Article

A methodology for determining wildfire burned areas and burn severity levels and post fire vegetation recovery using Sentinel-2 satellite images: The case study Australian wildfires

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ABSTRACT

Wild land fires occur in Australia at varying rates, durations, and burn severity. These sporadic disruptions have a variety of effects on biotic and abiotic cycles and trends. Due to the extreme longer duration taken to collect ecosystem features, detecting burn intensity and vegetation restoration is difficult. Multi-temporal remote sensing information may include multi-temporal analyses before, during, and after a wildfire, and can provide increased accuracy of detection of changes. The aim of this research is to look into the relationships among the multi-temporal spectral index and fire severity as measured in the forest, as well as to develop a realistic method for estimating burn intensity and vegetation restoration. The study site is Canberra in Australia that burned during 2019-2020 bushfires. Multi-temporal images from Sentinel-2 were taken for January 2020 (pre-fire) and March 2021 (post-fire). The normalised difference vegetation index (NDVI), solid adjusted vegetation index (SAVI), modified normalised difference water index (MNDWI), normalised burn ratio (NBR) and the delta normalised burn ratio (dNBR) these indices between pre-fire and post-fire were computed and analysed using google colab. The final results revealed that the variations in NDVI after post-fire some regions have showed vegetation regeneration and differences of SAVI after post-fire shows clear image of gained vegetation regeneration when compared with NDVI. The comparison of MNDWI index shows some regions have retained water resources and some regions have lost the water resource due to fire. The result of differences in NBR is used to determine the burn-severity in the region. The delta NBR produce the result of the burn-severity from difference in pre and post fire NBR results. The final result shows that the high burn severity regions have slower restoration when compared with medium and low burn severity regions.

Keywords: dNBR, NBR, NDVI, vegetation recovery, burn severity

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INTRODUCTION

Fire is a critical ecological phenomenon that has severe effects on land, marine, and atmospheric environments all over the globe. Furthermore, fires have an effect on a broad variety of temporal and spatial scales, and participants are just now starting to appreciate the connections between trend, mechanism, and possible remedial steps. Massive wildfire events have occurred all around world over last decade, causing significant social, economic, and environmental consequences. Forest fires, along with environmental issues and drought, are known one of the most significant disruptions in Australia, resulting in, among other things, the loss of vegetation. Changing climate poses a significant threat to forests, especially in Australia, where severe weather is expected to become more common. Temperatures have risen and precipitation has decreased in recent years, resulting in a higher risk of fire and, as a result, higher emissions of greenhouse gases (CO2, CO, and CH4). As a consequence of the large level of severity reached in some fires, human life, the climate, and biodiversity assets have all been affected (Llorens *et al.*, 2021).

Warmer and drier weather are anticipated to rise wildfire intensity, raising concerns among experts and land managers about habitat tolerance and post-fire vegetation recovery. The intensity of the burns, or how much the fire has damaged the vegetation and soil, may have a significant impact on post-fire vegetation restoration. Vegetation form, environment, and range to unburned areas and seed supplies are all variables that can impact post-fire vegetation restoration. Scientists and land managers looking to locate regions that may profit from post-fire restoration will use lengthy assessments of post-fire vegetation regeneration on behalf of various reforest forms and burn severity. Methods like the Landsat-based analysis of Trends in Intrusion and Restoration (Land Trendr) algorithms, which use time information from this enriched image archive to evaluate vegetation models, developed popular (Tran *et al.*, 2020).

According to studies, human-caused climate change has resulted in hot, dry weather that have increased wildfire occurrences in different areas. As it influences both vegetation cover and layout, wildfire forms landscape structures and environmental conditions. Alterations in wildfire behaviour can affect mortality and restoration cycles, resulting in new successional routes and differences in vegetation quality and landscape properties. The level of changes in the environment due to fire is measured by fire intensity, which includes direct fuel usage and carbon pollution as well as extended effects on plant degradation, successional structures, and soil surface. Alterations in wildfire intensity may have an effect on natural systems by altering the course of postfire vegetation regeneration, resulting in land cover cuts and relocation to vegetation that is not covered by trees. To predict the potential paths of forest ecosystems, a greater knowledge of variations in fire intensity is needed (Filkov *et al.*, 2020).

Australia is amongst the most fire-prone countries on the planet, with 30.4 million hectares burned in 2019–2020 alone. Global warming has and will likely to have an effect on Australian fire conditions and fire behaviour, according to surveys, with fires expected to be become bigger and much more severe. The Black Summer wildfires in Australia in 2019/20 erupted during one time of record-breaking conditions and abnormally low precipitation. The extent to which wildfires are now more serious is largely a mystery. The intensity of fires varies by location, ranging from limited litter intake and moderate searing of under-storey vegetation to near-complete canopy tree extinction. The intensity of a wildfire and the spatial distribution of intensity categories have major consequences for fire-related resistance and environmental depletion (Bright *et al.*, 2019).

Fires can alter the design form, and operation of the environment, as well as the rates and mechanisms of natural ecosystem and encroachment. Fires often spread in a non-standard pattern across the forest, and nature that has been destroyed by wildfire in multiple ways will recover in multiple ways. These mechanisms express themselves in a variety of aspects including modifications in genetic diversity and age structure, control of forest insect and disease outbreaks, nutrient cycles habitat efficiency, and ecosystems, to name a few (Hall *et al.*, 2008). In Australia, forestry fires is a major force of vegetation progression. The intensity and orientation of vegetation movements in Australia's forests are highly influenced by the magnitude of the subsequent burn. Tree saplings have a better chance of establishing and surviving in environments that have been burnt to soil surface or only few more cm in width of organic compounds. They are, furthermore, more vulnerable to erosion and permafrost depletion, which can result in the formation of thermokarsts, that can result in new rivers, streams, puddles, and "drunken woods" of stumbling and toppled woods. Massive differences in vegetation morphology and natural habitats may result from these variations in landscape pattern. To predict burn intensity, a landform remote sensing strategy is essential due to the remoteness and size of the target areas (Murphy *et al.*, 2008).

Understanding the ability for post-fire destruction and the environment's post-fire tolerance is therefore a significant challenge. The intensity of wildfire is characterized as (i) the level of destruction (ii) the chemical, physical and biological modifications or (iii) the magnitude of modification that wildfire brings to an environment. In this context, fire intensity measures the narrow impacts of a wildfire in the instant aftermath while burn intensity measures both the narrow and long-term consequences of a wildfire by taking into account overall experience. Whereas the remote sensing group recognises the significant variation in terms between burn and fire intensity, fire environmentalists prefer to blur the line by excluding ecosystem behaviours from the word burn intensity, lowering its definition to the very same extent as fire intensity making the two words interchangeable (Veraverbeke *et al.*, 2010). A graphical overview of post-fire consequences terms is shown in Fig. 1.

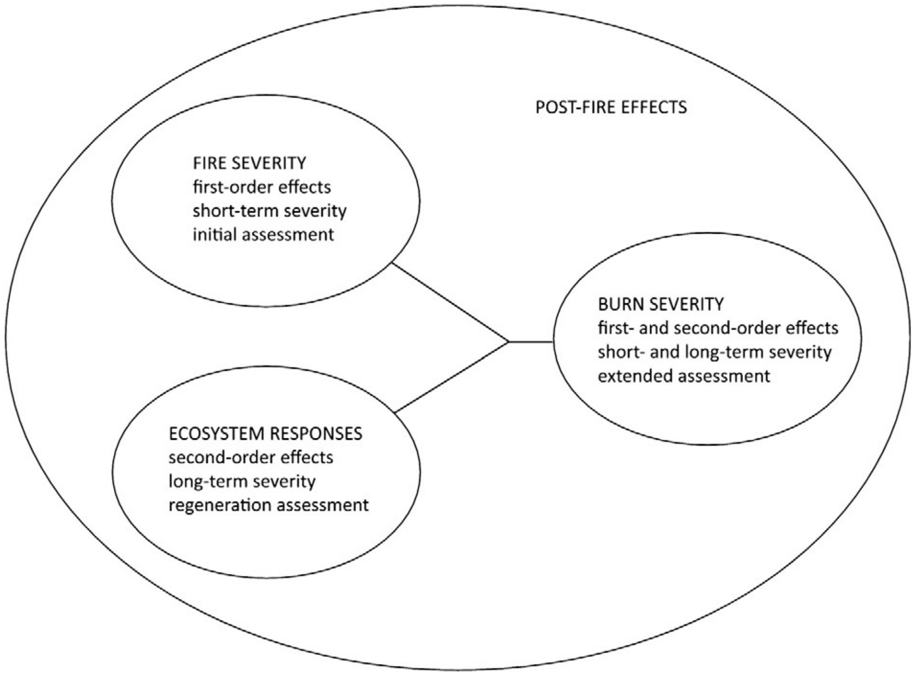


Fig 1. Representation of post-fire consequences (Veraverbeke *et al.*, 2010).

Usually, these post-fire vegetation alterations are sudden right just after wildfire, but a much more natural and incremental vegetation restoration phase starts many weeks later. Given the ongoing debate over the temporal element of fire/burn intensity research, few experiments have looked at the impact of evaluation duration on post-fire impact prediction. Since the Australian forest fires of 2019–2020 have been so devastating in regards of burnt region and intensity, a thorough investigation into the root factors is essential. According to previous research, the principal reason of flames is a variation of three factors: hot weather, fuel supply, and a combustion origin. Besides that, changes in sea surface temperatures are said to have powerful links to global drought conditions, that influence the spreading of wildfires.

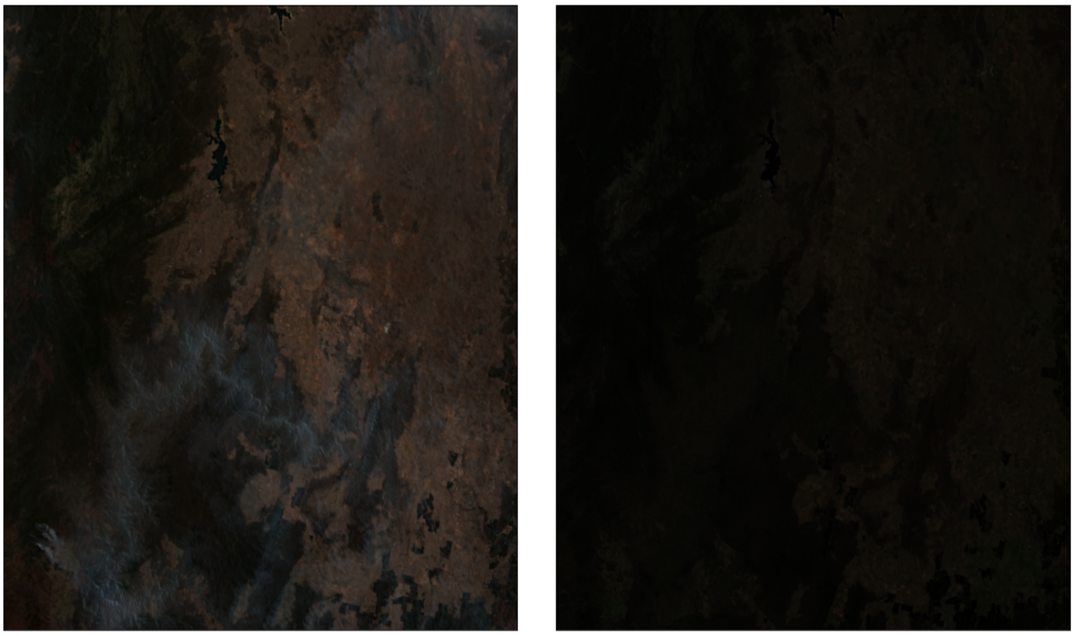
Furthermore, previous researches have shown that intense rising temperatures have exacerbated several of the big recorded wildfires outbreaks in the Southeast Australian nation. They also believed that fuel supplies were haphazard, provided that fuel accessibility was the same in unburned and burned areas/forests (Singh *et al.*, 2020). Latest surveys have clearly just looked at a handful of the most major sources of the wildfires. To our understanding, there is really no systematic research in the published studies that has discussed most, if not all, potential parameters regulating widespread wildfires, either separately or in combination, and it is also the report's uniqueness. The overall goal is to look at all conceivable factors that led to the widespread wildfires in Australia.

MATERIALS AND METHODS

Study Area:

The entire world attention was drawn to Australia in the early days of 2020, where country's endangered species struggled for survival in the face of catastrophic fires. Koalas drinking from firefighters' water bottle image went viral, making them the global face of a tragedy that could kill three billion animals. The fire season, nicknamed "Black Summer," resulted in more wildlife deaths and near-extinctions than any other single occurrence in Australian history. Australia's Black Summer serves as a stark warning to the international community as global warming accelerates and destructive wildfires become more frequent. However, my research focused on Australian wildfires, specifically in and around Canberra, using Sentinel-2, level-2 data, 20 Meter resolution (fig 2). I have acquired pre fire data Jan'2020 and post fire data March'2020. In this analysis, will be analysing the satellite images with some aspects of pre-fire and post-fire as follows (i) Vegetation and soil indices and (ii) Water indices.

Finally, here we will be calculating the Normalised Burn Ratio (NBR) for pre and post-fire and find the differences between them and classify them according to the burn severity.



(a) (b)

Fig 2. Natural colour RGB on (a) pre-fire and (b) post-fire satellite image in Canberra, Australia wildfire.

Sentinel – 2:

In 2015 the sentinel-2A was launched and the second version sentinel-2B was launched in 2017 stationed at sun-synchronous orbit. Its objective is to keep track of changes in land surface conditions with 10 days repeat cycle. They reach all of the Planet's ground areas vast territories, and highland and lowland waters every five days.

Sentinal-2 spectral band has the 13 bands as follows

	Spectral Band	Centre Wavelength (nm)	Band Width (nm)	Spatial Resolution (nm)
B1	Coastal aerosol	443	20	60
B2	Blue (B)	490	65	10
B3	Green (G) [1]	560	35	10
B4	Red (R) [1]	665	30	10
B5	Red-edge 1 (Re1) [1]	705	15	20
B6	Red-edge 2 (Re2) [1]	740	15	20
B7	Red-edge 3 (Re3) [1]	783	20	20
B8	Near infrared (NIR) [1]	842	115	10
B8a	Near infrared narrow (NIRn) [1]	865	20	20
B9	Water vapor	945	20	60
B10	Shortwave infrared/Cirrus	1380	30	60
B11	Shortwave infrared 1 (SWIR1)	1910	90	20
B12	Shortwave infrared 2 (SWIR2)	2190	180	20

Image source: USGS

Solid and Vegetation Indices:

Dense vegetation will be brighter in the index picture, while poor vegetation will have smaller value and desert landscape will be dark. Although the intensity of images is affected by shading from landscape variance (hills and valleys), the indices are designed such that the colour of a subject is highlighted instead of the intensity or object brightness.

Normalized Difference Vegetation Index (NDVI):

The variance among red and NIR, which vegetation highly reflects is measured by the Normalized Difference Vegetation index (NDVI).The NDVI value is always between -1 and 1 (Chen *et al.*, 2011).

The sentinel-2 NDVI will calculate by the below methods

NDVI = ((NIR - Red)/(NIR + Red))
Where, NIR - Near Infrared (Band - 8)
Red - Red band (Band - 4)

Water is most likely when the values are negative. However, if your NDVI score is equal to +1, you're probably aiming at heavy green plants. Even if the NDVI value is zero, there is no vegetation present, and the area can be grown.

Solid-Adjusted Vegetation Index (SAVI):

The Soil-Adjusted Vegetation Index (SAVI), correction factor for NDVI, the landscape indicator that uses a soil brightness adjustment factor to minimise soil brightness. This is widely used in dry areas with little vegetation.

The sentinel - 2 SAVI calculations as follows

SAVI = ((NIR - Red) / (NIR + Red + L)) x (1 + L)

Where, NIR - Near Infrared (Band - 8)
Red - Red band (Band - 4)

The L value is affected by the amount of green vegetation present. L=1 is no vegetation, L=0.5 is poor vegetation, and L=0 is abundant vegetation. The SAVI index has a range of values from -1.0 to 1.0.

Water Indices:

Changes in surface water are a primary indicator of environmental, climatic, and anthropogenic influences. There are many techniques for the surface water extraction, amongst the index-based methods are very popular and efficiency.

Modified Normalized Difference Water Index (MNDWI):

The Modified Normalized Difference Water Index (MNDWI) calculate by green band and SWIR bands to improve open water assets. It also decreases features of constructed areas which are frequently compared to open water in other indices.

MNDWI will calculated as follows:
MNDWI = (Green - SWIR1) / (Green + SWIR1)
Where, Green - Green band (Band - 3)
SWIR1 - Shortwave Infrared (Band - 11)

Fire Affected areas Detection:

Normalized Burn Ratio (NBR):

As previously stated, spectral reflectance can be used to distinguish various properties of the earth's surface, including vegetation, moisture, burnt areas, and water, among other things. Different indices utilize various bands of light to differentiate vegetation and water-based structures, like that of the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI). The Normalized Burn Ratio (NBR) has been used to distinguish burnt regions in fire environments by using satellite image's Near Infra-Red (NIR) and Short Wave Infra-Red (SWIR) bands (Escuin *et al.*, 2008).

A strong NBR value denotes fertile vegetation, while a poor NBR value denotes bare land or recently burned regions. Non-burned areas had values similar to zero.

The formula for calculating NBR as follows,

NBR = (NIR - SWIR)/(NIR + SWIR)
NIR - Near Infrared (Band-8)
SWIR - Shortwave Infrared (Band-12)

Burn Severity Detection:

Delta Normalised Burn Ratio (dNBR):

The burn severity is calculated using the Delta Normalized Burn Ratio (dNBR), which is really the variation among the pre-fire and post-fire NBR. The higher the dNBR value, the more serious the damage, while the lower the dNBR value, the more regrowth after the burn. The dNBR values will differ from one case to the next. As a result, the United States Geological Survey (USGS) has suggested various burn intensity standards for dNBR values. The table below illustrates how dNBR values are used to classify burn severity (Hall *et al.*, 2008).

The formula for calculating dNBR as follow,

$dNBR = NBR_{pre\text{-}fire} - NBR_{post\text{-}fire}$

Severity Level	dNBR Range (scaled by 10^3)	dNBR Range (not scaled)
Enhanced Regrowth, high (post-fire)	-500 to -251	-0.500 to -0.251
Enhanced Regrowth, low (post-fire)	-250 to -101	-0.250 to -0.101
Unburned	-100 to +99	-0.100 to +0.99
Low Severity	+100 to +269	+0.100 to +0.269
Moderate-low Severity	+270 to +439	+0.270 to +0.439
Miderate-high Severity	+440 to +659	+0.440 to +0.659
High Severity	+660 to +1300	+0.660 to +1.300

Image Source: USGS

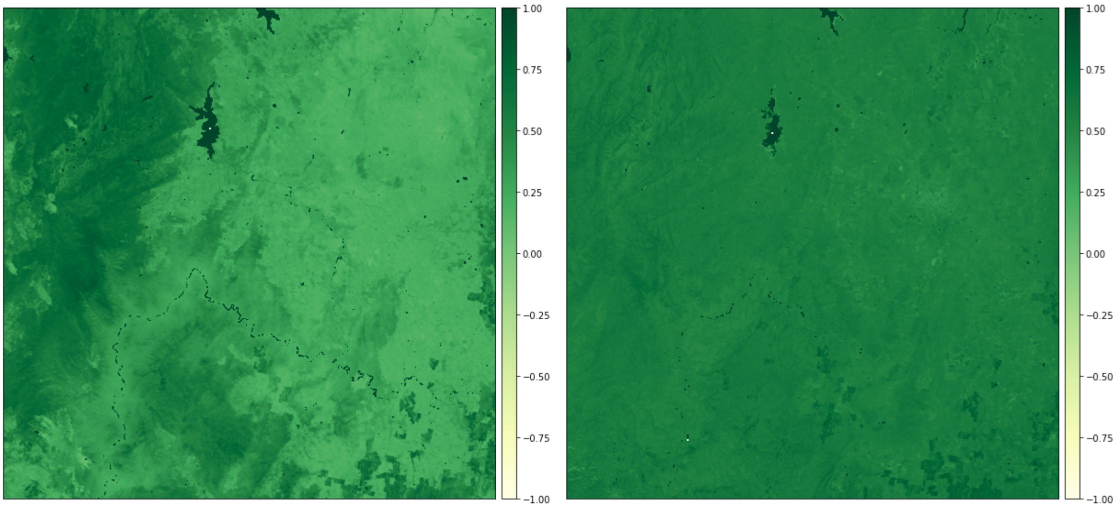
RESULTS AND DISCUSSION

Australia had just been through the midst of a major disaster, as the mainland was ravaged by the deadliest wildfires the country had ever seen. Heat and drought increased the amount of tinder available to fuel fires. It's important to investigate the Australian wildfires to learn more about what occurred there. Several animals and humans, have died, and approximately 2000 residences have been destroyed. Australia is no stranger to wildfires, but the severity was stronger in 2019-2020. Australia is no stranger to wildfires, but the severity was stronger in 2019-2020.

For each one of the wildfire regions, five spectral indices were derived, i.e. MNDWI, NDVI, SAVI, NBR, and the temporal difference of NBR that is delta NBR. The above indices are widely used to measure wildfire intensity and they were established as the best spectral indices for calculating wildfire damage in the survey region's forest types in a previous research.

NDVI for pre-fire and post-fire:

In the recovering time the NDVI images show significant spectral shifts. The key patterns of variation between the pre and post fire regeneration after a wildfire in Australia were studied using NDVI in this analysis. The NDVI pattern in this analysis was for a net decrease in vegetation after fire and an improvement in post-fire vegetation regeneration. The NDVI pattern confirmed that vegetation in severe burn regions had not restored entirely after post-fire in another analysis by Bisson et al. (2008). Good and thick vegetation regeneration was observed at sites with a medium burn severity. In our analysis data for NDVI was collected from January 2020 (pre-fire) till March 2021 (post-fire) in Canberra wildfire. After the comparisons of the both images of pre and post fire (fig 3) show that, the fire leads to some loss of the vegetation and some areas after these year we can see some vegetation over the regions.

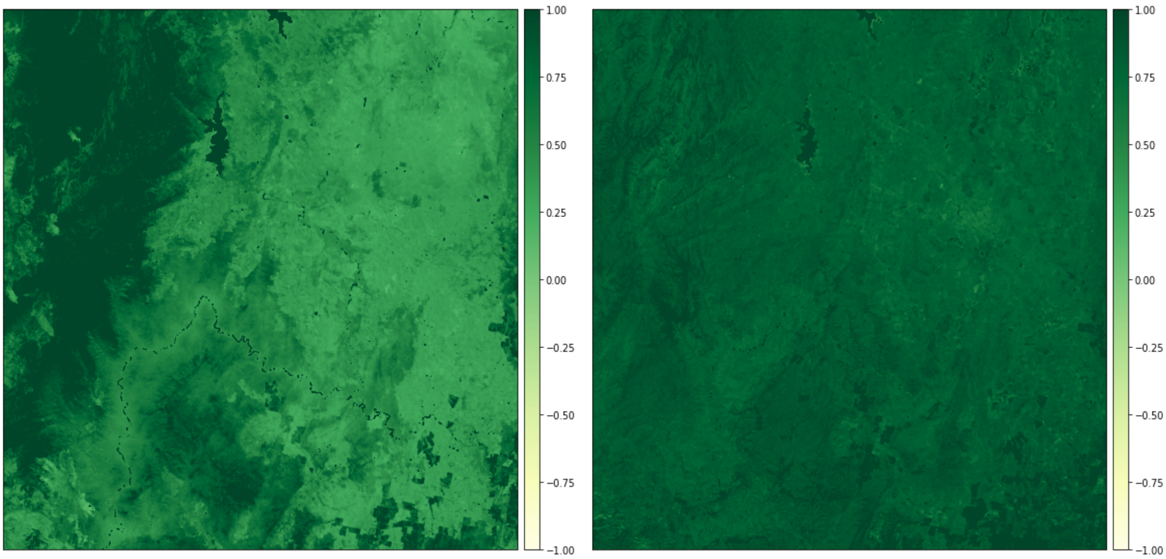


(a) (b)

Fig 3. NDVI on (a) pre-fire and (b) post-fire satellite image of Canberra, Australia wildfire.

SAVI for pre-fire and post-fire:

SAVI is used to adjust the Normalized Difference Vegetation Index (NDVI) for the consequence of soil brightness in areas with low vegetation. In areas with low forest cover (less than 40%) and a clear soil surface, specular reflection of light in the red and NIR spectra can influence vegetation scores. SAVI also equivalent towards NDVI in that spectral indicators can be adjusted so that soil differences are standardised and do not affect vegetation cover observations. Since SAVI provides for differences in soils, these NDVI improvements are beneficial. SAVI, discovered to be a crucial step in the development of modest "global" frameworks which can explain complex soil along with vegetation systems using remote sensing information. The NDVI seemed to be just as important for soil darkening as it was to vegetation growth. For both grass and the dense forest, the SAVI was also effective in reducing soil differences. The comparison between pre-fire and postfire SAVI images (fig 4), we can clearly see that some areas it has lost the vegetation, in some places, it has gained some vegetation in March'2021 after those wildfires.

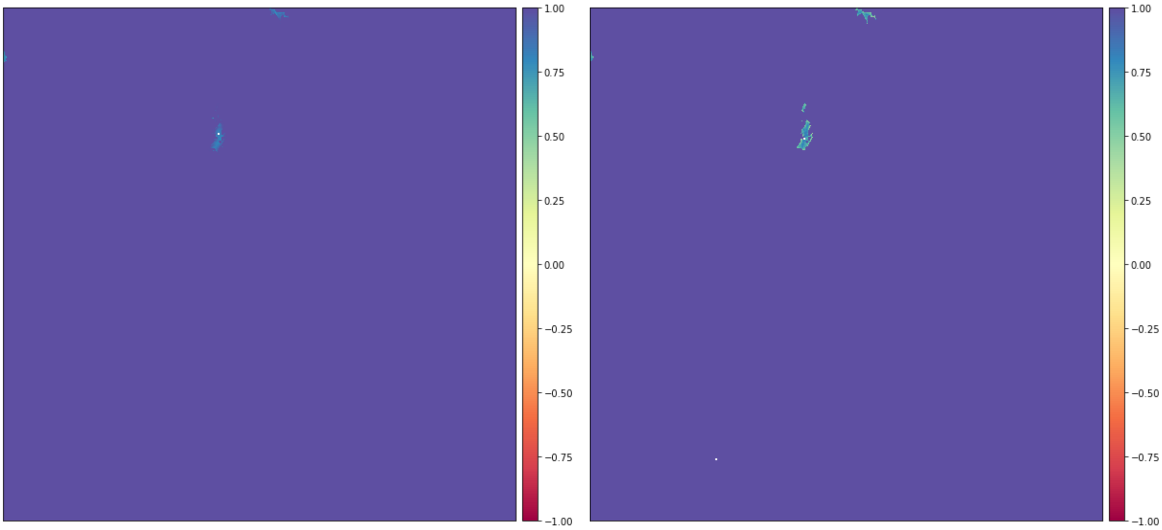


(a) (b)

Fig 4. SAVI on (a) pre-fire and (b) post-fire satellite image of Canberra, Australia wildfire.

MNDWI for pre-fire and post-fire:

The modified NDWI (MNDWI) will help to enhance natural water resources while reducing or even removing built property, vegetation, and soil disturbances. The NDWI's excellent water data is frequently combined with constructed land noise, resulting in an overestimation of the extracted water field. There are three possible outcomes from the MNDWI analysis: (1) Water can have greater good attributes than the NDWI because it absorbs much SWIR light than NIR light; (2) constructed land can have low traits as previously discussed; and (3) land and vegetation can have low traits because soil represents SWIR light more than NIR light and vegetation much more than soil. As a result, when related to the NDWI, the MNDWI's comparison between water and constructed land would be significantly increased due to rising water feature values and declining constructed land values from positive to negative. Since built ground, soil, and vegetation all have low traits and are thus substantially suppressed, if not excluded, increase in water amplification in the MNDWI image would aid in more successful extraction of open water supplies. The possible water extraction threshold points for the MNDWI are usually much smaller than the NDWI's, meaning that using zero as a default threshold level would give the MNDWI proper water extraction precision than the NDWI. This can be used to identify small changes in water content. The comparison between these two images (fig 5), Its shows that in some areas they have retained the water resources, in some areas they lost the water level due to fires.

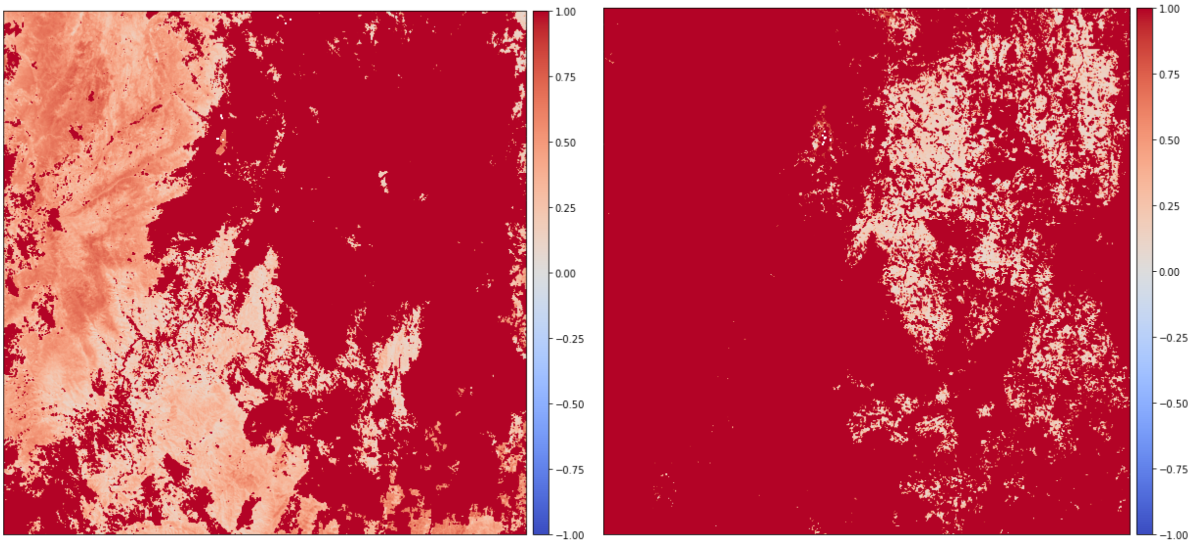


(a) (b)

Fig 5. MNDWI on (a) pre-fire and (b) post-fire satellite image of Canberra, Australia wildfire.

NBR for pre-fire and post-fire:

This index describes regions that have been destroyed in vast fire zones of more than 500 acres. Healthy vegetation has a higher NIR reflectance and a low SWIR reflectance, which is the polar difference to what is seen in regions destroyed by wildfire. This suggests that NBR has a benefit in detecting fire disturbances over NDVI, which had a much smaller gap between before and after the wildfire. In the vegetation regeneration patterns, NBR had a wider set of values than NDVI. These findings indicate that NBR is better than NDVI at identifying various intensity levels. After the post-fire, the low burn and medium burn dense forest NBR values were quite close to one another, comparable to NDVI results. After the wildfire, the dense forest had lower NBR values than before the fire. NBR's grass regeneration patterns were close to NDVI's, but there was a lot of variances owing to regeneration phenology. In the post-fire situation, there are still no significant variations in NBR measure for low and medium burn intensity of grass as contrast to the pre scenario. These findings reveal that NBR is a great predictor of vegetation restoration in dense forests, but it has drawbacks when evaluating grass restoration. The pre-fire and post-fire images of NBR are given below (fig 6).



(a) (b)

Fig 6. NBR on (a) pre-fire and (b) post-fire satellite image of Canberra, Australia wildfire.

dNBR for pre-fire and post-fire:

The delta NBR (dNBR or ΔNBR) is determined by calculating the variation between both the pre-fire and post-fire NBR acquired from the photos, and it can be utilized to measure the burn intensity. The dNBR is a form of change detector (fig 7). If time has passed and vegetation regrowth / regeneration has started after the burn, NBR will be less successful. Since healthy plants represent significantly in the NIR range of the spectrum due to the characteristics of chlorophyll, the fire scar will help to consider a bigger benefit in the NIR range of the spectrum once vegetation restoration has started. A higher dNBR result represents more serious destruction while negative dNBR values could indicate regrowth after a burn. Data and maps on burn intensity will help in the development of post-fire emergency recovery and reconstruction plans. They could be utilized to predict potential hazards such as floods, landslides, and soil erosion, as well as the magnitude of the soil burn.

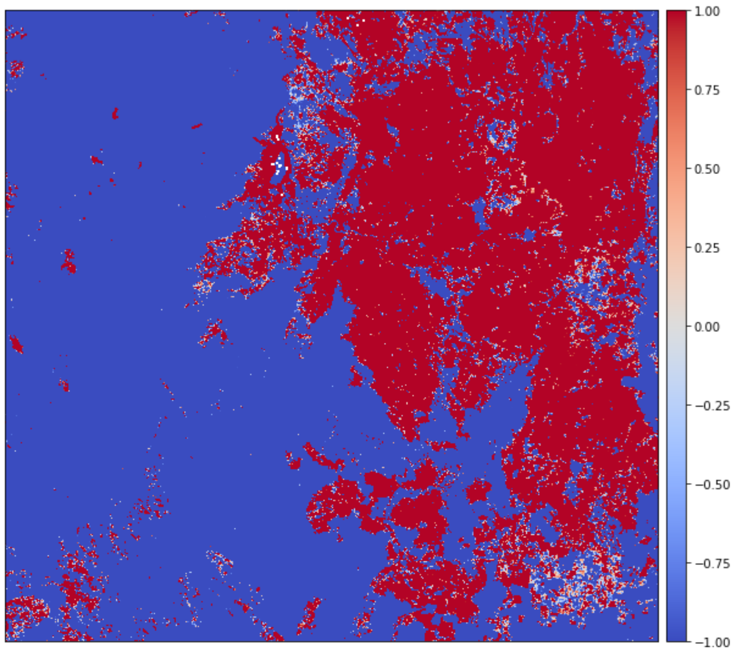


Fig 7. dNBR on both pre and post fire satellite image of Canberra, Australia wildfire.

Based on the dNBR values determined by USGS, the following classification image divides them into seven categories: Enhanced Regrowth(High), Enhanced Regrowth(Medium), Unburned, Low Severity, Moderate Low Severity, Moderate High Severity, and High Severity (fig 8).

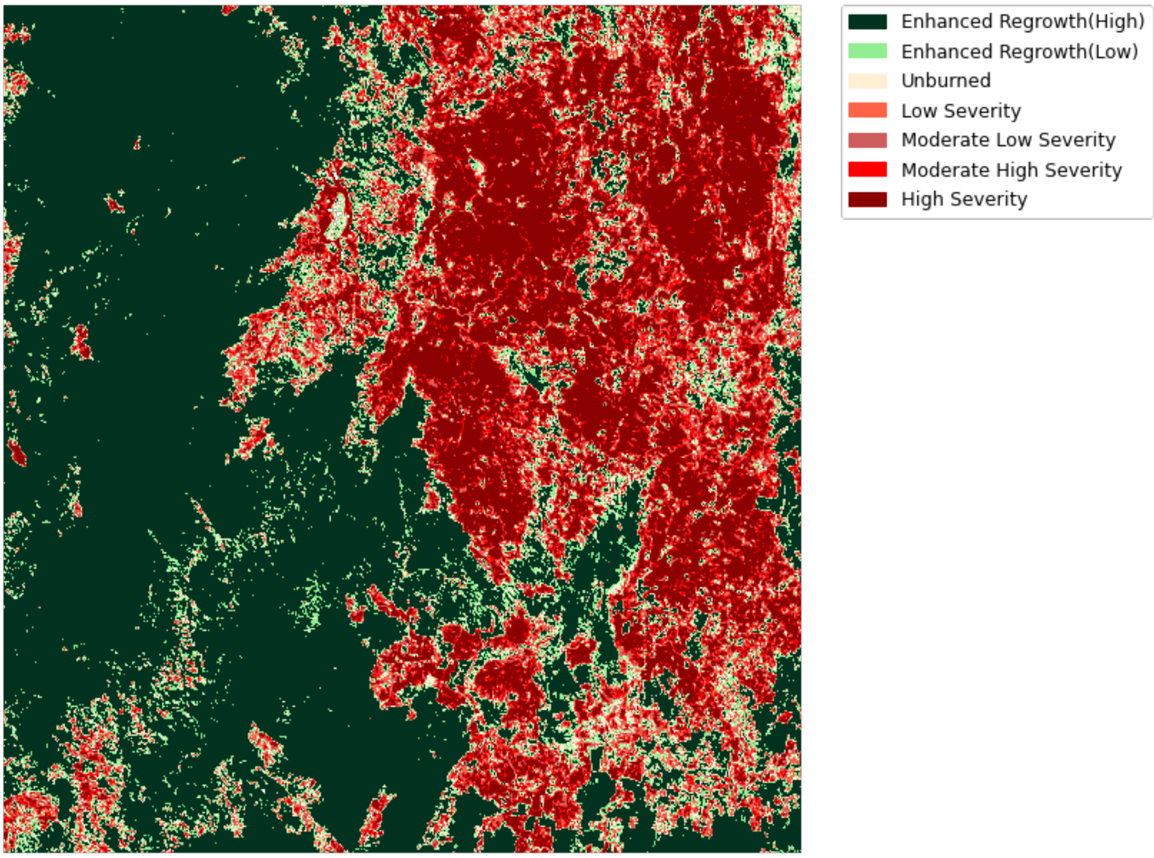


Fig 8. Classification of burn severity using dNBR values in Canberra, Australia wildfire.

CONCLUSION

The results showed that differences of NDVI after post-fire some regions have showed vegetation regeneration and differences of SAVI after post-fire shows clear image of gained vegetation regeneration when compared with NDVI. The comparison of MNDWI index shows some regions have retained water resources and some regions have lost the water resource due to fire. The result of differences in NBR is used to determine the burn-severity in the region. The delta NBR produce the result of the burn-severity from difference in pre and post fire NBR outcome. To sum up, modifications in the magnitude of a high-severity fire, as well as its length and spatial arrangement, can affect a variety of ecosystem processes in the region, which communicate to investigate post-fire regeneration, including migration to non-forest equivalent conditions. Between January 2020 and March 2021, our study reveals a rise in some regions and vegetation regeneration in both the total and proportion of high-severity burned regions in Canberra, Australia. High-severity burned regions have become more aggregated and irregular in appearance over the time. Adjustments in the spatial distribution of high-severity fire across time may have unanticipated effects on natural vegetation, highlighting the enhanced damage due to changing fire regimes to forest ecosystems.

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Appendix A

Google colaboratory file used to analysis this article :
https://colab.research.google.com/drive/1extUgWNqzNGnjXWpJ7WeTjoOTTEPGMyk?usp=sharing

Python code to plot the burn severity classification values determined by USGS.

+ Code + Text

```
# Assigning the class bins as per the USGS burn severity values
class_bins = [-.5, -.251, -.101, .099, .269, .439, 0.659, 1.3]
# Use numpy.digitize() to return the indices of the bins
dnbr_class = np.digitize(dnbr, class_bins)
# Apply the nodata mask to the newly classified NDVI data
dnbr_class = np.ma.masked_where(np.ma.getmask(dnbr), dnbr_class)
# Assign the classification categories
dnbr_cat_names = ["Enhanced Regrowth(High)",
                  "Enhanced Regrowth(Low)",
                  "Unburned",
                  "Low Severity",
                  "Moderate Low Severity",
                  "Moderate High Severity",
                  "High Severity"]
# Assign the colors to the classification categories
nbr_colors = ["#013220","#90ee90","#FFEFD5",
               "#FF6347","#CD5C5C","#FF0000","#8B0000"]
# Use the listedcolormap() function to assign the data
nbr_cmap = ListedColormap(nbr_colors)
# Get list of classes using numpy.unique()
classes = np.unique(class_bins)
classes = classes.tolist()
# The mask returns a value of none in the classes and removes that
classes = classes[0:7]
# Plot the data
# Use matplotlib.pyplot.subplots()
fig, ax = plt.subplots(figsize=(10, 14))
im = ax.imshow(dnbr_class,
               cmap=nbr_cmap)
# Add legends in the map using earthpy.plot.draw_legend()
ep.draw_legend(im_ax=im,
               classes=classes,
               titles=dnbr_cat_names)
# Subpolt to fit figure size
ax.set_axis_off()
# Plot the image using matplotlib.pyplot.show()
plt.show()
```