difference Vegetation Index (NDVI), an index originally proposed by Rouse et al. (1973) and developed by Tucker (1979). NDVI was developed as a measure of vegetation greenness (Gamon et al., 2015), and is typically used as a way to map photosynthetic activity. Values for NDVI range from -1 to +1, where vegetated areas have a pixel value exceeding 0.1, with the higher the pixel value, the more photosynthetically active the vegetation. The third product was generated implementing the Green Normalized Vegetation Index (GNDVI), an index that is more sensitive for denser canopies (Fernández-Manso et al., 2016; Buschmann & Nagel, 1993). NDVI and NBR tend to saturate where canopies are denser, and due to the varied characteristics of the study site, GNDVI was used as well as NDVI and NBR. The next derived product generated was the Mid-Infrared Burn Index (MIRBI), as described in Vhengani et al. (2015), Schepers et al. (2014) and Trigg et al. (2005). The MIRBI was designed to be the optimum indices for use in shrub/scrubland vegetation areas (Trigg et al., 2005) where NIR wavelengths are less useful due to vegetation being senescent in the fire season (Schepers et al., 2014). This indicates the advantage of MIRBI over NBR; however, both are used here due to the varied characteristics of the study site. The Modified Simple Ratio red-edge (MSRre), an index that uses the red-edge sensor capability of Sentinel-2 (Fernández-Manso et al., 2016), was also derived. The method uses a ratio of reflectance along the red-edge, to highlight plant and vegetation health (Tillack et al., 2014). The final index generated was the Chlorophyll Index Red-edge, an index that has been

statistically proven to discriminate burned areas (Fernández-Manso et al., 2016). This is a method that highlights the chlorophyll content of different vegetation (Clevers & Gitelson, 2013). The MSRre and Clre indices were normalized, as this is recommended when seeking relationships between different data sources (Maas & Rajan, 2010). To normalize these two indices, the Geomorphology and Gradient metrics toolbox was used in ArcMap 10.3 (ESRI, 2014).

Table 2. Spectral indices used in this study, implemented to Sentinel-2 images.

Spectral index	Abbr.	Formula	Reference(s)
Normalized Burn Ratio	NBR	$\frac{NIR - SWIR}{NIR + SWIR}$	Garcia & Caselles (1991)
Normalized Difference Vegetation Index	NDVI	$\frac{NIR - Red}{NIR + Red}$	Tucker (1979)
Green Normalized Difference Vegetation Index	GNDVI	$\frac{NIR - Green}{NIR + Green}$	Buschmann & Nagel (1993)
Mid-Infrared Burn Index	MIRBI	$10SWIR2 - 9.8SWIR + 2$	Trigg et al. (2005)
Modified Simple Ratio red-edge	MSRre	$\frac{(NIR/red\ edge\ 1) - 1}{\sqrt{(NIR/red\ edge\ 1) + 1}}$	Chen (1996) and Fernández-Manso (2016)
Chlorophyll Index Red-edge	Clre	$\frac{Red\ edge\ 3}{Red\ edge\ 1} - 1$	Gitelson et al. (2003) and Shang et al. (2015)

Following on the pre-processing of the radar and optical datasets, and the subsequent generation of spectral indices, the individual bands were combined to form a single multi-band GeoTiff (.tif) raster dataset. Bands 1-10 comprised of the Sentinel-2 bands, bands 11-17 were the spectral indices from Table 2, and bands 18-19 were the VVdB and VHdB Sentinel-1 products. Evidently, this was only applied to the post-fire scene.

2.4. Processing and analysis

2.4.1. Burnt area mapping

To delineate burned areas, five methods were employed. The first was a Support Vector Machines (SVM) classifier (Cortes & Vapnik, 1995), a machine learning method that performs a supervised classification with a background in statistical learning theory. SVM can be described as a binary classifier, which solves both linear and non-linear classification problems through the employment of a kernel function; this function transforms non-linear datasets into a high-dimensional feature space, allowing for the classification to be performed linearly (Vapnik, 1995). There are four commonly used kernel functions in the field of remote sensing; Radial Basis Function (RBF), Sigmoid, Linear and Polynomial. To classify burned areas in the scene, the RBF Kernel was employed on the optical Sentinel-2 dataset; a uni-temporal approach. The same parameters employed in previous studies that classified burned areas were used here, where the penalty parameter was set to its maximum value, meaning there were no unclassified pixels (Petropoulos et al., 2010a; Petropoulos et al., 2010b; Petropoulos et al., 2011; Petropoulos et al., 2012). The classifier was implemented in ENVI 5.0 after selecting and training 2000 pixels for burned/unburned.

The next two methods explored were derived from the NBR spectral index (Table 2). The first was a simple differenced NBR ($dNBR = NBR_{before} - NBR_{after}$). Thus, the subsequent image highlighted changed pixels. The theory behind this method is that unburned areas pixel values will have no change, whereas areas that have been affected by a fire event exhibit changes in pixels (Key & Benson, 1999). To binarize the image and remove any remaining background

pixels, an OTSU threshold was applied (Otsu, 1979). This then allowed results to be converted to a shapefile. The pre- and post-fire NBR scenes are shown in Figure 3. The third method employed again used the NBR spectral index; however, this time was an OBIA rule-based approach for the post-fire scene. This was achieved using the segmentation algorithm developed in Clewley et al. (2014). The algorithm uses a K-means clustering approach to segment the scene. The NBR scene was segmented and then a rule-based approach was implemented, where burned areas were identified as clumps having a mean NBR value >0.1 . Areas with mean NBR values less than this, were classified as unburned.

Figure 3. NBR Spectral Indices of the pre-fire (left) and post-fire (right) scenes.

The final two methods explored to map burned areas are hereafter referred to as “MultiIndex 1” and “MultiIndex 2”. These are derived from merging spectral indices, as discussed in Vhengani et al. (2015). The MultiIndex 1 was generated by Vhengani et al. (2015) and is a novel technique that uses Landsat 8 (LS8) data. However, with the enhanced spectral capability of Sentinel-2, this index has been adapted to use indices generated from Sentinel-2 bands. The MultiIndex 2 uses other suitable vegetation indices (Gitelson et al., 2003; Hill, 2013; Segl et al., 2015) to explore if red-edge indices generate a more accurate burn map than the LS8 index. More specifically:

$$\text{MultiIndex 1} = (1 - \text{NBR}) \cdot \text{NDVI} \cdot \text{MIRBI} \quad (4)$$

$$\text{MultiIndex 2} = (1 - \text{NBR}) \cdot \text{NCIre} \cdot \text{NMSRre} \cdot \text{GNDVI} \quad (5)$$

The advantage of merging indices in this way is that this removes the anisotropic nature of pixel values on the Earth’s surface (Vhengani et al., 2015). The indices complement each other, and within both equations, NBR is subtracted from 1. To calculate the burned area, for each MultiIndex, the value after the fire event is subtracted from the value before the event, i.e.: Burnt Area = $\text{MultiIndex}_{\text{before}} - \text{MultiIndex}_{\text{after}}$. Figure 4 exemplifies the $\text{MultiIndex}_{\text{before}}$ and $\text{MultiIndex}_{\text{after}}$ for MultiIndex 1 and 2. Again, an OTSU threshold was applied (Otsu, 1979) to

binarize the image, with the resulting output highlighting burned areas. An accuracy assessment was performed on the resulting images for each method discussed to distinguish the most suitable.

2.4.2. Burning severity mapping

To map levels of burn severity, two classification techniques were explored: Spectral Angle Mapper (SAM) and SVM. Both methods have been employed in wildfire studies with a focus mainly in distinguishing the burned areas (Dragozi et al., 2014; Petropoulos et al., 2011). However, to our knowledge, neither of those has been used so far to further delineate levels of burn severity. Four levels of burn severity were distinguished: destroyed area, highly damaged area, moderately damaged area, and negligible to slight damaged area (Kucera, 2016). To perform the SAM, training samples were collected for each class through the ROI tool in ERDAS Imagine 2015 (by Hexagon Geospatial), with each class consisting of around 1500 pixels. Class identification was based on visually identifying classes, spectral reflectance values and exploring relationships with spectral indices. This was performed on the optical dataset and the synergistic dataset.

The next classification method explored was an Object-based image analysis (OBIA) - SVM approach using eCognition 9.0. The advantage of using this approach in burned area studies is that contextual information can be derived that distinguish burn severity, such as shape and size of areas (Chen et al., 2015). Implementation of the OBIA-SVM approach in eCognition consists of a segmentation process of the image into spatially contiguous and homogeneous regions followed by a classification of these segments (Duro et al., 2012). In this study, a multi-resolution segmentation was implemented on the image, with different image layer weights applied; layer weight 2 for the NIR and NBR layer, due to the high level of burned area discrimination displayed in these layers. The first iteration was on the optical/indices dataset, and the second iteration used the VVdB and VHdB. The multi-resolution segmentation approach is a bottom-up region-merging technique (Aguilar et al., 2016). Three parameters are key in this process; scale, shape and compactness. After exploring different parameter values through visual outcomes, the object boundaries matched the natural borders visible in the image. After numerous visual tests on a subset, the optimum parameters were found to be a scale parameter of 1, shape of 0.01 and a compactness of 0.7. To increase the discrimination between the four levels of class, several object features (mean, standard deviation, skewness) were calculated. Geometry based object features were also used. The next step involved choosing objects to act as training samples for the SVM classifier. A total of 400 samples (objects) were selected per class, around 5% of the total number of objects. Once samples were collected, four iterations of the SVM classifier were run. This was due to the two datasets used (optical and synergistic) and the fact that eCognition 9.0 can only run the linear and RBF kernels. To run the classifiers using these kernels, the user needs to input values for one/two parameters, being (a) the C factor (linear and RBF) and (b) the gamma (γ) factor (just RBF). Very little guidance exists in the literature concerning these values (Petropoulos et al., 2012; Xun & Wang, 2015), therefore test classifications on a subset of the image were conducted to evaluate the C parameter, in ascending values of 50. It was found that once the C value reached 1000, there was a plateau in overall accuracy, therefore a C value of 1000 was used. A γ value of $1/n$, where n is the number of classes, was used. The algorithm was trained 4 times using each dataset/kernel combination, and implemented, resulting in four final classification maps.

Figure 4. MultiIndex 1 pre-fire (upper-left) and post-fire (upper-right). MultiIndex 2 pre-fire (bottom-left) and post-fire (bottom-right), derived from implementation of Eq. (4) and (5).

2.4.3. Soil Erodibility Mapping

Information on the land surface soil erodibility was derived from the Revised Universal Soil Loss Equation (RUSLE) implementation. RUSLE was originally developed in Wischmeier & Smith (1978) and adapted in Renard et al. (1997), with the equation predicting soil loss in a given area. It has been implemented within a GIS to show potential soil erosion (Karamesouti et al., 2016). The equation consists of 5 factors: rainfall erosivity (R), soil erodibility (K), topographic slope/slope length (LS), land cover (C) and agri-practice support (P). In this study, the R and K factors were obtained from the JRC's European Soil Data Centre (ESAC). Whilst these sources are relatively coarse resolution, they are Europe wide datasets and, in the event of a wildfire, prove to be invaluable for local planners in the Mediterranean; forecasting and decision making can be made quickly after the wildfire using these datasets.

Values for the LS factor were generated using QGIS 2.8.1 and R (version 3), the statistical computing project, in Windows operating system. This involved generating a depression less DEM and delineating a watershed from this output, as well as calculating slope angle in percentage. Next, flow direction and flow accumulation were calculated using the TauDEM algorithm (Tarboton, 2005), with this implemented in R. These constituent parts were combined to generate the *LS* value, using the approach suggested in Karamesouti et al. (2016):

$$LS = (sl/22.1)^m(65.41 \sin^2 a + 4.56 \sin a + 0.065) \quad (6)$$

where, *sl* = slope length in meters, *a* = angle of slope, and *m* = 0.5 if *sl* ≥ 4.51, 0.4 if *sl* = 3.01 to 4.5, 0.3 if *sl* = 1 to 3, and 0.2 if *sl* < 1. The C factor was calculated from the burn severity map, with a value of 0.55 assigned to areas ranging from moderately damaged to destroyed area, based on the recommendation in Karamesouti et al. (2016). Once the constituent factors were derived, the equation visualized in Figure 5 was implemented, with output an indicator of soil erosion across the study site.

Figure 5. Illustration demonstrating implementation of the RUSLE Soil Erosion model, providing a potential soil erosion indicator following on from a wildfire.

3. Results

3.1. Burned area delineation

Estimated burned area maps for each method are presented in Figure 6, while the corresponding total burned areas and estimation accuracies are provided in Table 3. Visual interpretation of the maps suggests that the overall shape is roughly the same. This indicates that each method is broadly correct in terms of classification, as they clearly highlight the majority of burned/unburned areas. Examples of where the five methods are in agreement include the unburned regions in the central southern region of the study site. This suggests a generally good spatial agreement between the compared herein methods. However, the area that each method struggled to classify is the Southern tip of the study site, with each method demonstrating varying sizes in burned areas. The segmentation method has a larger visible burned area region in this zone, indicative of the object size; the object had a mean NBR value >0.1. As shown in Table 3, SVM had the highest level of accuracy (99.38%), with a Kappa of 0.988; this indicates a strong agreement between predicted and ground-truth classes. For the NBR burned areas, the segmentation/rule-based approach provided a slightly better overall classification than the NBR differencing technique (93.12% and 91.88%, respectively), with the Kappa values for the two again showing the segmentation/rule-based approach to have a greater agreement (0.863 and 0.837, respectively). For the Multi-Index methods, Eq. (5)

provides a better overall classification (94.38%), with a Kappa value of 0.880. This is in contrast to Eq. (4), where overall classification is 92.50% with a Kappa value of 0.850. The SVM thematic image, which provided the highest accuracy and best agreement, was implemented in the next stage to derive burn severity levels.

Table 3. Total burned areas and estimation accuracies for each method of delineating burned areas.

Method	Burned area (Ha)	Overall classification (%)	Kappa
NBR Segmentation	6954.34	93.12	0.863
NBR Differencing	6874.54	91.88	0.837
SVM	7849.86	99.38	0.988
MultiIndex 1	6882.13	92.50	0.850
MultiIndex 2	6975.83	94.38	0.880
EMSR (Reference dataset)	7950.15	n/a	n/a

Figure 6. Burned area maps computed from Segmentation and NBR rule-base (A), NBR Differencing (B), SVM classification (C), MultiIndex 1 method (D), and MultiIndex 2 method (E).

3.2. Burned severity mapping

The estimates of burn severity levels (Chen et al., 2015; Schepers et al., 2014; Soverel et al., 2010) of the first classification method, i.e., SAM, are displayed in Figure 7 (A & B). From visual inspection, few regions are classified differently in each scene. Whilst the integration of radar derived values (synergistic dataset) improved the accuracy slightly, from 73.63% to 74.80% (corresponding Kappa coefficient values: 0.646 and 0.662, respectively), there was no discernible difference in visual interpretation. Table 4 presents the performance of the accuracy assessment. On the basis of the Producers Accuracy (PA) and Users Accuracy (UA) statistical measures, it is observed that each class is comparable between the techniques. The highest PA for both classifiers is the “negligible to slight, unburned” class. In comparison, the highest UA for both classifiers is the “destroyed area” class. The only class in the second methodology that is improved with the integration of radar was the “highly damaged area”, indicating that discrimination between the two classes is improved with the integration of backscatter.

Table 4. Performance of the SAM classification technique using the optical and the synergistic datasets (PA: Producers Accuracy, UA: Users Accuracy).

Class name	Optical dataset		Synergistic dataset	
	PA (%)	UA (%)	PA (%)	UA (%)
Destroyed area	63.80	95.70	63.32	91.02
Highly damaged area	61.86	70.31	65.63	73.83
Moderately damaged area	88.70	61.33	87.50	65.63
Negligible to slight, unburned	100.00	67.19	100.00	68.75
Overall accuracy (%)	73.63		74.80	
Kappa coefficient	0.646		0.662	

The burn severity thematic maps produced from the implementation of the two SVM kernels, using both the optical and synergistic datasets, are shown in Figure 7 (C, D, E & F), while a graphical representation of the four levels of burn severity, highlighting the total area for each class, is shown in Figure 8. This allows for discrimination between classes. As inferred from visual comparison of the thematic maps produced in Figure 7 (C-F), each classification technique using different SVM kernels performed well in delineating levels of burn severity. Table 5 summarizes the classification accuracy assessment results. The overall accuracies outperform those of SAM pixel-based classifications by about 20%. This is compounded when exploring the overall accuracies, with the SVM linear kernel approach providing overall accuracies of 89.06% (optical) and 92.97% (synergistic) and the SVM RBF kernel approach providing overall accuracies of 90.23% (optical) and 92.19% (synergistic). Kappa coefficient values also indicate a much greater level of agreement for the SVM approach.

456 **Table 5.** Performance of the SVM classification techniques (with linear kernel and
 457 with SBF kernel) using the optical and the synergistic datasets (PA: Producers
 458 Accuracy, UA: Users Accuracy).

Class name	Optical dataset				Synergistic dataset			
	SVM linear		SVM RBF		SVM linear		SVM RBF	
	PA(%)	UA(%)	PA(%)	UA(%)	PA(%)	UA(%)	PA(%)	UA(%)
Destroyed area	85.92	95.31	86.11	96.88	89.86	96.88	88.41	95.31
Highly damaged area	83.33	93.75	87.88	90.63	92.42	95.31	92.19	92.19
Moderately damaged area	91.94	89.06	90.48	89.06	92.31	93.75	90.77	92.18
Negligible to slight, unburned	98.04	78.13	98.18	84.38	98.21	85.94	98.28	89.06
Overall accuracy (%)	89.06		90.23		92.97		92.19	
Kappa coefficient	0.854		0.870		0.906		0.896

Figure 7. Thematic maps of burn severity levels with: the SAM classification technique (A & B), the SVM linear kernel (C & D), and the SVM RBF kernel (E & F). (A), (C) & (E) are derived using the optical dataset; (B), (D) & (F) are derived using the synergistic approach.

466
467

468 **Figure 8.** Graphical representation of total areas (Ha) of each burn severity level,
469 using different classification approaches.

470 Upon visual inspection between the four thematic maps, the destroyed area class are in
471 the greatest agreement. This is compounded by having high UAs, ranging from 95.31% to
472 96.88%. When a synergistic approach is used, the greater total area for destroyed area and
473 highly damaged area increases marginally, indicating that the backscatter values for these
474 areas play an important role in delineating the effects of a wildfire. Visually, the negligible to
475 slight, unburned, areas are also comparable within the synergistic approach.

476 Figure 8 shows a high level of discrepancy between the SAM pixel-based approach and
477 the SVM approach for the highly and moderately damaged areas. However, the higher levels of
478 overall accuracy for the latter four classification techniques indicate that most of the
479 classification for the SAM approach is not as accurate. The linear and RBF kernel, when used
480 with the synergistic approach, classify larger areas of destroyed and highly damaged areas,
481 whereas the opposite is true for negligible to slight, unburned. It is evident that the majority of
482 the study site experienced high severity burns; the destroyed area and highly damaged area
483 classification dominates, irrespective of the classification technique used.

484 *3.3. McNemar's test*

485 To evaluate the accuracy of the generated burned area images and the burn severity
486 maps, a confusion matrix was calculated for each output (Soverel et al., 2010). This allowed
487 for the computation of the overall accuracy, user's accuracy, producer's accuracy and the
488 Kappa statistic (Congalton & Green, 2008). To conduct the accuracy assessment, a Copernicus
489 EMS-grading map was considered as the reference dataset. This displays the same levels of
490 burn severity used in the classification process, and the grading map is based on Pleiades-1
491 data and validated by field plots. The grading map has the ID EMSR132. To build the error
492 matrices, 1024 validation points were generated, 256 per class.

493 To further assess the statistical significance of each classification method, a McNemar's
494 test was performed (de Leeuw et al., 2006). This test is based on a 2 by 2 contingency table,
495 and uses a chi-square (χ^2) statistics to compare two classifications. It is imperative to have a
496 frequency table for each classifier, as this displays correct/incorrect areas for each

classification. In conducting the McNemar's test, an χ^2 value of 3.84 was used at a 95% confidence interval. The null hypothesis is that no significant difference exists between classifications, therefore if χ^2 is greater than 3.84, the map accuracies are considered significantly and statistically different with a 95% degree of confidence (de Leeuw et al., 2006).

Results showed that each SVM outperformed the SAM method. The higher superiority of an OBIA-SVM approach over SAM indicates that this is a much more suitable method for burned area mapping. Furthermore, at a 95% confidence interval, the use of a synergistic approach statistically outperforms the optical approach each time, apart from for the OBIA-SVM RBF kernel. At a 99.9% confidence interval, where χ^2 is 10.83, only the OBIA-SVM linear and RBF kernel with a synergy outperform the other OBIA-SVM classifications statistically and significantly. From examining the overall accuracy (92.17%) and the McNemar's test result, the conclusion can be drawn that the OBIA-SVM linear kernel classification using a synergistic approach is the most effective method for this study.

3.4. RUSLE model evaluation

The prediction of post-wildfire erosion rates in the study site was explored through the implementation of the RUSLE model to the Sentinel-2 post-fire imagery in a GIS environment (Figure 9). The total area affected by different erosion rates is also shown in Figure 10. From visual interpretation, the areas at risk of high soil erosion rates are located around the North-western region of the study site. This corresponds with where the highest level of burn severity was located; the greatest amount of soil erosion is predicted to occur where the wildfire has destroyed the surface. The greatest level of soil loss is predicted to be between 2-5 tons per Ha, with this affecting 37.6% of the study site. As soil loss increases in tons per Ha, total affected area decreases substantially. The highest level of predicted sediment loss (>50 tn* Ha) only affects 0.011% of the area; however this is still relevant for local management practices. The vast majority of sediment loss is predicted to be under 20 tons per Ha, with 98.887% of areas predicted to experience this level of erosion. Whilst the destroyed area exemplifies higher levels of soil erosion, another factor that influences erosion rates is the LS factor. This is shown in Figure 9, where in the aforementioned Northwest area, the LS factor had the greatest influence. The conclusion can be made that whilst the R, K and P factors influence erosion rates, the factors that have the greatest influence are the C factor (burn severity) and LS factor. Whilst few areas of the study site are expected to experience high levels of sediment loss, this remains an important factor to consider post-wildfire effects on the landscape.

Figure 9. Soil erosion rates in post-fire setting (left) estimated by the RUSLE model, alongside a visualization of the area in 3D (right) to demonstrate the effects the LS factor has on the erosion rate.

Figure 10. Total areas affected by predicted sediment losses.

4. Discussion

4.1. Burned area delineation

Considering burned area delineation, the different methods used, experienced differences in the estimates derived, with the SVM classifier closest to the reference dataset used to assess

accuracy. One error observed with the reference dataset, however, was that this product incorporated lakes into the final burned area product, indicating that perhaps this dataset was not derived as part of a wholly accurate methodology. If this is the case, then the SVM classifier can be considered the best classifier for mapping burned areas, as advocated in Petropoulos et al. (2011) and Dragozi et al. (2014), amongst others. The NBR rule-based approach for this study is a novel method that had a comparable accuracy to previous studies (Mallinis & Koutsias, 2012), with the proposed Multi-Index approach achieving a higher Kappa value than previous studies using this method (Vhengani et al., 2015). The overall classification accuracy has also improved, for the original Multi-Index 1 and for the new MultiIndex 2. Fernández-Manso et al. (2016) suggest that replacing the red band with the improved red-edge bands on the Sentinel-2 MSI improves accuracy in delineating burned areas. It has been observed that for dense canopies, a saturation effect can occur when employing the red band (Gu et al., 2013), therefore replacing this with a red-edge band will decrease the saturation effect and, in theory, improve accuracy. Vhengani et al. (2015) used Landsat 8 OLI, they only used a red band. In comparison, this study employed indices derived from different red-edge bands, and subsequently an improvement in accuracy for delineating burned areas has been observed.

4.2. Monitoring of burn severity

When conducting burned area and burn severity mapping with radar datasets, it has been observed that unburned low vegetation areas and burned areas exhibit similar variations in backscatter. Similarly to Tanase et al. (2015), the use of SAR data in our case, has provided useful information for a more accurate classification of negligible to unburned areas and completely destroyed areas, but less so for the severity classes in between these. As the study area comprises of shrubs, agricultural lands and sclerophyllous vegetation, as well as forested areas, this could explain why there was little discrimination for the highly and moderately damaged areas. The advantage of using red-edge derived indices in conjunction with backscatter values, has led to the slight increase in accuracy in these regions. With completely destroyed areas, additional vegetation elements have been altered and/or consumed (Kolden et al., 2012; Tanase et al., 2015). If Sentinel-1 data was used in isolation in a similar study, then perhaps distinctions within burned areas may be considerably harder to define. However, due to the integration with other indices and the optical dataset, delineation within the burned class has improved in accuracy, as noted in Tanase et al. (2015). Our approach has, therefore, validated the use of Sentinel-2A MSI images integrated with Sentinel-1 images in a synergistic approach to quantify levels of burn severity.

4.3. Wildfire dynamics in relation to soil erosion

Concerning soil erosion and land degradation processes, the RUSLE model was applied in the immediate aftermath of the wildfire event under consideration, to demonstrate the potential of this approach as a rapid mapping method to help mitigate further damages in the post-fire setting. It has been observed that the RUSLE model is very sensitive to the LS and C factor (Karamesouti et al., 2016), with this perhaps being indicative of the relatively low predicted losses of soil exhibited in our application. Previous studies have observed ranges of 45-56 t ha⁻¹ yr⁻¹ in the Mediterranean environment (Shakesby, 2011). Studies in Greece produced values closer to those presented here, with potential post-fire soil erosion rates ranging from 11 to 69.2 t ha⁻¹ yr⁻¹ (Mallinis et al., 2009). However, it should be noted that previous studies have explored soil erosion a year after the event. Our approach has not been designed with this in mind, as the vulnerability to soil erosion can be indicated immediately

after a fire event has occurred, hence the slightly lower values presented. Lower values presented can be attributed to the combination of LS and C factor used, as smaller values of sediment loss were shown where the areas of negligible to slight, undamaged, and moderately damaged areas and where the slope was less pronounced. The steeper a slope is, the greater the heat transfer between flame and fuel, leading to increased burn severity rates (Ireland et al., 2015), leading to increased erosion on sloped regions. Our results show that the regions observed to have higher sediment loss are in the north-west region and around the northern fringes in the study site, where the slope is significantly greater and where wildfire led to a destroyed burn severity class. Therefore, the values presented are understandable, as the LS and C factor significantly contribute to predictions made by the RUSLE model (Karamesouti et al., 2016). A further factor to consider is the observation of Shakesby (2011), who notes that perhaps soil in the Mediterranean is becoming resilient to wildfires, leading to a decrease in erosion rates. This, in combination with the influence of the LS and C factor, explain the results presented and discussed.

5. Conclusions and Future Work

The present study aimed at assessing the potential of the recently launched Sentinel-1 and -2 data for wildfire assessment. Those data is data freely available through the European Space Agency's (ESAs) Copernicus mission.

EO data from the Sentinel-2 satellite were explored through different uni-temporal and multi-temporal methodologies to evaluate their potential to delineate burned areas. An SVM classifier on a uni-temporal scale produced the most satisfying accuracy, with an overall accuracy of 99.38% with a kappa value of 0.988. The most effective classification technique was found to be an OBIA-SVM approach using the linear kernel with a synergistic dataset. The integration of radar increased accuracy both significantly and statistically, as demonstrated by the McNemar's values presented. Classification improvements were made as a result of incorporating Sentinel-1 data into a dataset consisting of Sentinel-2 data and indices, for both the linear and RBF kernel. However, the linear kernel was the most effective classifier, providing an overall accuracy of 92.97% and a kappa value of 0.906. The findings of this research support the argument that implementing an OBIA-SVM classification approach is an effective method, and has been shown to accurately delineate levels of burn severity with a synergistic approach. Further analysis conducted in this study demonstrated that the red-edge bands on the Sentinel-2 MSI are extremely suitable for delineating levels of burn severity, as shown by the integration of red-edge specific indices into datasets herein.

Finally, the RUSLE soil erosion model was implemented on the outputted accurate burn severity thematic map. This is after calls for further research into rapid and cost-effective methods of mapping the effects of wildfires, particularly advocated in Shakesby (2011). Results from this showed that 37.619% of the study site is expected to lose between 2 and 5 tons of sediment per hectare, with few areas of the study site expected to experience particularly high levels of sediment loss. The results of this final step can assist forest managers to better understand and appreciate the changing dynamics of a post-fire landscape, and can allow for the pooling of resources in an effective way. Therefore, the methods presented in this study can support policies in the European and wider Mediterranean region, particularly those put in place by EFFIS.

All in all, this study has demonstrated the possibilities of each step, and offers vast potential for the Copernicus Mission moving forwards in to the future. Regarding results obtained, an despite the outcome from statistical tests, differences obtained with the different approaches are quite small and it should be emphasized that results respect to a single fire

episode that cannot be taken as representative over a region such as Mediterranean Europe. This potential is currently explored worldwide and the full utilization of the datasets in wildfire studies acquired from the Copernicus mission is a topic currently intensively explored at a worldwide scale. The potential of our proposed technique to become operational is subject to further validation experiments to be carried out at different experimental sites globally and it remains to be seen.

Acknowledgments

GPP's contribution to this work has been supported by the EU Marie Curie Project ENViSIon-EO (project contract ID 752094) and the NERC's Newton Fund RCUK project Towards a Fire Early Warning System for Indonesia (ToFEWSI).

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