QUANTIFYING BUSHFIRE MAPPING UNCERTAINTY USING SINGLE AND MULTI-SCALE APPROACH: A CASE STUDY FROM TASMANIA, AUSTRALIA

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ABSTRACT:

More than 72,000 hectares of western Tasmania were burnt in 2016 due to bushfires. Bushfires in Tasmania has high social, economical, and environmental impacts. The remote delineation of these bushfires has paramount importance for decision-making authorities to help people in emergencies and planning. Considering the fact that delineation uncertainty from Earth Observation [EO] data is inevitable, this study uses MODIS, Landsat and Sentinel-2 imageries covering the 2016 burnt areas from Tasmania. We test the hypothesis that the difference in Normalised Difference Vegetation Index (NDVI) before and after the fire event can detect the accurate delineation of burnt areas and hence the changes. MODIS, Landsat and Sentinel-2 products before and after fire are used independently in delineating and mapping bushfire boundaries. We map in three thematic classes burnt, damaged and both. Delineated boundaries are examined for uncertainty and error maps are produced. The uncertainty examination and validation are performed using ground truth data obtained from local fire authorities. Developed error metrics are used to obtain statistical measures like sensitivity, specificity, positive predictive value, negative predictive value, kappa coefficient and overall accuracy. Our results show that there is minimal difference in overall accuracy from both the sensors MODIS: [0.94 vs 0.92] and Sentinel [0.94 vs 0.93] for the classes burnt & damaged *vs* only burnt.

Furthermore, we propose a conceptual framework for bushfire mapping uncertainty in a multiple-scale environment incorporating sensitive thematic parameters that could affect initiation of fire and blaze direction. The parameters considered in our framework are: vegetation type [landcover], vegetation density [vegetation indices], drought [soil moisture, air moisture, precipitation], temperature [air temperature, soil temperature], topography [elevation, slope, aspect, ruggedness, topography position index], and wind [speed, direction]).

1. INTRODUCTION

1.1 Bushfires in Australia

Bushfires have been part of the Australian environment since before human settlement of the continent (ABS, 2016). Bush-fires in Australia are increasing (Dutta et al, 2016). Bushfires are complex natural disasters that bring catastrophic consequences to the socio-economic and ecological environment of a country. Due to its unique continental position, Australian states and territories experience different sizes of bushfires. In the past, Tasmania suffered their worst bushfires on 'Black Tuesday' 7th February 1967 when approximately 264,000 ha were burnt, 1,700 houses destroyed and 61 people killed (ABS, 2016). Recently, in January 2016, north and north-west Tasmania (Fig.1) experienced bushfires. The burnt areas were located within the World Heritage Area (WHA) and attracted wide attention. The bushfires devastated areas which are home to unique and iconic Tasmanian alpine flora including pencil pines, king billy pines, and cushion plants. Some of these vegetation communities were more than 1,000 years old. Fire ecologists and experts declared that these killed vegetation communities wouldn't grow back and this incident may be sign of a system collapse due to drier summer caused by climate change (Radionz, 2016). Considering the significant heritage importance of the affected areas and the lost vegetation communities, it is essential to know the accurate extent of the affected areas. In this study, the bushfire affected areas that are extremely important to nature conservation and heritage are chosen for remote delineation using Earth Observation [EO] data. The main motivation of this research work is to quantify the uncertainty associated with the delineation of bushfire affected areas. The uncertainty is observed with the calculation of various accuracy measures based on ground truth data. These measures include: sensitivity, specificity, false positive rate, false negative rate, positive predictive value, negative predictive value, kappa coefficient and overall accuracy. These measures are calculated for multi-sensor data. In this study, we used the change of Normalised Difference Vegetation Index (NDVI) combined with k-means clustering to map the removal of vegetation caused by bushfires. The difference in the NDVI before and after the fire event can provide delineation of burnt areas and these can be improved then by clustering. Mapping burnt areas based on NDVI have been widely tested (van Leeuwen et al., 2010). Other indices such as the Normalised Burn Ratio (NBR) (Veraverbeke et al., 2011) and the Burned Area Index (BAI) (Chuvieco et al., 2002) are also used in mapping burnt areas. In order to test the

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proposed method we analysed the multi-sensor products. Landsat 8 image before the fire (27 December 2015) is analysed and the results are compared with the analysed Sentinetal-2 image after fire (14th March 2016). Sentinel-2 was used because Landsat 8 cloud-free images were not available. The Sentinel-2 Multispectral Instrument (MSI) acquires 13 spectral bands ranging from Visible and Near-Infrared (VNIR) to Shortwave Infrared (SWIR) wavelengths along a 290-km orbital swath. The MSI sensor data are complementary to data acquired by the U.S. Geological Survey (USGS) Landsat 8 Operational Land Imager (OLI) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+). Being complimentary to Landsat 8 OLI, Sentinel-2 is used for comparison. Independently, we analysed MODIS burned area products from 27th December 2015 and 14th March 2016. We discuss in section 2 the specifications on data, details on study area and methodological approach. Section 3 presents results and discussions, and in section 4 we present conclusions and future directions.

2. DATA, STUDY AREA AND METHODOLOGY

2.1 Earth Observation [EO] and Ground Truth Data

The EO data used for the analysis are Landsat 8 OLI, Sentinel-2, and MODIS.

2.1.1 Before fire

Landsat 8 OLI is used for before the fire analysis. The specifications of the product are as follows:

(a) Product: Landsat 8 Operational Land Imager, 9 bands, date: 27/12/2015 (361/2015), spatial resolution: 30 m, temporal resolution: 16 days.

Similarly, MODIS terra is used for before the fire analysis. The specifications of the product are as below:

(b) Product: MODIS Terra, bands: 1 to 7, date: 27/12/2015 (361/2015), spatial resolution: 500 m, temporal resolution: daily.

2.1.2 After fire

For after fire event analysis, Sentinel-2 is used and compared with Landsat 8 OLI and, MODIS is analysed and compared with MODIS product. The specifications are as follows:

(c) Product: Sentinel-2, 13 bands, date 14/03/2016 (74/2016), spatial resolution: 10, 20, and 60 m, temporal resolution: 10 days.

Near infrared band (band 8) and red band (band 4) with 10 m spatial resolution are used in computing NDVI from Sentinel-2 product.

(d) Product: MODIS Terra, bands 1 to 7, date 14/03/2016 (105/2016), spatial resolution: 500 m, temporal resolution: daily.

2.1.3 Ground Truth Data

The fire ground truth data is brought together from several sources / agencies (e.g, Tasmania Fire Service; Parks and Wildlife; Forestry Tasmania; Forico). The ‘official’ fire history is released in late July of each year. It is available on LISTmap (The state mapping authority of Tasmania) where we can see the source and method of data capture for each polygon. General information from previous year’s metadata can be seen at the link below (The LIST, 2016):
https://data.thelist.tas.gov.au/datagn//srv/eng/main.home?uuid=b94d4388-995d-416a-9844-a39de2798bed

Generally, larger fires have had their boundary mapped by viewing from a helicopter during the fires providing us real-time ground truth data. The ground truth in this study is real-time data captured from helicopter. The ground truth data (Figure 1) are used in validating the produced maps based on normalised difference vegetation index, difference and un-supervised classification.

2.2 Study Area

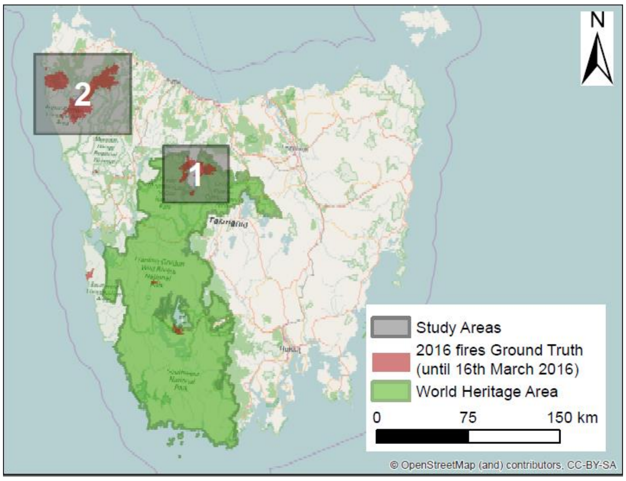

Figure 1. Two bushfire affected areas from north and north-west Tasmania, Australia

The study area 1 is the part of the World Heritage Area. As depicted in Figure 1, two study areas are considered: ‘study area 1’ and ‘study area 2’. The real-time picture of fire (Figure 2) shows the surrounding environment of the study area including vegetation communities.

Figure 2. Real-time picture of a fire event including vegetation communities, Tasmania, Australia

2.3 Methodology: Single-scale approach

2.3.1 True / infrared colour composite

All EO data are visualised by forming two different colour composites namely true colour composite and infrared colour composite. This visualisation help to better understand the burnt areas after and before the fire, i.e. presence / absence of vegetation. True colour composites for Landsat 8 (Bands 4, 3, 2), Sentinel-2 (Bands 4, 3, 2) and MODIS (Bands 1, 4, 3) and infrared colour composite for Landsat 8 (Bands 5, 4, 3), Sentinel-2 (Bands 8, 4, 3) and MODIS (Bands 2, 1, 4) are observed in ascertaining the burnt area and vegetation area. This manual visualisation provides confirmation for NDVI calculation.

2.3.2 NDVI Difference Map

NDVI is calculated using the following equations for the respective EO data.

$$\text{NDVI for Landsat 8} = \frac{band\ 5 - band\ 4}{band\ 5 + band\ 4} \quad (1)$$

$$\text{NDVI for Sentinel} - 2 = \frac{band\ 8 - band\ 4}{band\ 8 + band\ 4} \quad (2)$$

$$\text{NDVI for MODIS} = \frac{band\ 2 - band\ 1}{band\ 2 + band\ 1} \quad (3)$$

Where for Landsat 8, Sentinel-2 and MODIS, the near-infra red bands are respectively band 5, band 8, and band 2; and the red bands are respectively band 4, band 4 and band 1. The calculated NDVI is used to produce change detection map based on difference of NDVI. The difference is computed by subtracting NDVI value after the fire event from NDVI value before the fire event. Since burnt areas are spaces where there is no more vegetation, fire events should correspond to a positive NDVI before the fire and a negative NDVI after the fire. Therefore, NDVI difference values inferior to 0 is selected as a first step to delineate bushfires. Mathematical morphology is then used to correct these extents. A mask layer is created and used with the other bands in EO data after the fire in order to refine the bushfires delineation based on clustering.

2.3.3 Spectral signature extraction, unsupervised classification, and validation using ground truth

For Sentinel-2 and MODIS after fire data, the unsupervised classification is made using k-means clustering based on observed spectral signatures (eg; Figure 3) and false colour composite visualisation, reclassification is made in three categories namely: “burnt”, “unburnt”, and an intermediary class we called “damaged” which should represent slightly burnt areas. The classified map is validated using ground truth data and error maps are produced along with statistical measures.

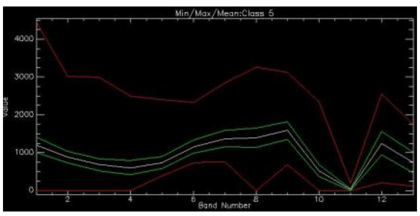

Figure 3: Spectral signature for the class “damaged”, flatter than burnt.

2.4 Methodology: Multiple-scale approach and proposed conceptual framework

The single-scale approach provides information on one level. However, a phenomenon like bushfire is the outcome of many variables not only vegetation. With this in mind, we wish to extend the developed method in this work for multiple scales. We propose a framework that can integrate thematic parameters contributing for fire in hierarchies (Aryal and Josselin, 2014; Blaschke et al 2014). The framework integrates parameters like vegetation type [landcover], vegetation density [vegetation indices], drought [soil moisture, air moisture, precipitation], temperature [air temperature, soil temperature], topography [elevation, slope, aspect, ruggedness, topography position index], and wind [speed, direction]) in delineating the likely fire from Earth Observation data. This conceptual framework is not presented in this paper.

3. RESULTS AND DISCUSSIONS

3.1 Visualisation of ground truth and MODIS product overlay for study area 1 and 2

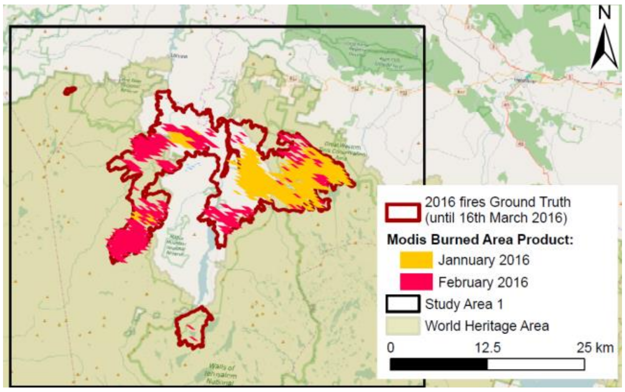

Figure 4: Visualisation of an overlay of ground truth data and MODIS product for study area 1

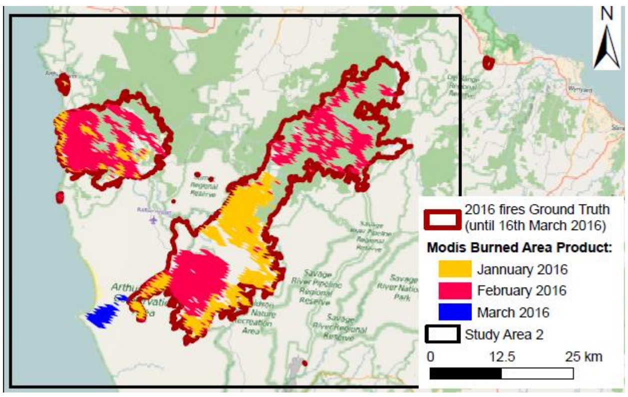

Figure 5: Visualisation of an overlay of ground truth data and MODIS product after fire event for study area 2

The above visualisations (Figure 4 and 5) show alignment of fire ground truth data in many places with MODIS product for both the study area. However, uncertainty is further visualised with the aid of colour composite, difference maps and error maps.

3.2 Visualisation of colour composite, NDVI difference map, and error maps for study area 1 and 2

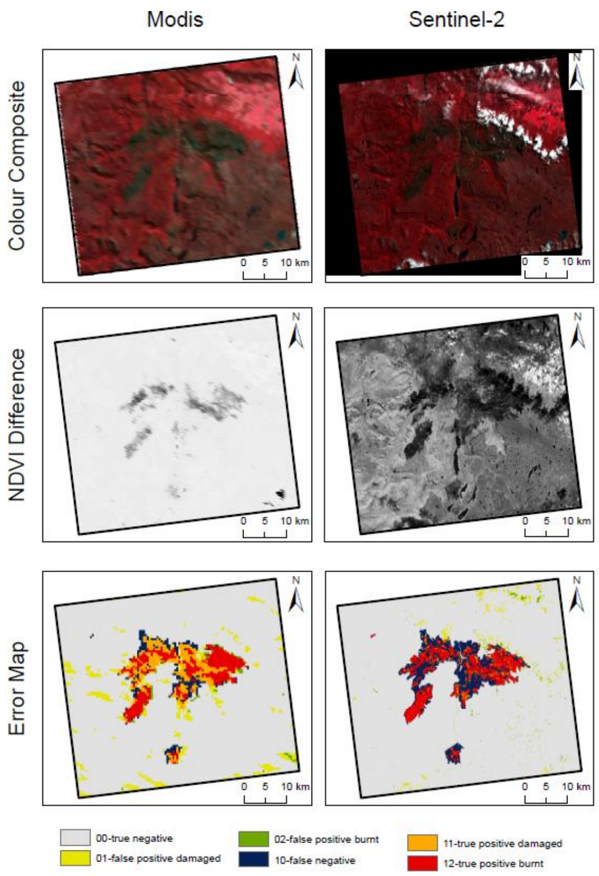

Figure 6. Colour composite, NDVI difference map and error map for study area 1

For both study areas 1 and 2 uncertainty of delineation is visualised (Figures 6 and 7). Statistical measures for associated uncertainties are computed using the “confusionMatrix()” function from the caret package (*C*lassification *A*nd *RE*gression *T*raining) in R, an example for burnt class is provided in Table 1. This shows that there is minimal difference between the sensors in extracting these bushfires extent when considering only the “burnt” class, but an increase in precision for MODIS when adding the intermediary class “damaged” with more true positives (Table 2). The difference between the classifications according to the sensor are statistically significant based on the McNemar’s test (p-value < 2.2e-16) even the accuracies are close.

Table 1: Statistical measures for MODIS and Sentinel-2 in extracting burnt area based only on burnt class.

	Accuracy	Sensitivity	Specificity	Kappa
MODIS	0.92	0.56	0.99	0.65
Sentinel-2	0.93	0.56	0.99	0.67

Table 2: Statistical measures for MODIS and Sentinel-2 in extracting burnt area using burnt and damaged classes.

	Accuracy	Sensitivity	Specificity	Kappa
MODIS	0.94	0.89	0.94	0.78
Sentinel-2	0.94	0.64	0.98	0.72

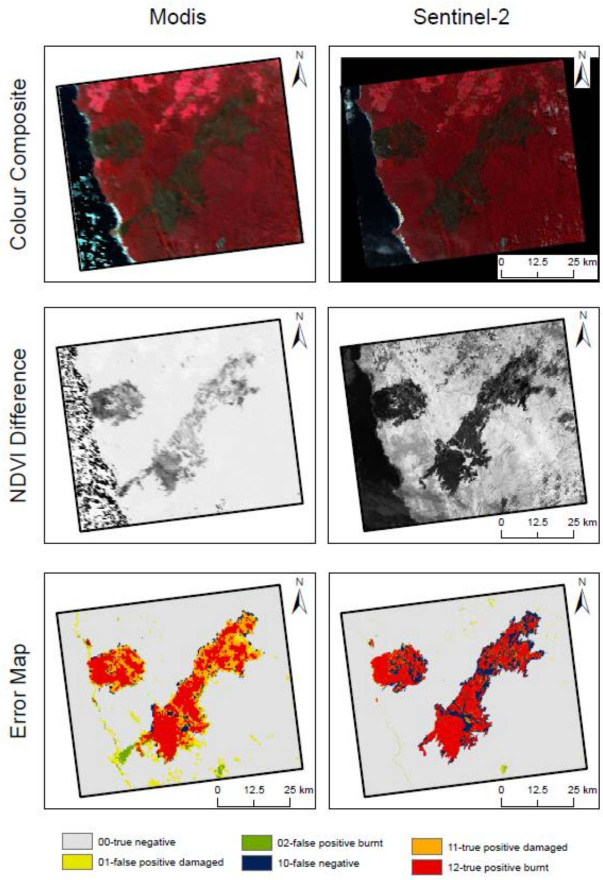

Figure 7. Colour composite, NDVI difference map and error map for study area 2

3.2 Discussions

The largest error is false negative. When looking at the colour composites, it seems that those false negatives are indeed unburnt vegetation (red in false colour) surrounded by burnt area. This could be due to the ground truth data having a convex shape and considering unburnt vegetation within that shape as burnt. On the other hand, false positive are mostly isolated pixel. Therefore this could be improved with more mathematical morphology (closing).

In terms of real-world features, clouds, shadows, and lakes, were included in the mask layers based on the NDVI differences of Landsat 8 and Sentinel-2. This was later corrected by using k-means clustering algorithm. The “damaged” class improves the true positives more for MODIS than for Sentinel-2, and add most of the false negatives for both: a sensitivity of 0.89 vs 0.55 and positive predictive value of 0.74 vs 0.9 with MODIS, while in the case of Sentinel-2 the sensitivity of 0.64 vs 0.56 and positive predictive value of 0.90 vs 0.97.

The overall accuracy doesn’t really change neither according to the sensor nor using both damaged and burnt classes. For example, in the case of MODIS 0.94 vs 0.92 overall accuracies; 0.78 vs 0.65 Kappa values while in the case of Sentinel-2 it is 0.94 vs 0.93 overall accuracies and 0.72 vs 0.67 Kappa values (Table 1 and 2).

4. CONCLUSIONS AND FUTURE RESEARCH

This study shows that there is little difference in overall accuracies from both EO data MODIS and Sentinel-2 in mapping the fire event in single analysis scale. The proposed framework for multiple-scale will be implemented and compared in the future extension of this work.

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