Determining the Use of Sentinel-2A MSI for Wildfire Burning and Severity Detection

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Abstract

Accurate, reliable, and timely burn severity maps are necessary for planning, managing and rehabilitation after wildfires. This study aimed at assessing the ability of the Sentinel-2A satellite to detect burnt areas and separate burning severity levels. It also attempted to measure the spectral separability of the different bands and derived indices commonly used to detect burnt areas. A short investigation into the associated environmental variables present in the burnt landscape was also performed to explore the presence of any correlation. As a case study a wildfire occurred in the Sierra de Gata region of the province of Caceres in North-Eastern Spain was used. A range of spectral indices were computed, including the Normalized Difference Vegetation Index (NDVI) and the Normalized Burn Ratio (NBR). The potential added value of the three new Red Edge bands that come with the Sentinel-2A MSI sensor were also used. The slope, aspect, fractional vegetation cover and terrain roughness were all derived to produce environmental variables. The burning severity was tested using Spectral Angle Mapper (SAM) classifier. European Environment Agency's CORINE land cover map was also used to produce the land cover types found in the burned area. The Copernicus Emergency Management Service have produced a grading map for the fire using 0.5m resolution Pleiades imagery, that was used as reference. Results showed a variable degree of correlation between the burning severity and the tested herein spectral indices. The visible part of the electromagnetic spectrum was not well suited to discern burned from unburned land cover. The NBR_{b12} (short-wave infrared 2 – SWIR2) produced the best results for detecting burnt areas. SAM resulted in a 73% overall accuracy in thematic mapping. None of the environmental variables appeared to have a significant impact on the burning severity. All in all, our study result showed that Sentinel-2 MSI sensor can be used to discern burnt areas and burning severity. However, further studies in different regions using the same dataset types and methods should be implemented before generalizing the results of the current study.

Keywords: *Sentinel-2, Burn Severity, burned area mapping, Separability*

1. Introduction

Fire is an important mechanism in many of the Earth's ecosystems and environments along (De Santis & Chuvieco, 2007; Ireland et al., 2015). The global carbon cycle is an essential part of the Earth's system and fires in all its forms are a required part of that (Prentice et al., 2001; Knorr et al., 2011; Karamesouti et al., 2016). Widespread lightning strikes, volcanic eruptions and the relatively recent introduction of anthropogenic ignition sources, have caused wildfires throughout the Earth's history (Bowman et al., 2009). Wildfires can have both a positive and negative effect on the burned areas. The removal of vegetation from forest floors allows increased regrowth in some areas. Conversely, massive devastation to ecosystems can also be caused, which takes hundreds of year to recover from (Wimberly et al., 2009). Wildfires can affect humans in several ways. Some of the most common include the damage to property, loss of crops, destruction of infrastructure, and the possible loss of life (Keeley et al., 2009; Petropoulos et al., 2014).

The increase in wildfire occurrence and severity throughout the world in the last 10 years has led to an increase in the need for detailed and timely burnt area mapping techniques (Cansler & McKenzie, 2012; Kalivas et al., 2013; Keeley & Syphard, 2016). Global climate change is an important environmental, social and economic subject in many regions of the world (Leblon, 2001; Ireland & Petropoulos, 2015). Wildfire frequency, intensity and consequences is a subject encompassing a wide range of areas including but not limited to atmospheric science (Huang et al., 2015), remote sensing (Chuvieco, 2012), ecology (Ricotta et al., 2001), forest management (McRae et al., 2001) and natural resources (Steel et al., 2015). Historical research on the global drivers of climate change indicate that there is an increase in wildfire activity on a yearly basis (Pechony & Shindell, 2010). It is believed the increase in global temperatures will lead to an increase in fire frequency and severity (Remy et al., 2017).

The environmental impacts of burning can be felt in various ways. It is estimated that about 25%-35% of greenhouse effect gases are a result of wildfire and biomass burning events and therefore they are considered an important factor in climate change (ESA, 2016). Changing wildfire seasons have been attributed to extended droughts, with Littell et al. (2016) predicting a 50% increase in wildfire events across the western United States. Every year fires burn millions of km^2 of land, with an estimated 3.5 million km^2 having been burnt in the year 2014 (Yang et al., 2014). The main aspects of burning events are the removal of vegetation and the remnants of combustible materials that are left behind after the fire. In Southern Europe, around 45,000 fires have burnt around half a million hectares of land (Moreira et al., 2011).

While the initial results of wildfires are well-documented through ecological and economic factors, the longer term fire effects through carbon sequestration and vegetation regrowth are lesser known due to the temporal periods required understanding them (Conrad et al., 2002). Since the advent of remote sensing, techniques for wildfire detection and observation have been an extensively studied topic (Walz et al., 2007). Monitoring of active burning events (San-Miguel-Ayanz et al., 2012), the emissions from wildfires (Reid et al., 2004), burnt area detection (Schepers et al., 2014) and burning severity analyses (De Santis & Chuvieco, 2007) are just a few of the many areas of wildfires that have been, and are currently being studied.

Fires often ignite and are located in areas far from human habitation and observation, so access to field locations can be both difficult and potentially dangerous to achieve. Remote sensing can provide rapid, inexpensive, timely, and repetitive results from varying satellite and airborne sources (Heward et al., 2013). The constant imaging of the Earth has resulted in a better global coverage of areas affected by fires on a regular basis. The non-invasive method prevents humans having to enter affected areas either during burning events or shortly afterwards. The access to remote sensing allows previously inaccessible fires to be monitored and recorded (Fraser et al., 2003). However, recoding of images from fires can be difficult, as smoke from fires can obscure sensors and make visual interpretations problematic (Gedalof et al., 2005; Said et al., 2015).

Burned area mapping has been implemented for many years, but there is a constant need to better understand wildfires characteristics (Kushla & Ripple, 1997; Kalivas et al., 2013). The fires' impact on vegetation is a useful metric for the amount of carbon released into the atmosphere, while the severity levels within a burnt area indicate the possible regeneration rates that may occur following the fire suppression. Sentinel-2 satellite is a recent addition to the Earth observation network, with the 2nd satellite (2B) in constellation launched on the 13th of March 2017. This has increased the observation rates of the Earth substantially and allows for better understanding of earth processes.

The main study goals are to use the relatively new Sentinel-2A MSI senor to: i) to determine the ability of the Sentinel-2A sensor to accurately delineate burnt areas and burn severity, ii) to assess the spectral separability of the individual bands and created environmental indices in separating burning severity within the burnt area,, and, iii) to compare the local environmental variables against the burn severity to establish any relationships that might exist.

2. Materials and Methods

2.1. Study site

The European fire season is generally between May to September during the summer months, with occasional fires outside of this time-period. Since the release of the Sentinel-2A MSI sensor in June of 2015, there has been a limited number of fire seasons with temporal coverage. The main requirement for the study site selection was that it needed to have a large enough burned area with a range of burning severity and a long enough post fire temporal history to be able to conduct the investigation appropriately. The European Space Agency Forest Fire Information System (EFFIS) website (EFFIS, 2017), as well as the fire news website were used to investigate possible study site locations. The Copernicus (EFFIS) mission has been producing burned area delineation and grading maps for various sizes of forest fires throughout Europe since the release of Sentinel 2 data. The maps use high resolution Worldview, Spot and Pleiades data to produce fire severity and grading maps for these areas.

The chosen wildfire occurred in the Sierra de Gata region of the province of Caceres in North-Eastern Spain (Figure 1). The fire occurred between the 5th and 10th of August 2015 and burned approximately 80 Km^2 of the surround area. The site is located in the Mediterranean region, where largescale wildfires are common. The reason the specific fire event was selected, was the need to have a temporal aspect to the investigation. The land cover in the region is predominantly shrub land and forest, with predominant vegetation being Quercus pyrenica, a deciduous species of Mediterranean oak (Santa Regina, 2000). The lower regions of the area are dominated by agriculture in the form of Olive Groves and pastoral fields.

[FIGURE 1]

Figure 1. Location of the area of interest (Sierra de Gata region, Spain).

2.2. Datasets

The Sentinel-2A data sets were acquired from the Copernicus Open Access Hub (scihub) website (ESA, 2016). The images were downloaded in the Level-1C product format. These Level-1C products are composed of 100x100 km^2 tiles. The images were orthorectified in the UTM/WGS84 projection and geometrically corrected. Per-pixel radiometric measurements were provided in Top of Atmosphere (TOA) reflectance along with the parameters to transform them into radiances. Level-1C products were resampled with a constant Ground Sampling Distance (GSD) of 10, 20 and 60 m depending on the native resolution of the spectral band. Table 1 lists the band names, spatial resolutions and wavelengths of all the MSI sensors. Bands 1/9/10 have a spatial resolution of 60m, these bands were not included in any part of this study due to their low resolution. The pre-fire and post-fire images were acquired as close together as possible, in order to minimize spectral differences due to seasonal changes in the landscape. The pre-fire image was acquired at 10:30 am on the 25th of July 2015, and the post-fire image was acquired at 11:05 am on the12th of August. The images were cloud free and both were acquired mid-morning in order to reduce atmospheric variation due to changes in the solar incidence angle.

Table 1. Sentinel-2 bands with resolution, central wavelengths and bandwidths.

An ASTER 30m (N40W007 tile) Digital Elevation Model (DEM) was acquired from the United States Geological Society, Earth Explorer website (USGS, 2017). The DEM was used to produce an elevation map for the region, and raster's for the slope and aspect were derived from this images using the raster tools within QGIS 2.8.9. The terrain roughness index was also calculated to investigate whether the roughness of the landscape could increase or decrease the severity of a fire. Table 2 lists all the variables used and their deceptions.

Table 2. List of used environmental variables.

The fractional vegetation cover (FVC) (Li et al., 2005) is the amount of vegetation given on a per pixel basis (Jiménez-Muñoz et al., 2009). The FVC is normally done by taking the Maximum NDVI ($NDVI_v$ – completely vegetated land cover), Minimum NDVI ($NDVI_s$ – thought to be the reflectance of bare soil or rock in an area) and mean NDVI values from an image and converting these into a per pixel account of FVC:

$$\mathrm{FVC} = \frac{\mathrm{NDVI} - \mathrm{NDVI_s}}{\mathrm{NDVI_v} - \mathrm{NDVI_s}} \quad (1)$$

These values vary from region to region and they have no universal constant values. For the specific study area those values ranged roughly from 0 to 1.1. The main issue when applying equation (1) is the correct identification of the NDVI for soil and NDVI for vegetation, as these can be difficult to establish in a region (Song et al., 2017). The bare soil land cover type form the Corinne land cover map and the maximum NDVI for the pre-fire image was used to produce the indices. (Bingfang et al., 2004). The land cover map was acquired from the European Space agency to coincide with their already created, CORINE land cover map. The classification consists of 44 classes with a minimum area of 25 ha and a thematic accuracy of ≥ 85% (ESA, 2016). The overall land cover can be seen in Figure 2. The map has been subdivide into four land cover types based on the CORINE Sub Type classification (Table 3). This was done to provide a large enough area to allow for interpretation. The four classes have been chosen because they cover the majority of the land types in the area: trees, grassland, scrubland and cropland.

Table 3. General CORINE land cover classes of the study site.

The Copernicus Emergency Management system Grading Map (EMSR132) was used as reference truth in order to validate the different techniques. This dataset is available in both raster and vector formats and consists of a four-class burn severity index: High Burn (HB), Moderate Burn (MB), Low Burn (LB), and Unburned or Very Low Burn (VLB). It was created using Pleiades 1A 0.5m data, validated by field plots. The produced image used pre- and post- event images to produce a grading map of the affected area at a fine resolution. The data set was consider to be accurate to 85%.

[FIGURE 2]

Figure 2. True color and CORINE land cover maps of the study site.

2.3. Data pre-processing and information extraction

The level 1C Sentinel-2A data comes pre-processed radiometrically and geometrically to produce Top of Atmosphere values (TOA) (Chavez, 1996; Whyte et al., 2018). To obtain the required L2A values for Bottom of Atmosphere, atmospheric correction of the data was required. The scattering of electromagnetic (EM) waves as they pass through the atmosphere causes variations in spectral responses image to image and needs to be accounted for. Image-wide dark-object subtraction (DOS1) was undertaken using the Semi-Automatic Classification (SCP) plugin in QGIS. The DOS1 is an empirical correction method which assumes that the darkest pixel in every band reflects no light back to the sensor, thus, this is then subtracted from every other pixel in the band. This method requires no user input and makes assumptions about the reflectance values being recorded. The images did not require cloud masking as there was no cloud coverage within the area of interest. The image bands were homogenized to 10m resolution by using the nearest neighbor sampling techniques in QGIS. All other ancillary data sets were also resampled to 10m resolution.

To derive the burned areas and burn severity maps, spectral indices from the Sentinel-2A band data was required to be computed. All data processing was performed with the band math tool in QGIS 2.8.9. The derived indices were the commonly found ones, specifically the Normalised Burn Ratio (NBR, Garcia & Caselles, 1991) and Normalised Difference Vegetation index (NDVI, Levin & Heimowitz, 2012; Chatziantoniou et al., 2017), but also the use of the new Red Edge bands were tested to see how they responded. Two NBR indices were calculated, using both short-wave infrared (SWIR) bands found on the Sentinel-2A sensor. NBR_{b11} uses the near infrared (NIR) Band 8 and the SWIR Band 11, and NBR_{b12} uses the NIR Band 8 and the SWIR Band 12. This was done to compare the two SWIR and their responses (Huang et al., 2016). The

Sentinel NDVI has been assessed by D'Odorico et al. (2013) and has recently been validated by Lange et al. (2017). The premise is that living green plants absorb the red region of the EM spectrum and reflect high values of Near infra-red, the result of an NDVI calculation normally gives a result of -1/+1 with the +1 indicating a high value of green vegetation. The three Red Edge bands of the Sentinel-2A sensor were used (Bands 5/6/7) to derive separate indices, and the narrow band Near Infra-red bands were also used. The red edge band of any spectrum has been used to detect changes in vegetation since its inception and is based on the sharp rise between the red and NIR regions of the EM spectrum. The equations use the narrow band of the NIR region. All used indices are listed in Table 4.

Table 4. Details of spectral indices used.

2.4. Data analysis

2.4.1. Burnt area mapping

Delineation of the burned areas was based on the computation of various radiometric indices, removing subsequently the pre-fire image from the post-fire image. This a common method developed by Key & Benson (1999) for delineating burned areas. The differentiation is a change detection technique, which comprises a quantitative measurement of change between two images. The image is then thresholded using an OTSU threshold (Otsu, 1979). Subsequently, the image is processed to remove groups of 6 pixels or less to clean the image for vectoring using the sieved tool in QGIS. The implementation of this step (sieving) could potentially result into missing some burnt areas. However, the extent to which this could happen is always dependent on a number of parameters, some of the most important ones being the sensor's spatial resolution, the burning characteristics in respect to the characteristics of the area burned, and the spectral information used in the burnt area algorithm. The decision of using 6 pixels was made after taking into consideration all the above points, and also after a "trial & error" process assessing visually the impact of the number selection in the sieving processing step implementation, ensuring that impact is minimized. The image is then converted to a shapefile in order to calculate the area of created image vs the area of the reference image. This was performed for all differentiated spectral indices.

To assess the accuracy of the different radiometric indices vector files, the skipped area, false area and detected area was calculated (e.g. Petropoulos et al., 2012). The results from the production of each index were compared to the reference data set from EMSR132. Three results were produced: i) the Detected Burned Area (DBA), which measured the ability of the index to correctly map the burned area compared to reference, ii) the Skipped Burned Area (SBA), which measured the amount of area missed by the index that is registered on the reference image, and iii) the False Burned Area (FBA), which measured the extra area produced by the index that is not present in the reference data. In order to compare the details of the indices, the outputs of the indices were converted to Vector files and the sizes compared for each variation. The evaluation of the accuracy was based on the following metrics:

$$\text{Detected Area Efficiency} = \frac{\text{DBA}}{\text{DBA} + \text{SBA}} \tag{2}$$

$$\text{Skipped Area Rate} = \frac{\text{SBA}}{\text{DBA} + \text{SBA}} \tag{3}$$

$$\text{False Area Rate} = \frac{\text{FBA}}{\text{DBA} + \text{FBA}} \tag{4}$$

2.4.2. Burn severity mapping

Once the burnt area had been delineated, a burn severity map was produced. For this purpose, the Spectral Angle Mapping (SAM) classification technique was used to classify the four levels of burn severity (Tanase et al., 2015). SAM is a supervised classifier that uses the collection of spectra from selected regions of interest (ROI) to differentiate spectrally different classes. The Sentinel-2 image bands and indices were stacked in order to be observable in a single image. Different combinations of true color and false color images were observed with various stretches applied to regions in order to make selection possible. The ROI's and the SAM classifier were conducted in QGIS 2.8.9, using the base tools and the SCP plugin.

The spectral angle mapper uses an angle (in radians) to define separate classes between spectra. The process has been used before in several studies to detect burnt areas and burn severity (e.g., Petropoulos et al., 2011). The relationship between spectral values and the relationship between indices was explored. The lower the spectral angle between the reference material and the image spectrum, the better the relationship and the higher the spectral agreement. In our study, a series of different angles from 0° to 0.5° were tested to find the highest accuracy (Petropoulos et al., 2011).

To assess the accuracy of the SAM classification, the produced image was compared to the reference EMSR dataset. The error matrix was produced to determine how each severity class type compared to the reference (Congalton & Green, 2008). 300 validation points were created for each class for a total of 1200 points; these were viewed on both images and the class difference recorded in an error matrix. The matrix allows every class to be evaluated as to how accurate it is in reference to both how the samples were collected (Users Accuracy – UA) and how the classification technique produced the map (Producers Accuracy – PA). The table also creates an overall accuracy (OA) and a Kappa (K) statistic. An accuracy assessment was performed after each index was used to determine the accuracy of the indices relative to that of the reference Copernicus emergency management image. The assessment technique has been implemented many times in various land class/land cover assessments (Delegido et al., 2011), and also in burned scar mapping techniques (Keeley et al., 2009). The use of commission/omission errors to determine the accuracy of whether any given pixel in an image is accurately determined to be that of the class assigned to it, is a common technique. The omission error determines how many pixels of a particular ground truth class have been misclassified. The guideline values for values set out by Landis & Koch (1977) sets a Kappa value of greater than 0.80 as "very good agreement", 0.61 to 0.80 as "substantial agreement", 0.41 to 0.60 as "moderate agreement" and below that as "poor to no agreement".

2.4.3. Spectral separability

The spectral separability of all the bands and derived indices was extracted from the created ROI's for the severity classification. The values for each band and index were extracted from each layer using the Zonal Statistics plugin in QGIS. This allows the statistical values for each polygon to be extracted. A Shaprio-Wilk normality test was conducted to check for normality within the data sets (Parks et al., 2014). The test has a null hypothesis that the samples are drawn from a normally distributed dataset (Razali & Wah, 2011). The test was done on unburned to burned pixels, but extra data was extracted from surrounding pixels to check the unburned to unburned pixels (Huang et al., 2016). The test was performed because some metrics of separability require normally distributed datasets to be able to perform adequately (Matongera et al., 2016).

Transformed divergence (TD) was used to determine the parametric separability of the unburned to burned bands and indices, a control of unburned to unburned separability was also quantified as reference (Redmond et al., 2002). The higher the separability the better the suitability for mapping burnt areas, with reference to the unburned to burned class separability. The separability is bounded between 0 and 2 with 0 being no separability and 2 being completely separable (Chauhan 2016). The TD provides a covariance weighted distance between class means to determine whether they are separable.

3. Results

3.1. Burnt area mapping assessment

The ability for the derived spectral indices to delineate the burned areas is presented in Figure 3. The results of the DBA are shown in green, the SBA in blue, and the FBA in red. Table 5 shows the accuracy results for the three areas and the efficacy rates at which they classified the burned area. The dNBR using bands 12/11 are shown in Figures 3-A and 3-B. The NBR_{b12} (Figure 3-A) shows a very similar area to that of the validation with only small areas of skipped data in the lower parts of the image. There are small areas of FBA in the lower left area of the image. The overall detection efficiency rate is at 0.97% meaning that it is very close to the validation dataset. There is a higher Omission error than Commission error but both are very low. NBR_{b11} (Figure 3-B) has a lower detection efficiency rate at 0.859% although still quite high. The error is higher in the commission area, with almost 5 times as much SBA as the $dNBR_{b12}$. The FBA is only 0.7 higher than the $dNBR_{b12}$. The square shape of the FBA in the images indicates that they maybe agricultural features.

The dNDVI and dNDVIre1n images are shown in Figures 3-C and 3-D. The NDVI has a very similar appearance to that of the $dNBR_{b12}$, it has a lower FBA at only 0.93 but a much higher SBA of 22.56. The detection efficiency rate of 0.778% reflects this higher SBA. The dNDVIre1n shows a large area of SBA with the appearance becoming more speckled throughout the image. The efficiency rate of just 0.582 shows the effects of the large area of SBA.

Table 5. Results obtained from classification accuracy assessment.

The NDVIre2n and NDVIre3n are shown in Figures 3-E and 3-F, respectively. The detection efficiency rate for NDVIre2n (0.516%) and NDVIre3n (0.379%) show the low correlation between the DBA and SBA. There is a large area of FBA data on the outside with the fields in the bottom left being picked out prominently in the NDVIre2 image, but there is sparse coverage of the DBA and the increased area of FBA in the bottom left corner. The NDVIre3n has less FBA than the NDVIre2, but also a very small area of DBA.

The total areas for each detected indices can be seen in Figure 4. The EMSR reference map is shown in the chart. The $dNBR_{b12}$ has the highest correlated area with the three dNDVIrex bands being the least similar. The graph takes into account all the areas produced by the classification, so false burnt areas are also included.

[FIGURE 3]

Figure 3. Thematic maps for burnt area detection, using $dNBR_{b12}$ (A), $dNBR_{b11}$ (B), dNDVI (C), dNDVIre1n (D), dNDVIre2n (E), and dNDVIre3n (F).

[FIGURE 4]

Figure 4. The total amount of burnt area created by each differentiated index, in km^2. EMSR value is the reference.

3.2. Burn severity analysis

A thematic burn severity map was produced from the SAM classification. Figure 5 shows the thematic map of the four burning severity levels. The overall accuracy compared to the reference was 73.73% with a Kappa of 0.65. PA shows that the high burn severity area (HB) had the highest accuracy with the other three classes having roughly the same accuracy. UA shows that the unburned or very low burn (VLB) areas had the highest accuracy with the moderate burn (MB) ones having the lowest user accuracy. The moderate Kappa agreement of just 0.65, shows that the classification is not particularly suitable.

[FIGURE 5]

Figure 5. Thematic map for Spectral Angle Mapper Burn severity index. (HB: High Burn, MB: Moderate Burn, LB: Low Burn, VLB: Unburned or Very Low Burn).

3.3. Spectral separability analysis

The first process in assessing the spectral suitability was to check the normality of the datasets to see how it performs. The results from the Shapiro-Wilk's normality test show that most of the data is not normally distributed with all the bands except 6 and 11 being near 0 (Figure 6). The burned pixels in band 12 show the biggest correlation to normalization of any of the bands, but still being below 0.5 p-value. The NDVI and NDVI red edge bands all show a separation between the burned and unburned distribution, the unburned areas all show a large increase in normalization. The burned areas show no normalization at all. The NBR b11 and b12 show similar normalization effects for both burned and unburned areas. The NDVIre3n has the highest overall p-value with the burned being around 0.7.

[FIGURE 6]

Figure 6. Shaprio-Wilk's normality test for the spectral bands and indices (abbreviations re1n, re2n, and re3n correspond to NDVI-based bands, while b11 and b12 correspond to NBR bands).

The Transformed Divergence (TD) separability analysis was used to determine the separability of the different bands and indices. The boundaries were between 0 (no separability) and 2 (completely separable). Figure 7 shows the spectral variability of unburned to burned (U – B) pixels and unburned to unburned (U – U) reference pixels. All the Unburned – Unburned pixels show low separability with none being over 0.5. The visible spectrum bands 2, 3 and 4 show very low separability between the U - B pixels. The Red Edge bands show a moderate to good separability between the U – B being in the 1 – 1.5 range. The NIR and NIRn bands have almost complete separability. SWIR1 has a significantly better separability of burned pixels then SWIR2. The indices also show low separability between U – U, with the NDVI, NDVIre1n and the NBR_b12 having good 1.5+ separability.

[FIGURE 7]

Figure 7. Transformed Divergence class separability between burned and unburned images and between locations with both unburned to unburned images.

The box plots in Figure 8 show the variation within each spectral band and indices. The unburned pixels are higher in each band although there is somewhat of similarity in band 12. The range of the unburned pixels tends to be slightly greater than that of the burned pixels. The variation within the visible part of the spectrum is very small, supporting the TD analysis, which showed a similar response. The variation between the Red Edge bands is very distinct with only minimal overlap of the outside values. The NIR shows a clear decrease in response for both Band 8 and 8a.

[FIGURE 8]

Figure 8. Box plots for all bands and spectral indices for burnt and unburnt areas.

3.4. Spectral separability for burn severity

The variation in the post-fire indices is shown in Figure 9. Once the severity map was created, the mean values for the different regions were extracted. Visually there is a clear variation between the differenced indices, as they all show a reduction in variability as severity decreases. The post-fire means for CD, HD and MD show a gradual increase in response for all the indices. The ND shows a similar response from post-fire to pre-fire. This could be expected as the area is designated as unburned or very low burn severity, so a smaller response would be expected for this region. The pre-fire response for ND is lowest across all the indices with a similar mean for CD, HD and MD.

The responses from the three Red Edge bands are shown in Figure 10. The response to dNDVIre1 is similar to that of the NDVI and two NBR, with the post-fire ND being a similar value to the pre-fire ND, and the differential showing a clear downward trend as the burn severity decreases. NDVIre2 and NDVIre3 show almost no change in their variation both pre- and post-fire. The differentiation between them is minimal and there is no indication of variation between severities. This supports the evidence found in the burnt area mapping technique that the variation between pre- and post-fire NDVIre2n and NDVIre3n is minimal and is not suited to distinguish burnt areas.

[FIGURE 9]

Figure 9. Box and plot of spectral indices NDVI, NBR_{b11} and NBR_{b12} for the overall burned area based on fire grading. (HB: High Burn, MB: Moderate Burn, LB: Low Burn, VLB: Unburned or Very Low Burn).

[FIGURE 10]

Figure 10. Box and plot of spectral indices NDVIre1n, NDVIre2n and NDVIre3n for the overall burned area based on fire grading.

3.5. Environmental variables

The last part of this study aimed at exploring if any of the local environmental variables had an impact of the severity of the fire. NBR was used as a metric for fire severity. Scatter plots for the different environmental variables against the post-fire NBR did not show any strong relationship between any variable and NBR. Aspect appears to be very random with an almost 0 R^2 value, while none of the other variables have a strong R^2 value. A statistical analysis including the Pearson's *r* correlation showed that most of the variables show a slight negative correlation.

The land cover spectral variations were extracted to establish if any relationships could be determined between them and burn severity. The spectral responses from the different spectral bands showed varying differences from burned - unburned. The Grasslands showed a small variation in B12 (SWIR2) with very little change from burned - unburned. The NIR showed large unburned to burned changes in all the land cover types (Figure 11). The responses from the individual land cover types to the various indices are displayed in Figure 12. None of the land cover types seemed to particularly respond to the NDVIre2 and NDVIre3n indices. The Grassland shows a limited variation in NDVI response with only a limited separability between burned and unburned areas. The Trees, Cropland and Scrub, all have a clear separation between burned and unburned areas.

Finally, the histogram in Figure 13 displays the cumulative mean post-fire NBR for each land cover type collected from the 2000 random sample points. The Scrub was the largest area that was burnt, and this is evident by the amount of samples that were extracted as scrub. The -0.3 was the largest cumulative response for Scrub, while Cropland showed a slightly lower response with very little in the -0.3 and more showing in the -0.2 to -0.1 range. The Grassland had a low throughout and the Trees was roughly evenly spread in the -0.3 to 0.10 range.

[FIGURE 11]

Figure 11. Wavelength Normalised (Um) spectral responses from burned and unburned images for the Sentinel-2A spectral bands.

[FIGURE 12]

Figure 12. Wavelength Normalised (Um) spectral responses from the indices created from the Sentinel-2A spectral bands, for the different land cover types present in the burnt area.

[FIGURE 13]

Figure 13. Histogram of post-fire NBR responses to land cover types.

4. Discussion

The use of simple differentiation methods to delineate burned areas requires minimal effort to achieve with virtually no supervision to produce the map. The only interaction that may need to be done is for areas outside the actually delineated area that have been misclassified due to other environmental factors. This is backed up by many previous studies conducted on multi-temporal analysis. The response from different spectral bands to wildfires is well-documented. Chuvieco et al. (2002) described the benefits of the NBR over NDVI, as the response from the SWIR region is more susceptible to burnt areas. The technique proposed by the authors using the variation in the SWIR and NIR to map the burned area has been used for a long time. The comparison of post-fire indices patterns has yielded different results (Tanase et al., 2011; Jin & Roy, 2005). The false classification given in the differentiated indices appears to be due to the removal of vegetation from the agricultural areas of the image that has probably just ploughed during the pre- and post-fire images. These are less prominent in the NBR indices than the NDVI indices, due to the reduced responses from the red parts of the spectrum included in the NDVI indices. These parts of the image could probably be removed with observation by the user. The growth in the fields or harvesting of the fields shows the removal of vegetation in the area.

The dNBR b12 and dNDVI showed comparable results to the higher resolution reference data. The three Red Edge indices showed diminishing returns from the spectral indices, as they got closer to the short wave infra-red bands. The Red Edge 2 and Red Edge 3 when produced became very fuzzy between burned and not burned. Due to the size of the fields that have been ploughed, these remain intact and only the dense upper area of the high burn section of the burned image showed any consistency across the image.

SAM for establishing burn severity is a time consuming and labor intensive method of classification. The need to define and select training areas requires detailed analysis of spectral signatures and a thorough understanding of burning severity responses. The accuracy of the SAM was at 73% overall, with a Kappa of 0.65 (Congalton & Green, 2008). The map produced by the SAM did not take into account surrounding pixels or any spatial relationships; this would have aided in its ability to relate severity levels in regions which produced a less speckled map caused by the per pixel classification. Petropoulos et al. (2011) comparing SAM to Support Vector Machines, showed that development of machine learning and decision tree based methods can result to producing improved classification results based on both spectral and spatial relationships. A possible reason for the lower accuracy is the grouped nature of the EMSR reference data. This raster data tends to be homogenous in areas of different burning severity. Homogenizing the SAM classification could have produced a higher accuracy. Finally, it should be noted that the results from the comparisons where the EMSR has been used, should be interpreted cautiously, given the limited knowledge on the detailed validation results on this product.

The TD test undertaken showed a clear separability between unburned – burned areas. The Shapiro-Wilk normality test showed that most of the datasets were not normality distributed.

This indicated that the parametric TD test undertaken might not have been appropriate for the datasets. A non-parametric test such as decision tree base analysis, might have yielded more significant results (Huang et al., 2016). The training data collected through visual interaction with the datasets means that misidentification of spectral signatures is possible, leading to misrepresented samples. The analysis of spectral separability supported previous findings by Levin & Heimowitz (2012) and Huang et al. (2016), that the visible bands of the EM spectrum have a low burned to unburned spectral separability (Picotte et al., 2016). This is due to the similarity of non- photosynthetic vegetation, bare soils and the burned areas themselves (Lasaponara, 2006). The large area of scrubland present in the land cover type would add to the homogeneity of the response. The performance of the spectral indices showed a varying degree of separability, the NDVI indices showed a general relationship for this specific region area. The NDVI response can be limited by the canopy cover in certain land cover types (Zhang et al., 2003). The response becomes saturated in denser canopies leading to limited separability (Huang et al., 2016). There are not many studies conducted on multiple red edge bands present on the Sentienl-2A sensor. The indices created for Red Edge 2 and 3 were not conducive to burned area mapping, but the bands themselves showed good separation between burned and unburned pixels. The use of just these bands may have been more suited for burned detection (Navarro et al., 2017). Fernández-Manso et al. (2016) have provided an initial investigation with the Sentinel-2A MSI, indicating that the Red Edge (B1) and its derived indices were the most suitable for deriving burn severity. This is due to its closeness to the Red (B4) wavelength. The low responses to the SWIR in some regions may have been due to the presence of the shrub and agricultural land in the area (Schepers et al., 2014). The presence of non-photosynthetic vegetation and the removal of soils by agriculture can influence the response from the SWIR.

The environmental variables effect on the fire severity appeared to have low correlation within the study area. High FVC is normally associated with high burn severity as there is a relationship between FVC and the fuel available to a wildfire (Chu et al., 2016). The low correlation does not agree with other research by Epting and Verbyla (2005), who indicated that FVC was a key component in the severity of wildfires, due to the relationship between severity and the increase in fuel availability. The relatively small change in elevation from 283m to just over 1200m indicates that the site may not have been a large enough scale to influence burn severity. There have been several studies conducted on the influence of elevation on burn severity. Although all four severity types appear below 1000m, only the CD severity appears above the 1000m height. There appears to be no strong correlation between any environmental variable and severity, there is high variation within each variable with large areas of overlap within each category. There was poorly defined positive or negative trends in all the variables. With the lack of significant correlation in this category, it is appropriate to say that none of the variables had an influence on the burn severity.

Finally, the use different of classification methods to produce the burn severity map could have aided in improved accuracy. The use of classifiers such as Support Vector Machines, Random Forests and various machine learning techniques have been studied and found to be effective at delineating both burned areas and burn severity (Whyte et al., 2018). In addition, the use of multiple study sites with varying attributes would have given a better scope for discerning the effects of landscape variables on the severity. Using a single study site limits the range and extent of variables that accessible to the user. Also, it should be noted that the obtained results concern the current study only, thus further studies in other regions (using the same dataset types and methods) should be implemented before generalizing the results.

5. Conclusions

The objective of this work was to establish the suitability of the Sentinel-2A sensor to delineate the burnt area, burn severity and what the possible environmental effects are on the severity. The Sentinel-2 mission has a higher spatial, spectral and temporal resolution than most current orbiting sensors (Landsat-8, MODIS). The recent release of the Sentinel-2B MSI sensor will increase the temporal resolution to 6 days allowing for consistent global coverage. The study showed that it is possible to separate burned and unburned regions using specific spectral bands and indices. The NBR_{b12} was overall the best index to be used to delineate burned areas. The NDVI Red Edge bands did not compare well compared to ordinary NDVI. That being said, the individual Red Edge bands showed a better separation than the derived indices. Finally, the environmental influence on the wildfire was not well established, as it was limited by the size of the fire and the topographic properties present in the area.

Finally, it should be noted that some important factors like downslope wind, abundance of fuel, and the moisture of fuel were not considered in this study, as it was not within its purpose to conduct this kind of investigation, and in addition, the necessary data to support such analysis were not available. However, future steps in relation to this study should incorporate the analysis of these factors. Also, further studies in different regions using the same dataset types and methods should be implemented before generalizing the results of the current study.

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Author Contributions

CA conducted the research described in this study under the supervision of GPP, and KPF and GPP prepared the manuscript for submission to the journal and made all necessary revisions.

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