This paper proposes a novel approach for fire severity, with a focus on the escalating wildfire activity in southern Australia. By introducing a vegetation-type specific fire severity classification method applied to satellite imagery, the paper lays the groundwork for more accurate prediction and assessment of wildfire impacts on ecosystems. The paper is well written and organized, but there are few items that could be addressed to strengthen the importance of the work.

Respond: We appreciate the reviewer's constructive comments on the manuscript to further improve the quality and the contribution of our work. Below are the authors' responses on all of the reviewer's questions and suggestions. The reviewer's comments are marked as **red**, while our responses are marked as **blue**.

Introduction

The authors state that no classification scheme for southern Australia exists, however literature showed works towards this, see for example (Collins et al., 2018; Dixon et al., 2022; Gale et al., 2023; Gibson et al., 2020). There are also accessible datasets on fire severity available from other sources, for the country, https://datasets.seed.nsw.gov.au/dataset/fire-extent-and-severity-mapping-fesm

Respond: We are sorry didn't state this sentence clearly. While most fire severity classifications are based on the field assessed index, like Composite Burn Index (CBI), and interpretation from aerial photographs, which are always labor intensive and time consuming, especially for large regions. And those prediction models rely on establishing the relationships between satellite-derived index (dNBR) and CBI or appearances from aerial photographs.

Our study tried to propose a more straight dNBR-based fire severity classification scheme based on the statistical analysis of dNBR for historical wildfire events, without relying on the CBI or aerial photographs.

From line 63 to line 72 in the revised manuscript:

"The most prevailing fire severity classification scheme mainly rely on the in-situ measurements of Composite Burn Index (CBI, Key and Benson, 2006; Lutes et al., 2006) and aerial photographs identification (Collins et al., 2018; Dixon et al., 2022) which are available for certain regions and for limited vegetation types under certain climate (Eidenshink et al., 2007; Keeley et al., 2009; Tran et al., 2018). However, obtaining CBI and interpreting aerial photographs are always labor-intensive and time-consuming, especially over large areas, while inferring fire severity levels directly from satellite-derived dNBR is more efficient for large-scale applications, yet no dNBR-based fire severity classification scheme has been proposed for regions such as the southeast coast of Australia, which is subject to annual wildfire seasons and varies greatly in vegetation types with high richness of endemic plant species adapted to particular fire regimes (Gallagher et al., 2021)"

References:

Key, C.H. and Benson, N.C., 2006. Landscape assessment (LA). FIREMON: Fire effects monitoring and inventory system, 164, pp.LA-1.

Lutes, D.C., Keane, R.E., Caratti, J.F., Key, C.H., Benson, N.C., Sutherland, S. and Gangi, L.J., 2006. FIREMON: Fire effects monitoring and inventory system. Gen. Tech. Rep. RMRS-GTR-164. Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station. 1 CD., 164.

Collins, L., Griffioen, P., Newell, G., Mellor, A., 2018. The utility of Random Forests for wildfire severity mapping. Remote Sensing of Environment 216, 374–384. https://doi.org/10.1016/j.rse.2018.07.005

Dixon, D.J., Callow, J.N., Duncan, J.M.A., Setterfield, S.A., Pauli, N., 2022. Regional-scale fire severity mapping of Eucalyptus forests with the Landsat archive. Remote Sensing of Environment 270, 112863. https://doi.org/10.1016/j.rse.2021.112863

Eidenshink, J., Schwind, B., Brewer, K., Zhu, Z.L., Quayle, B. and Howard, S., 2007. A project for monitoring trends in burn severity. Fire ecology, 3(1), pp.3-21.

Keeley, J. E. (2009). Fire intensity, fire severity and burn severity: a brief review and suggested usage. International journal of wildland fire, 18(1), 116-126.

Tran, B.N., Tanase, M.A., Bennett, L.T. and Aponte, C., 2018. Evaluation of spectral indices for assessing fire severity in Australian temperate forests. Remote sensing, 10(11), p.1680.

Fire severity:

As the technique for dNBR relies on NIR and SWIR, would it be possible to apply the proposed methods to other imagery sources, such as Sentinel or the new Landsat missions? If applicable, it would be beneficial to highlight this point as well for researcher wanting to apply the proposed approach.

Respond: Yes, this technique is applicable to other imagery source, with the correct band settings for NIR and SWIR.

From line 105 to line 108 in the revised manuscript,

“NBR can be computed by the Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) sensors on using Band 7 as the short-wave infrared (SWIR) and Band 4 for Landsat 4-7 and Band 5 for Landsat 8 as the near infrared (NIR) reflectance, respectively. While in Sentinel-2, SWIR and NIR are represented by Band 8 and Band 12, respectively.”

And from line 451 to 453 in the revised manuscript:

"The NBR images are derived from the Landsat 5,7 and 8 in this study, while it is also applicable to other image sources based on the reflectance information form NIR and SWIR, such as the new launched Landsat 9 and Sentinel-2 (Mallinis et al., 2018; Howe et al. 2022)."

References:

Mallinis, G., Mitsopoulos, I. and Chrysafi, I. Evaluating and comparing Sentinel 2A and Landsat-8 Operational Land Imager (OLI) spectral indices for estimating fire severity in a Mediterranean pine ecosystem of Greece. GIsci Remote Sens, 55(1), 1-18, https://doi.org/10.1080/15481603.2017.1354803, 2018.

Howe, A.A., Parks, S.A., Harvey, B.J., Saberi, S.J., Lutz, J.A. and Yocom, L.L. Comparing Sentinel-2 and Landsat 8 for burn severity mapping in Western North America. Remote Sensing, 14(20), 5249, https://doi.org/10.3390/rs14205249, 2022.

Topography:

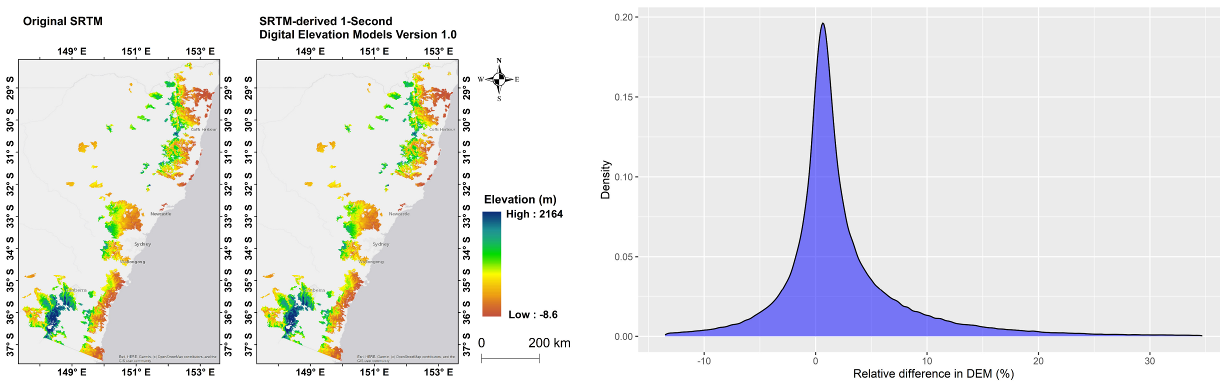
The authors consider the SRTM as main DEM source, and in the discussion, they highlight how topography appears as an important variable in their model. SRTM however presents limits, especially in areas covered by vegetation, and in general, its error values have strong correlation with terrain slope and certain aspect values (See e.g. (Gorokhovich and Voustianiouk, 2006; Shortridge and Messina, 2011).

For Australia specifically, there is the availability of an upgraded SRTM [SRTM-derived 1 Second -and 3 seconds- Digital Elevation Models Version 1.0, which are an improved DEM compared to the original SRTM. Literature also highlighted that COPDEM30, and the underlying TanDEM-X data, as the most recent and accurate global DEM, and (Hawker et al., 2022) provided a further cleaned version of such a DEM without buildings and Vegetation. Did the authors consider using this upgraded terrain information for the model?

Respond: Thank you for bringing to attention the limitations of SRTM data, especially in vegetated areas and terrains with pronounced slopes or certain aspects. The points raised about the correlation of SRTM error values with terrain characteristics, and the availability of improved DEM sources such as the upgraded SRTM for Australia and the COPDEM30, are indeed very pertinent.

We compared the original SRTM used in this study with the upgraded SRTM [SRTM-derived 1 Second Digital Elevation Models Version 1.0] for Australia, over the burn area from 2000 to 2019. The results, as Figure 1 (a) shown in the response letter, indicate that the original SRTM and the upgraded SRTM present similar spatial patterns in terms of the elevation over the burn area. We also calculated the relative differences between the elevation from original SRTM and the upgraded SRTM to the elevation from the upgraded SRTM, e.g. relative differences = 100*(original SRTM - upgraded SRTM)/ upgraded SRTM and present the result as Figure 1 (b) in the response letter. We find that most of the difference range from -10 % to 10 %, which is not the markable difference.

While this study mainly focuses on proposing a vegetation specific classification method to improve the performance of fire severity prediction model, we acknowledge the potential benefits of incorporating more refined elevation data to enhance the accuracy of our model, yet did not utilize the upgraded SRTM or the cleaned version of COPDEM30 in our present analysis. However, the prospect of applying these more accurate DEM sources is an exciting direction for our future research endeavors.



(a) (b)

Figure 1. (a) Spatial patterns of elevation from original SRTM and the SRTM-derived 1 Second Digital Elevation Models Version 1.0 and (b) the distribution of relative difference between DEM from original SRTM and the SRTM-derived 1 Second Digital Elevation Models Version 1.0, over burn area from 2000 to 2019 in NSW;

From line 428 to line 431 in the revised manuscript:

"The advances in DEM technology, as evidenced by the improvements in the SRTM data, such as SRTM-derived 1 Second -and 3 seconds- Digital Elevation Models Version 1.0 for Australia, and the introduction of global COPDEM30 and TanDEM-X data [Hawker et al., 2022], offer opportunities for refining fire-topography relationship analyses and potentially providing more precise fire severity prediction results."

Weather:

How was the ‘1 day window’ decided to get the weather event? Is there a physical meaning linked to this choice or was it operationally decided? I am not sure if it is possible, but have the authors investigated the sensitivity of the results to this window? Literature reported a known potential limitation of the fire history database as the fact that the date of the fire attribute does not always represent the exact burn date (Dixon et al., 2022). Dixon for example proposed a semi-automatic MODIS date-adjustment method to obtain the start and end fire dates: have the authors considered something similar?

Respond: In this study, the daily FFDI value for the day prior to the start of the wildfires is used as the input variable in the model. We use daily FFDI because FFDI is typically calculated on a daily basis, indicated by Australian Bureau of Meteorology (BoM, http://www.bom.gov.au/climate/maps/averages/ffdi/). This daily calculation allows for the assessment of fire danger to reflect current weather conditions, including temperature, humidity, wind speed, and recent rainfall, which are critical for determining the day-to-day fire risk.

We use the daily FFDI for the day prior to the start of the wildfires because we found that extreme values of the FFDI appeared at times close to the start of the wildfires, as presented by Figure 22, Figure 26, Figure 30, Figure 34, Figure 43 in Dowdy et al. (2009). The physical rationale behind this choice is rooted in the understanding that weather conditions can change rapidly and have immediate effects on fire behavior. Using the most potential extreme FFDI, indicating the extreme weather conditions, in the period leading up to a wildfire could address the impact of weather on wildfire risk.

From line 154 to line 158 in the reviser manuscript,

“The daily FFDI and KBDI values for the day prior to the start of the wildfires are used as the predictors in predicting burn severity, owing to the strong correlation in time between extreme values of the FFDI and the start of the wildfires [Dowdy et al., 2009]Using the most potential extreme FFDI, indicating the extreme weather conditions, in the period leading up to a wildfire could address the impact of weather on wildfire risk.”

References:

Dowdy, A.J., Mills, G.A., Finkele, K. and De Groot, W., 2009. Australian fire weather as represented by the McArthur forest fire danger index and the Canadian forest fire weather index (p. 91). Melbourne: Centre for Australian Weather and Climate Research.

Regarding the sensitivity of the results to the selected time window, we have not yet conducted an extensive sensitivity analysis. Future research could explore varying the window of observation to assess the impact on model results and address the issue raised by Dixon et al. (2022). The burn area and the associated burn date data are from NPWS Fire History - Wildfires and Prescribed Burns Dataset (https://datasets.seed.nsw.gov.au/dataset/fire-history-wildfires-and-prescribed-burns-1e8b6), which we think has good data quality preserved by NSW Department of Climate Change, Energy, the Environment and Water.

From line 492 to 494 in the revised manuscript:

“In addition, the sensitivity analysis of the selected time window to define the fire event and obtain the associated weather conditions is promoted to improve our understanding of the relationship between weather conditions and fire occurrences. By adjusting the time window and possibly integrating more precise burn date data, we can work towards a more accurate and physically meaningful analysis of fire events and their contributing factors.”

Fire severity classes:

As it is my understanding, the severity is based on the dNBR which ranges from -n to +n. Is there a meaningful range of this value representing the severity? (I assume the higher in the positive, the higher the expected impact of the fire -if this is the case, please can you clarify it for the readers not too familiar with the approach? When selecting the quantiles, does the author use the full range of dNBR or focus on a selected part of the distribution (would that matter, if that’s the case?).

Respond: The differenced Normalized Burn Ratio (dNBR) is a metric used to quantify burn severity by analyzing the difference in the spectral signature of an area before and after a fire event. The dNBR is calculated by subtracting the post-fire NBR from the pre-fire NBR, resulting in values that theoretically range from -2 to +2. The scale of dNBR values indeed reflects the severity of a fire with high positive values indicate severe burn damage where the vegetation has been completely consumed. Values around zero suggest either unburned areas or areas where the fire had a very low impact. Negative values can indicate an increase in vegetation, which might be due to vegetation recovery over time or errors in the analysis.

From line 117 to line 120 in the revised manuscript:

“The dNBR typically ranges from -2 to +2, with high positive values indicate severe burn damage where the vegetation has been completely consumed. Values around zero suggest either unburned areas or areas where the fire had a very low impact. Negative values can indicate an increase in vegetation, which might be due to vegetation recovery over time or errors in the analysis.”

In selecting the quantiles for analysis, the full range of dNBR values is generally considered to capture the complete spectrum of burn severity, the results will provide a comprehensive overview of all fire severities. In the context of our study, we have utilized the full range of dNBR values to ensure a broad assessment of fire severity across the landscape. This inclusive approach allows us to capture all degrees of burn severity, from low to extreme, offering a complete view of the fire's impact.

I find it a bit confusing that the methods describe a threshold selection, but the whole approach is clarified better in the discussion of the results at chapter 4.2. Would it be possible to restructure a bit this chapter in the method, to clarify how the selection is done?

Respond: Thanks for the suggestion. We have rewritten the method section to better clarify how to use the quantile based threshold in burn severity classification.

From line 161 o line 165 in the revised manuscript,

“The dNBR of all burnt pixels for each vegetation type are collected and a set of dNBR values at the quantiles varying from 5% to 35% representing the threshold for low severity classification, quantiles varying from 35% to 65% representing the threshold for moderate severity classification, and quantiles varying from 65% to 95% representing the threshold for high severity classification. For example, a classified burn severity sample can be obtained using the thresholds for high, moderate and low severity at 85% quantile, 55% quantile and 25% quantile, respectively.”

Maybe this comes from my misinterpretation of the result chapter, but my understanding is that the ground truth for the severity is the ‘observed severity’ from Landsat for some specific fires (Figure 7). If this is the case, and the severity level is defined by a ‘moving’ threshold which in turn is defined by the best model in the training phase, how do you objectively define if the severity is ‘under’ or ‘over’ estimated as compared to the reality of the events? The observed severity is defined using a threshold derived from a ‘training’ of the model.

Would it be possible to compare your severity to some data independent from the threshold choice? I see for example for Australia some other datasets are available, such as

https://data.gov.au/dataset/ds-nsw-c28a6aa8-a7ce-4181-8ed1-fd221dfcefc8/details?q=

Respond: Thanks for the suggestion. In the revised manuscript, we have used the fire severity classification maps from the Fire Extent and Severity Mapping (FESM) preserved by NSW Department of Climate Change, Energy, the Environment and Water as the independent source to validate the burn severity prediction maps from the model in this study.

From line 318 to line 339 in the revised manuscript:

“Figure 7 displays the fire severity maps for the 2016, 2017, 2018 and 2019 wildfires in NSW from FESM, along with predictions based on vegetation specific and fixed thresholds. For the wildfire in 2016, predictions based on vegetation specific thresholds show similar spatial patterns of fire severity to those from FESM, while predictions based on fixed thresholds significantly underestimate the fire severity in the high and extreme fire severity areas of the FSEM. Similarly for the wildfire in 2018, predictions based on fixed thresholds significantly underestimate high and extreme severity compared to the FESM map, while predictions based on vegetation specific thresholds slightly underestimate extreme severity. For the wildfire in 2017, both the FESM and predictions display similar spatial distributions of fire severity level with predictions based on fixed thresholds presents more low severity compared to FESM map. For the wildfire in 2019, however, predictions based on fixed thresholds tend to overestimate the fire severity as extreme in regions found to be high severity in FESM map, while predictions based on vegetation specific thresholds agreed better with FESM map.

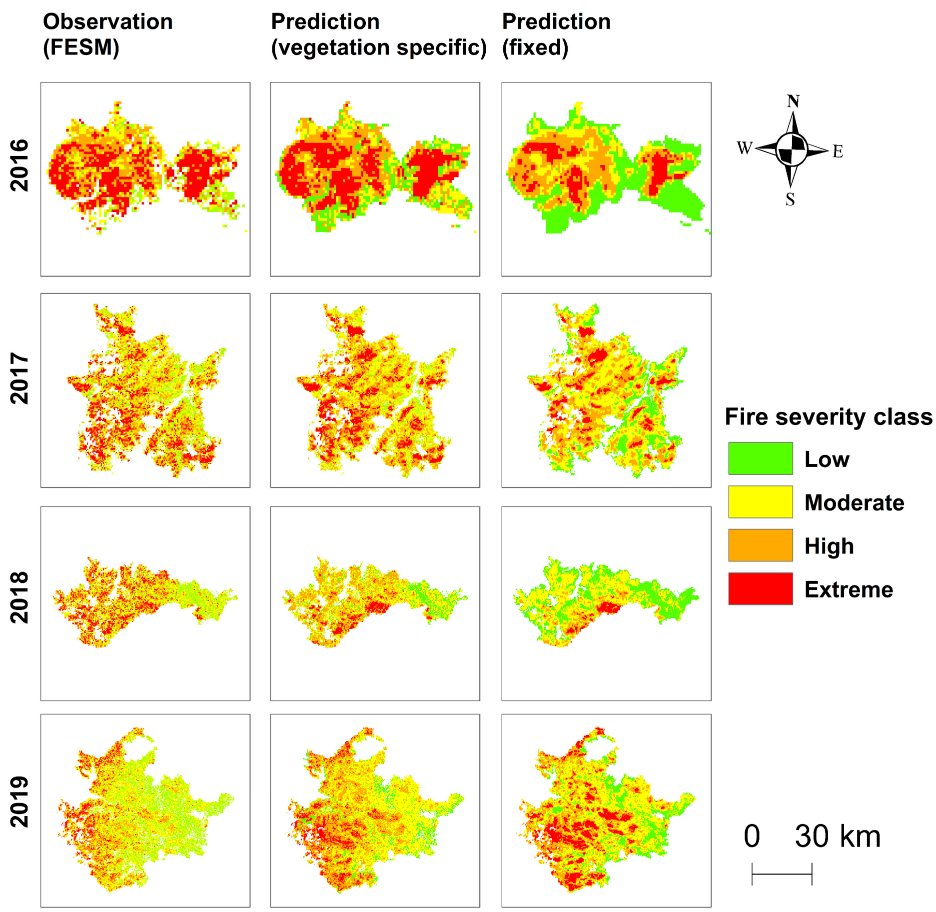


Figure 7. Fire severity classification maps from FESM and predictions based on vegetation specific and fixed thresholds for wildfires in 2016 to 2019 in NSW.

Table 3 shows the confusion matrix for fire severity classification between FESM and predictions based on vegetation specific and fixed thresholds. It is noted that predictions based on vegetation specific thresholds exhibit better ability of classing extreme and high severity with accuracy of 0.64 and 0.76, respectively. While the classification accuracy for extreme and high severity of predictions based on fixed thresholds are 0.21 and 0.39, respectively. Predictions based on vegetation specific thresholds also have better accuracy of classifying moderate severity with value of 0.62, compared to those based on fixed thresholds with value of 0.47. Both predictions based on vegetation specific and fixed thresholds show poor performance in classifying low severity, with accuracy of 0.24 and 0.26 respectively. The overall classification accuracy for predictions based on vegetation specific thresholds is 0.57, which is better than predictions based on fixed specific thresholds with accuracy of 0.36.

Table 3. Confusion matrix for fire severity classification between FESM and predictions based on vegetation specific and fixed thresholds.

Vegetation specific					Fixed				
	Extreme	High	Moderate	Low		Extreme	High	Moderate	Low
Extreme	4345	2378	6	3	Extreme	1448	2822	2027	435
High	1490	6947	605	1	High	1430	3561	3358	694
Moderate	3	5702	9338	5	Moderate	998	4633	7084	2333
Low	0	172	7125	2372	Low	161	1722	5264	2522

Minor comments

Figure 1: it is a bit hard to visualize the ‘wildfire for cross validation’ in the map: is it underlaid to the colored burned areas? I assume the burn years refer to the dataset mentioned in the following page.

NSW National Parks and Wildlife Service 88 (NPWS) Fire History – Wildfire and Prescribed Burns dataset (https://data.nsw.gov.au/data/dataset/1f694774-49d5-47b8- 89 8dd0-77ca8376eb04)

IF so, maybe mention this in the caption.

Also, it appears that the link is not working [I tried and accessed it on 05-feb-2024]

Respond: We have redesigned the Figure to make it clearer to see. We also mentioned the source for the burn area map and fixed the link (https://datasets.seed.nsw.gov.au/dataset/fire-history-wildfires-and-prescribed-burns-1e8b6).

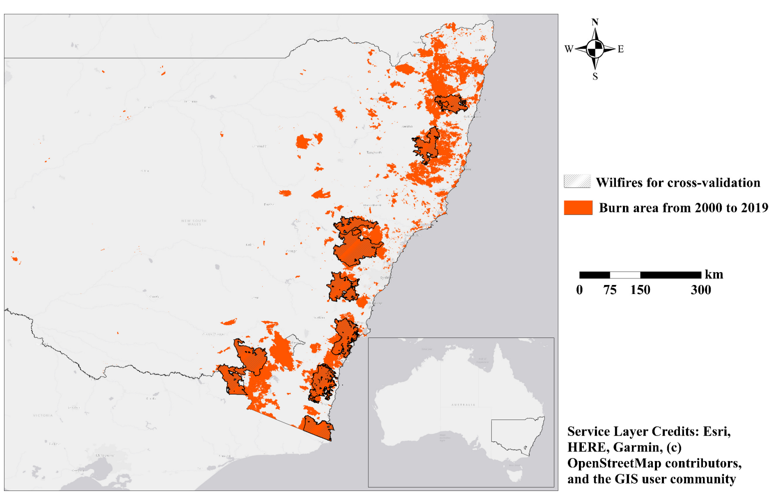


Figure 1. Locations of study wildfires over New South Wales (NSW), Australia. The burn area is from NSW National Parks and Wildlife Service (NPWS) Fire History – Wildfire and Prescribed Burns dataset.

Paragraph from line 206-217: Figure 2 should be Figure 3, Same for the references in the following chapters, it seems the authors refers to figure 3 as 2 (Eg line 221)

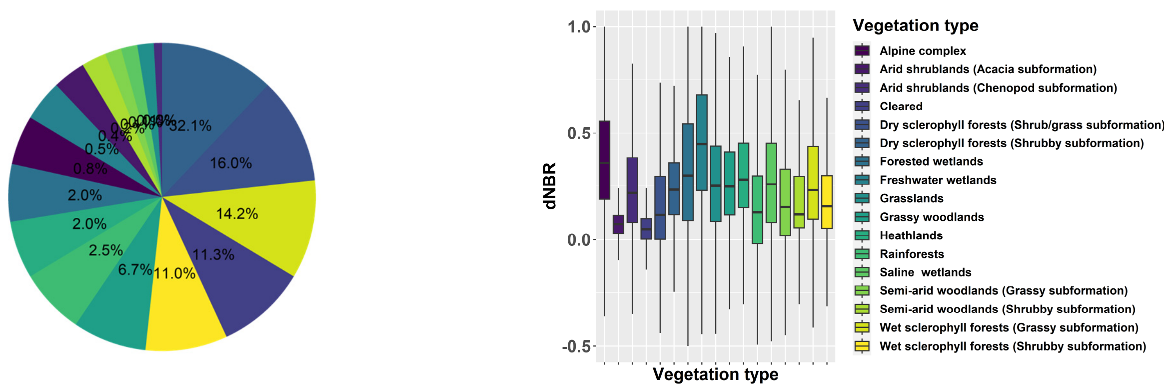
Respond: We have revised them accordingly.

Line 212: typo on the number, should be 6.7% not 6,7%

Respond: We have revised it accordingly.

Figure 3: are the vegetation numbers from n to 16 in figure b referring to the legend in figure a? if so maybe leave only one legend to avoid confusion on what the number represents, or add the names of vegetation on the x axis rather than as an additional color bar

Respond: We have redesigned the Figure 3.



(a) (b)

Figure 3. (a) The proportion of burnt area and (b) the distribution of fire severity grouped by vegetation type, over NSW from 2000 to 2019

References

Collins, L., Griffioen, P., Newell, G., Mellor, A., 2018. The utility of Random Forests for wildfire severity mapping. Remote Sensing of Environment 216, 374–384. https://doi.org/10.1016/j.rse.2018.07.005

aerial photos for validation. Maps produced using the RF classifier in GEE had similar spatial patterns in fire severity classes as maps produced using time-consuming hand digitisation of aerial images

Dixon, D.J., Callow, J.N., Duncan, J.M.A., Setterfield, S.A., Pauli, N., 2022. Regional-scale fire severity mapping of Eucalyptus forests with the Landsat archive. Remote Sensing of Environment 270, 112863. https://doi.org/10.1016/j.rse.2021.112863

aerial photo observations

Gale, M.G., Cary, G.J., van Dijk, A.I.J.M., Yebra, M., 2023. Untangling fuel, weather and management effects on fire severity: Insights from large-sample LiDAR remote sensing analysis of conditions preceding the 2019-20 Australian wildfires. Journal of Environmental Management 348, 119474. https://doi.org/10.1016/j.jenvman.2023.119474

Gibson, R., Danaher, T., Hehir, W., Collins, L., 2020. A remote sensing approach to mapping fire severity in south-eastern Australia using sentinel 2 and random forest. Remote Sensing of Environment 240, 111702. https://doi.org/10.1016/j.rse.2020.111702

Aerial photo interpretation classification of fire severity

Gorokhovich, Y., Voustianiouk, A., 2006. Accuracy assessment of the processed SRTM-based elevation data by CGIAR using field data from USA and Thailand and its relation to the terrain characteristics. Remote Sensing of Environment 104, 409–415. https://doi.org/10.1016/j.rse.2006.05.012

Hawker, L., Uhe, P., Paulo, L., Sosa, J., Savage, J., Sampson, C., Neal, J., 2022. A 30 m global map of elevation with forests and buildings removed. Environ. Res. Lett. 17, 024016. https://doi.org/10.1088/1748-9326/ac4d4f

Shortridge, A., Messina, J., 2011. Spatial structure and landscape associations of SRTM error. Remote Sensing of Environment 115, 1576–1587. https://doi.org/10.1016/j.rse.2011.02.017