FIRE SEVERITY ASSESSMENT OF AN ALPINE FOREST FIRE WITH SENTINEL-2 IMAGERY

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ABSTRACT:

Fire is a common phenomenon in many forests and is considered an important ecological tool. Fire severity mapping presents an effective way to assess post-fire management intervention and is helpful in environmental and climate change research. The objective of this study was to determine the severity of a forest fire event that occurred from 24th to 27th October 2019 at Taibon Agordino using Sentinel-2A satellite images and creating a severity map suitable as a decision-making tool for post-fire management intervention. The Sentinel-2A satellite data was classified into the following five classes: Unburned, Low Severity, Moderate Severity, High Severity, and Shadow with the non-parametric Random Forest (RF) classifier, and the resulting classified image was validated using validation sites. The RF classifier was applied first to the ten original band reflectance of Sentinel-2. In a second step, additional variables were added to the classification, namely the digital elevation model (DEM), the slope, and five vegetation indices (i.e., Differenced Normalized Burn Ratio (dNBR), Relative Differenced Normalized Burn Ratio (RdNBR), Differenced Bare Soil Index (dBSI), Global Environmental Monitoring Index (GEMI) and Burn Area Index (BAI)) The inclusion of vegetation indices and DEM-related variables increased the classification accuracy from 99.26% to 99.61% and the overall accuracy from 70.51% to 83.33%. In the classification with the ten original band reflectance, the variable of importance plot ranked the Red-Edge-3, Red, and SWIR 1 band reflectance as the top three most important input features, while for the classification with 17 variables, RdNBR, DEM and dNBR were the top three most important input features.

1. INTRODUCTION

Forest fires are natural disturbances affecting forest ecosystems in many parts of the world. Fire is an essential component of natural dynamics in fire-dependent ecosystems, while in other ecosystems, it can lead to forest degradation and hinder ecosystem services provision. Fire severity mapping presents an effective way to assess post-fire conditions, providing helpful information for identifying priority areas for management interventions (Morresi et al. 2022). Furthermore, it could provide insights for understanding trajectories of vegetation recovery, biological legacies distribution, and eventually is helpful in environmental and climate change research. Most fire severity mapping studies using remote sensing were performed using MODIS imagery (see the review of Leblon et al., 2016). While MODIS imagery is available daily, the imagery has a too coarse resolution for a detailed fire severity map. Landsat series have also been used for fire severity mapping (e.g., Matricardi et al. 2010**,** Escuin et al. 2008**,** Wimberly, Reilly, 2007). The European Space Agency has recently launched the Copernicus Sentinel-2 satellite carrying the Multispectral Instrument (MSI) capable of acquiring images in 13 bands at higher spatial resolutions. Also, given the availability of two satellites (2A and 2B), the revisiting time of the Sentinel-2 satellites allows a suitable temporal resolution (revisit time) of 5 days in the imagery acquisition (Li, Roy, 2017). Some studies tested Sentinel-2 imagery for burned area mapping (Filipponi 2018, DeSimone et al. 2020, Han et al. 2021, Fassnacht et al. 2021), but very few on fire severity mapping in southern Australia (Gibson et al. 2020), in Greece (Mallinis et al. 2018) or Spain (Quintino et al. 2018), and recently in the Western Italian Alps (Morresi et al. 2022).

The objective of this study was to map the severity of a forest fire event that occurred in the Dolomites Mountains (Eastern Italian Alps) from 24th to 27th October 2018 at Taibon Agordino (Italy) using Sentinel 2A images and creating a severity map suitable as a decision-making tool for post-fire management intervention. Such mapping is quite challenging, given the rough topography of the area.

2. MATERIALS AND METHODS

2.1 Study area

The study area is in the northeastern part of Taibon Agordino municipality (Lat. 43.92N; Long. 12.13E) (Figure 1). The study area has a typical dolomitic alpine vegetation mainly comprising of Norway spruce (*Picea abies* (L.) Karst.), pines (*Pinus sylvestris* L, *P. mugo* Turra), and European larch (*Larix decidua* Miller). Norway spruce is the dominant species. Due to the steepness of the slopes, the forest stands have preeminent protective rather than productive functions. The bedrock is predominantly dolomite, calcium, magnesium, and carbonate compound. The snow in the area begins to accumulate in December and lasts until the end of March in the valleys and up to August at the highest elevation. The area's elevation ranges between 698and 2294m above sea level.

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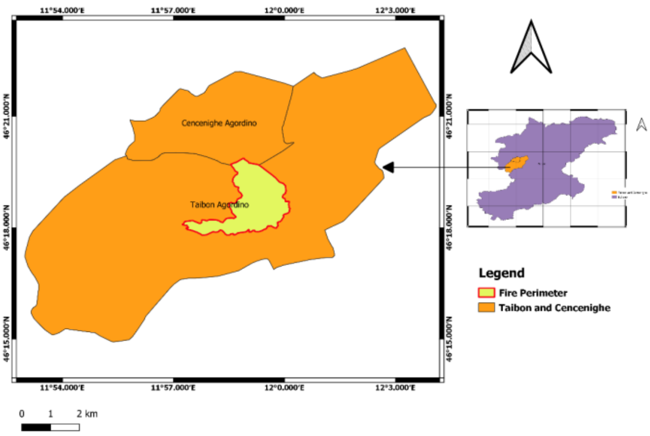

Figure 1. Location of the study area in Taibon Agordino, Belluno Province, Italy

2.2 Data

The study uses two cloud-free (<10%) Sentinel 2 Level 1C images. The first image was acquired just before the fire and the second after the fire (Table 1). Both images were orthorectified top-of-atmosphere reflectance images having the UTM 32N map projection and the WGS84 datum. They had a swath width from nadir of 290 km and were acquired using the descending orbit 22. The study also uses a shapefile that delineates the fire perimeter provided by the Veneto regional administration and a Digital Terrain Model (DTM) that was downloaded from the ARPA-Veneto website (http://geomap.arpa.veneto.it/layers/geonode%3ADTM_5M_GBO). The data has a 5m resolution distributed under the Creative Commons Attribution 3.0. We also used a set of geolocalized field pictures collected in situ that correspond to the different fire severity classes. Samples of ground pictures taken in the Unburned, Low Severity, Moderate Severity, High Severity areas are presented in Figure 2.

Table 1. Characteristics of the Sentinel-2 images used in the study

Characteristics	Pre-fire Image	Postfire Image
Tile Number	L1C_T32TQS_A008342_20181011T101020	L1C_T32TQS_A018180_20181215T101420
Date of acquisition	11/10/2018	15/12/2018
Local time of acquisition	12h20	14h20
Cloud cover (%)	7.04	9.55
Sun zenith angle (°)	54.21	70.53
Sun azimuth angle with respect to the north (°)	167.85	168.31

Figure 2. Samples of ground pictures of the various fire severity classes.

2.3 Methodology

The methodology used in the study is described in Figure 3. First, the study area's pre- and post-fire Sentinel-2 imagery were subjected to atmospheric correction using Sen2cor version 2.9. Sen2cor is a Level-2A processor used to correct single-data Sentinel-2 Level-1C Top-Of-Atmosphere (TOA) products from the effects of the atmosphere in order to deliver a Level-2A Bottom-Of-Atmosphere (BoA) reflectance product (Main-Knorn et al. 2017). The atmospheric correction is done using a set of look-up tables generated via libRadtran (Emde et al., 2016). The resulting BoA reflectance images were produced at either 10m or 20m as a function of the band. The images having a 20m resolution were resampled to 10m using the *RESAMP* algorithm in PCI Geomatica.

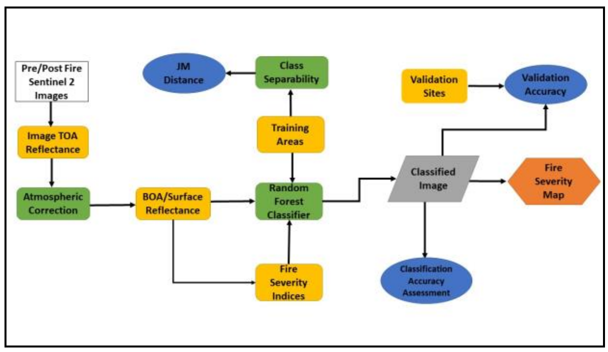

Figure 3. Flowchart of the methodology used in the study

To further strengthen the separability between the classes and the accuracy of the classification, following Gibson et al. (2020), the following vegetation indices relevant to burned sites were computed using both the pre-and post-fire images:

1) Differenced Normalized Burn Ratio (dNBR) (Li, Roy, 2017):

$$dNBR = preNBR\text{-}postNBR \quad [1]$$

where

$$preNBR = \frac{preNIR - preSWIR1}{preNIR + preSWIR1} \quad [2]$$

$$postNBR = \frac{postNIR - postSWIR1}{postNIR + postSWIR1} \quad [3]$$

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2) Relative Differenced Normalized Burn Ratio (RdNBR) (Gibson et al. 2020)

$$RdNBR=\left(\frac{dNBR}{\sqrt{|preNBR|}}\right) \quad [4]$$

3) Global Environmental Monitoring Index (GEMI) (Pinty, Verstraete, 1992)

$$GEMI= eta * (1 - 0.25 * eta) - \frac{Red - 0.125}{1 - Red} \quad [5]$$

Where

$$eta = \frac{2(postNIR^2 - postRed^2) + 1.5 * postNIR + 0.5 * post\ Red)}{postNIR + postRed + 0.5} \quad [6]$$

4) Burn Area Index (BAI) (Chuvieco et al. 2002)

$$BAI = \frac{1}{(0.1 - postRed)^2 + (0.06 - postNIR)^2} \quad [7]$$

5) Difference in Bare Soil Index (BSI) (Gibson et al. 2020)

$$dBSI= postBSI-preBSI \quad [8]$$

where:

$$preBSI= \frac{(preSWIR2 + preRed) - (preNIR + preBlue)}{(preSWIR2 + preRed) + (preNIR + preBlue)} \quad [9]$$

[24]

$$postBSI = \frac{(postSWIR2 + postRed) - (postNIR + postBlue)}{(postSWIR2 + postRed) + (postNIR + postBlue)} \quad [10]$$

[24]

The post-fire imagery was classified with the non-parametric Random Forest (RF) classifier (Breiman 2001) into the following five classes: Unburned, Low Severity, Moderate Severity, High Severity, and Shadow. Since Random Forest is a supervised classifier, it requires delineating training areas, which was done for each fire severity class. In total, 59 training polygons were delineated for the five classes (Unburned, Low, Moderate, High, and Shadow) with the aid of an aerial photograph acquired in July 2019 over the study area. The training polygons were also used to compute the J-M distances between class pairs with the 10 Sentinel-2 band reflectance. The classifier was applied first to the ten original Sentinel-2 band reflectance. In a second step, additional variables were added to the classification, namely the digital elevation model (DEM), the slope, and the five vegetation indices. The classification was assessed by comparing the resulting classified image with an independent set of validation points extracted from photo-interpretation of an aerial photograph taken after the fire and from GPS ground pictures. In the comparison, we used a total of 780 randomly selected validation points.

3. RESULTS AND DISCUSSION

3.1 Class spectral separability

The average J-M distance with all the Sentinel-2 bands is 1.965, indicating an excellent spectral separability between the classes (Table 2). The lowest separability was between the Unburned and Low Severity classes, with a value of 1.615. Although it falls below 1.9, the magnitude is still good enough considering the degree of similarity between the two classes, making it difficult to differentiate on the Sentinel-2 imagery. Indeed, both classes have similar reflectance, mainly in the red, red-edge, and near-infrared bands. The highest J-M distance (1.9999) was found between two class pairs: High Severity and Unburned classes, Shadow and High Severity classes. These classes share notable differences both physically and spectrally. Areas classified in the High Severity class are distinguished by extreme burns and total loss of foliage against unburned areas with healthy green foliage (Figure 2). Also, the Shadow class, which is a result of topography and nadir angle of the satellite when the image was taken, shows markedly different spectral characteristics from the High Severity Class. The difference in reflectance was most notable in almost all the bands, especially the green, red and red-edge bands. The reflectance of the High severity class is markedly higher across the bands but is distinctively prominent in the red, green, and blue (RGB) bands. Conversely, the reflectance of the moderate severity class is lowest in the RGB bands but more prominent in the red-edge and shortwave infrared bands. The Low severity and Unburned classes have low reflectance in the RGB bands but high reflectance in the red-edge, near-infrared, and SWIR bands.

Table 2. J-M distance between the classes computed with the ten Sentinel-2 band reflectance

Class	Unburned	Low severity	Moderate severity	High severity
Low severity	1.6153			
Moderate severity	1.9944	1.9395		
High severity	1.9999	1.9949	1.9856	
Shadow	1.9888	1.9996	1.9979	1.9999

3.2 Classification

The ten original band reflectance of the postfire Sentinel-2A image were imputed into the RF algorithm. The resulting confusion matrix of Table 3 shows that the classification achieved an overall accuracy of 99.27% and a kappa coefficient of 0.99. The lowest User's accuracy (UA) (98.94%) and Producer's accuracy (PA) (98.6%) correspond to the Unburned and Moderate Severity classes, respectively. Likewise, the highest User's accuracy (99.64%) and Producer's accuracy (100%) were recorded for the Moderate and High Severity classes, respectively. The inclusion of vegetation indices and DEM-related variables increased the classification accuracy from 99.26% to 99.61% (Table 3). The resulting classified image is presented in Figure 4. In the classification with the ten original band reflectance, the variable of importance plot ranked the Red Edge 3, Red, and SWIR 1 bands as the top three most important input features (Figure 5). The variable importance plot produced for the classification with all the variables ranked RdNBR, DEM, and dNBR as the top 3 most important variables (Figure 6).

3.1 Validation

When only the ten bands were used in the classification, we achieved an overall accuracy of 70.5% and a Kappa coefficient of 0.42 (Table 4). When the DEM metrics and the vegetation indices were added to the classification, the overall validation accuracy increased from 70.51% to 83.33% (Table 4). The highest Producer's validation accuracy (92.30%) and User's validation accuracy (92.30%) were recorded for the Unburned class (Table 4). The lowest User's validation accuracy (71.42%) occurred for the Shadow class. The lowest Producer's validation accuracy (68.42%) occurred for the Moderate Severity class (Table 4).

Table 3. User's and Producer's classification accuracies as a function of the input features

Class	User's accuracy (%)		Producer's accuracy (%)	
	Ten bands	All variables	Ten bands	All variables
Unburned	98.95	98.95	98.95	99.47
Low Severity	99.02	99.02	98.70	98.70
Moderate Severity	99.65	100.00	98.60	99.65
High Severity	99.48	100.00	100.00	100.00
Shadow	99.24	100.00	99.62	100.00
Overall accuracy (%)	99.26	99.61	99.26	99.61
Kappa coefficient	0.99	0.99	0.99	0.99

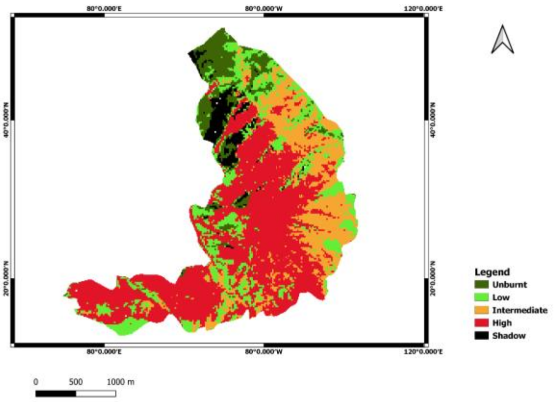

Figure 4. Classified image produced by applying the Random Forest classifier to the original post-fire band images, associated vegetation indices, DEM, and slope data.

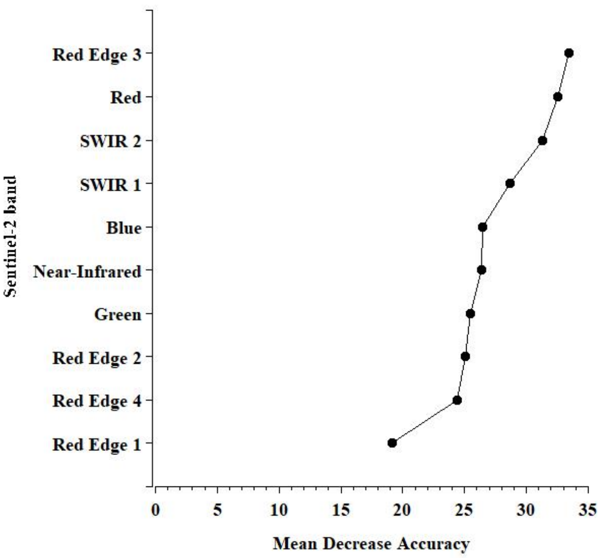

Figure 5. Variable importance plot produced by applying the Random Forest to all the original band reflectance of the postfire Sentinel-2 image

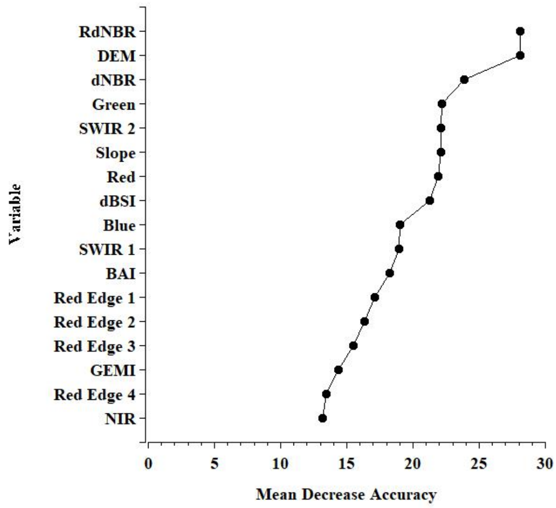

Figure 6. Variable Importance Plot produced by applying the Random Forest classifier to the postfire Sentinel-2 original band reflectance, associated vegetation indices, the DEM, and slope.

Table 4. User's and Producer's validation accuracies as a function of the input features

Class	User's accuracy (%)		Producer's accuracy (%)	
	Ten bands	All variables	Ten bands	All variables
Unburned	55.56	92.30	83.33	92.30
Low severity	82.60	78.57	73.08	88.00
Moderate Severity	68.75	86.67	57.89	68.42
High Severity	78.57	86.67	73.33	86.67
Shadow	57.14	71.42	66.67	83.33
Overall accuracy (%)	70.51	83.33	70.51	83.33
Kappa coefficient	0.42	0.51	0.42	0.51

4. DISCUSSION

Our study showed that fire severity could be adequately mapped by applying the Random Forest supervised classifier to a combination of DEM metrics and Sentinel-2 raw band reflectance and associated vegetation indices. We achieved an overall classification accuracy of 99.61% and an overall validation accuracy of 83.33%. Mallinis et al. (2018) obtained an overall classification accuracy of 73.3% when applying a threshold method on Sentinel-2 imagery for mapping fire severity in Mediterranean forests in Greece. Our Kappa coefficient was 0.99 for the classification and 0.51 for the validation. Gibson et al. (2020) obtained Kappa coefficients ranging from 0.424 to 0.799 when applying Random Forests to Sentinel-2 images for mapping fire severities in Australia using various combinations of vegetation indices. Our better results with the inclusion of the vegetation indices agree with Gibson et al. (2020)'s study. We still observed some misclassifications between the Unburned and Low Severity classes due to the spectral similarity of both classes. Physically, low fire severity areas are marked by mild ground fire and therefore share significant physiological similarities such as healthy foliage,

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greenness, etc. hence the resultant misclassification. The lower User's validation accuracy (71.42%) for the Shadow Class is due to the difference in shadow effect on the Sentinel 2 data used for classification and the aerial photograph used for validation. Conversely, the delineation of Shadow class is helpful in this study in reducing classification error. Indeed, the shadow effect from satellite data obtained from optical sensors, especially in complex scenes, could influence radiance results if ignored (Leblon et al. 1996, Lachérade et al. 2008, Fujiwara et al. 2020)

5. CONCLUSIONS

The study assessed the severity of a forest fire event that occurred from 24th to 27th October 2018 at Taibon Agordino using Sentinel 2 imagery to create a severity map suitable as a decision-making supporting tool for post-fire management intervention. The fire severity map was produced by applying the Random Forest classifier to a combination of Sentinel-2 raw band reflectance, associated vegetation indices, and metrics. The best accuracies were achieved when the classification was done with the original band reflectance, associated vegetation indices, DEM, and slope data, with a classification accuracy of 99.61% and a validation accuracy of 83.33%. The confusion matrix shows that there is still some confusion between the Moderate and High Severity classes. This study presents preliminary results on the use of Sentinel 2 imagery to map fire severity classes in the case of a fire in an alpine forest at Taibon Agordino, Belluno Province, Italy. Further work may be necessary to test the methodology in other locations in Italy and elsewhere. Additional work is also needed to correct the reflectance for the topography effect.

REFERENCES

Breiman, L. 2001. Random forests. *Mach. Learn.*, 45, 5–32.

Chuvieco, E, Martín, M.P., Palacios, A., 2002. Assessment of different spectral indices in the red-near-infrared spectral domain for burned land discrimination. *Int. J. Remote Sens.* 23, 5103–5110, doi:10.1080/01431160210153129.

De Simone, W., M. Di Musciano, V. Di Cecco, G. Ferella, A.R. Frattaroli. 2020. The potentiality of Sentinel-2 to assess the effect of fire events on Mediterranean mountain vegetation, *Plant Sociology* 57(1), 11–22, DOI 10.3897/pls2020571/02

Emde, C., Buras-Schnell, R., Kylling, A., Mayer, B., Gasteiger, J., Hamann, U., Kylling, J., Richter, B., Pause, C., Dowling, T., Bugliaro, L. 2016**.** The libRadtran software package for radiative transfer calculations (version 2.0.1). *Geosci. ModelDev.*, 9, 1647–1672, doi:10.5194/gmd-9-1647-2016.

Escuin, S., Navarro, R., Fernández, P. 2008. Fire severity assessment uses NBR (Normalized Burn Ratio) and NDVI (Normalized Difference Vegetation Index) derived from LANDSAT TM/ETM images. *Int. J. Remote Sens.*, 29, 1053–1073, doi:10.1080/01431160701281072.

Fassnacht, F.E. Ewald, E.S. Schmidt-Riese, T. Kattenborn, J.-H. Andez. 2021. Explaining Sentinel 2-based dNBR and RdNBR variability with reference data from the bird′s eye (UAS) perspective, *Int. J. Appl. Earth Obs. Geoinformation*, 95, 102262

Filipponi, F. 2018. BAIS2: Burned Area Index for Sentinel-2, Proceedings 2nd International Electronic Conference on Remote Sensing, *Proceedings* 2,364, doi:10.3390/ecrs-2-05177

Fujiwara, T., Takeuchi, W. 2020**.** Simulation of Sentinel-2 bottom of atmosphere reflectance using shadow parameters on a deciduous forest in Thailand. *ISPRS Int. J. Geo-Information*, 9, 582, doi:10.3390/ijgi9100582.

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 Sens. Environ*, 240, 111702, 13 p. doi:10.1016/j.rse.2020.111702

Han, A., Qing, S., Bao, Y., Na, L., Bao, Y., Liu, X., Zhang, J., Wang, C. 2021. Short-term effects of fire severity on vegetation based on Sentinel-2 satellite data. *Sustainability* 13, 432. https://doi.org/10.3390/su13010432

Lachérade, S., Miesch, C., Boldo, D., Briottet, X., Valorge, C., Le Men, H. 2008. ICARE: A physically-based model to correct atmospheric and geometric effects from high spatial and spectral remote sensing images over 3D urban areas. *Meteorol. Atmos. Phys.*, 102, 209–222, doi:10.1007/s00703-008-0316-5.

Leblon, B., Gallant, L., Granberg, H. 1996**.** Effects of shadowing types on ground-measured visible and near-infrared shadow reflectances. *Remote Sens. Environ.*, 58, 322–328, doi:10.1016/S0034-4257(96)00079-X.

Leblon, B., San-Miguel-Ayanz, J., Bourgeau-Chavez, L., Kong, M. 2016. Remote sensing of wildfires. In *Land Surface Remote Sensing: Environment and Risks*, pp. 55–95 ISBN 9780081012659

Li, J., Roy, D.P., 2017. A global analysis of Sentinel-2a, Sentinel-2b, and Landsat-8 data revisit intervals and implications for terrestrial monitoring. *Remote Sensing*, 9(9), 902, 17 p. doi:10.3390/rs9090902

Main-Knorn, M., Pflug, B., Louis, J., Debaecker, V., Müller-Wilm, U., Gascon, F. 2017. Sen2Cor for Sentinel-2. In SPIE Proceedings Volume 10427: Image and Signal Processing for Remote Sensing XXIII, Lorenzo Bruzzone, Editor(s), 1042704 (2017), , p. 12. doi: 10.1117/12.2278218

Mallinis, G., Mitsopoulos, I., Chrysafi, I. 2018. 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. *GIScience Remote Sens.*, 55 (1), 1–18, doi:10.1080/15481603.2017.1354803.

Matricardi, E.A.T., Skole, D.L., Pedlowski, M.A., Chomentowski, W., Fernandes, L.C. 2010. Assessment of tropical forest degradation by selective logging and fire using Landsat imagery. *Remote Sens. Environ.*, 114, 1117–1129, doi:10.1016/j.rse.2010.01.001.

Morresi, D., Marzano, R., Lingua, E., Motta, M., Garbarino, M. 2022. Mapping burn severity in the western Italian Alps through phenologically coherent reflectance composites derived from Sentinel-2 imagery. *Remote Sens. Environ.*, 269, 112800, doi:10.1016/j.rse.2021.112800

Pinty, B., Verstraete, M.M. 1992. GEMI: a non-linear index to monitor global vegetation from satellites. *Vegetatio*, 101, 15–20

Quintano, C., A. Fernández-Manso, O. Fernández-Manso, 2018. Combination of Landsat and Sentinel-2 MSI data for initial assessing of burn severity, *Int. J. Appl. Earth Obs. Geoinformation*, 64 (2018) 221–225

Wimberly, M.C., Reilly, M.J. 2007**.** Assessment of fire severity and species diversity in the southern Appalachians using Landsat TM and ETM+ imagery. *Remote Sens. Environ.*, 108, 189–197, doi:10.1016/j.rse.2006.03.019.