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Conference Proceedings Paper

Observing post-fire vegetation regeneration dynamics exploiting high resolution Sentinel-2 data

Federico Filipponi [1,*], Giacinto Manfron [2]

[1] Istituto Superiore per la Protezione e la Ricerca Ambientale, Roma, Italy
[2] European Commission Joint Research Centre, Ispra, Italy
* Correspondence: federico.filipponi@isprambiente.it; Tel.: +39-06-5007-2438

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Abstract: Information related to the impact of wildfire disturbances on ecosystems is of paramount interest to account for environmental loss, to plan strategies for facilitating ecosystem restoration and to monitor the dynamics of vegetation restoration. Phenological metrics can represent a good candidate to monitor and quantify vegetation recovery after natural hazards like wildfire disturbances. Satellite observations have been demonstrated to be a suitable tool for wildfire disturbed areas monitoring, allowing both the identification of burned areas and the monitoring of vegetation recovery. This research study aims to identify post-fire vegetation restoration dynamics for the area surrounding Naples (Italy), affected by severe wildfires events in 2017. Sentinel-2 satellite data were used to extract phenological metrics from the estimated Leaf Area Index (LAI), and related such metrics to environmental variables, in order to evaluate the vegetation restoration and landslide susceptibility for different land use classes.

Keywords: wildfires; vegetation restoration; Sentinel-2; post-fire monitoring; natural hazards; time series; Leaf Area Index

1. Introduction

Wildfires represent one of the major agent of change as far as forest ecosystems are concerned. These natural hazards are monitored and studied at different stages, exploiting many and innovative tools. For example, post-fire studies are mainly targeted in quantify the impact of wildfire events on forests and monitor the recovery of natural environments. The study of post-fire vegetation restoration is of great importance for decision makers and landscape planners, as it can provide useful information to update landscape vulnerability maps, monitor forest recovery processes and identify forest repopulation areas.

Besides being natural hazards, wildfires could determine the reduction of vegetated surface and consequently reduce the effect of soil protection provided by the tree root system triggering therefore the possibility of landslides activation. Proper evaluation of post-fire vegetation restoration should not exclusively rely on fire severity and post-fire conditions, but also consider the plant conditions before the wildfire occurrence.

In this contest, satellite remote sensing represents a time- and cost-effective tool to monitor post-fire vegetation dynamics, especially over large areas. In particular, the Sentinel-2 MSI sensors, represents a concrete and available opportunity ho access free of charge data, featuring unprecedented trade-off in spatio-temporal resolutions (10-60 m pixel size and 5-days revisit time). represents a great occasion of improvement on such topic.

Objective of this contribution is to identify and characterize post-fire vegetation restoration dynamics for the study area surrounding Naples (Italy) using Leaf Area Index (LAI) generated from Sentinel-2 satellite data. The study case was interested by severe wildfire events during summer 2017 **[1].** Specific objectives are: (i) identify representative trajectories of vegetation restoration for different land use classes and (ii) evaluate the land use vulnerability (e.g. landslide susceptibility) from identified restoration dynamics.

2. Materials and Methods

A database of 218 Sentinel-2 A and B acquisitions was processed in order to produce smoothed temporal series of LAI values for the period 2016-2018. Sentinel-2 L2A data atmospherically corrected using the MACCS-ATCOR Joint Algorithm (MAJA) [**2**] and distributed by Theia in MUSCATE format were downloaded and used for the analysis. All the spectral bands contained in the Sentinel-2 L2A product were first masked from cloud contaminated data and successively resampled to a 20 m spatial resolution according to the procedure described in [**3**]. Later, the biophysical processor [**4**] available in SNAP software was used to compute leaf area index (LAI) and multitemporal LAI observations stacked in a multi-dimensional datacube, after applying an image co-registration step [**3**]. Finally LAI time series were first smoothed using a Whittaker approach [**5**], to avoid the residual noise rate affecting time series due to cloud contamination, and secondly masked using a reference burned area map [**3**].

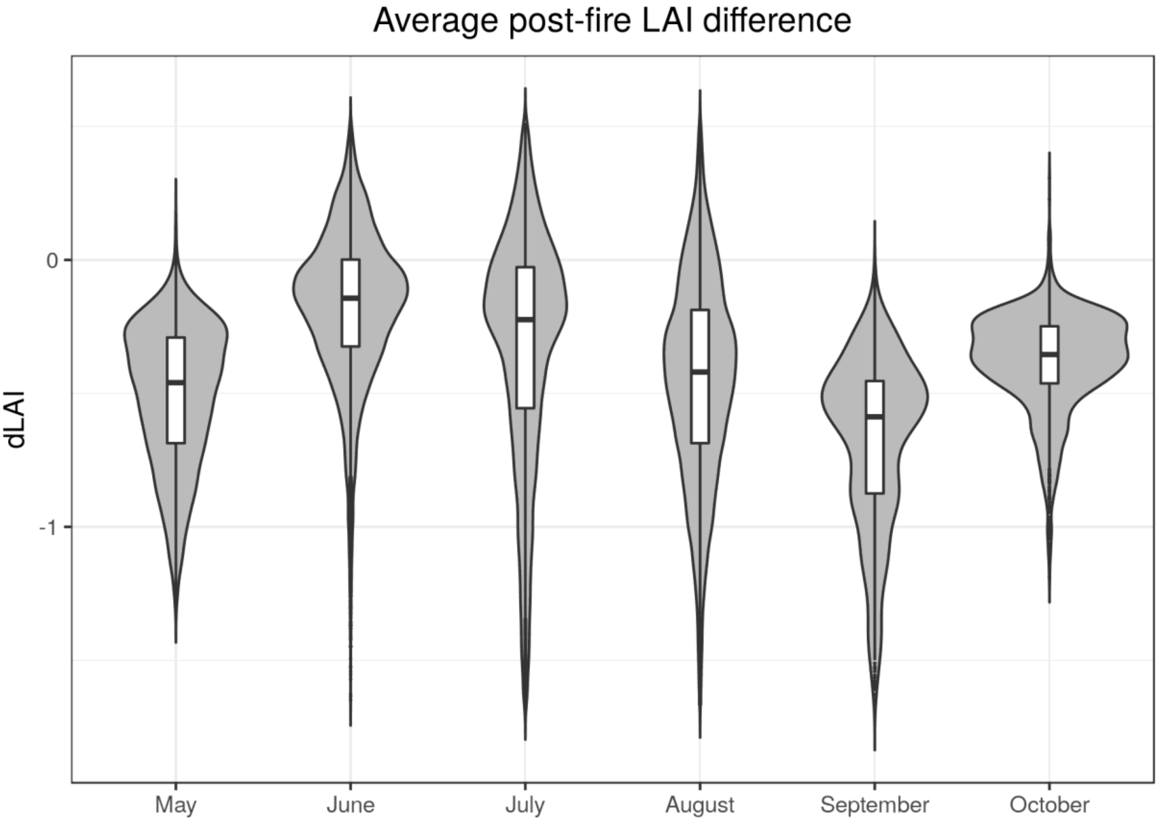

Figure 1. Post-fire dLAI distribution aggregated by the month of wildfire occurrence in 2017.

During the time series analyses phase, each burned area was considered as a single Region of Interest (ROI) and a used to compute phenological metrics from LAI, for the pre-fire (year 2016) and post-fire (year 2018) periods. Phenological metrics, specifically the peak LAI and the seasonal cumulated value were computed from LAI in the time period 01 March - 30 September, and divided by the number of observation days in order to obtain thedaily average LAI value of the smoothed time series. The 2012 Corine Land Cover (CLC) thematic map, was used to aggregate time signatures according the land cover types. The difference Leaf Area Index (dLAI) phenological metric, was finally computed subtracting the seasonal cumulated value of 2018 to the seasonal cumulated value of 2016, divided by the number of observation days.

Successively, dLAI values were compared against already available topographic and landslides hazard maps, in order to qualitatively investigate the environmental drivers related to specific fire vegetation restoration processes. Italian national landslide hazard maps (Piani di Assetto Idrogeologico, PAI [**6,7**]) represents the hazard in 5 PAI classes: 0=Controlled area; 1=Moderate; 2=Medium; 3=High; 4=Very High.

3. Results and discussion

During year 2017 wildfire events mainly occurred in July (45.4%) and August (37.7%), mostly in areas of very high landslide hazard (PAI 4 and PAI 3 classes representative for more than 43.15% the analized LAI time series).

Wildfires occurred during spring and early summer resulted in a lower dLAI (Figure 1), suggesting that vegetation had the time to start the restoration process before the end of the growing season. An hypothesis to explain the lower values of dLAI resulted for May is the presence of high residuals (dry leaves or branches) as heritage of the previous season, that still has not started to be part of natural degradation processes due to already chilly temperatures and that represents ready-to-burn biomass in case of fire events. Incrementing therefore fire severity and damage, constraining therefore the activities of post fire vegetation regrowth in the successive season. Similarly, fire events taking place in autumn result intense (lower dLAI values) due to the higher presence of dry biomass at the ground level.

The most represented land cover classes were “transitional woodland-shrubs” (CLC code 324 - 32,48%), “natural grasslands” (CLC code 321 - 27,87%) and “broad-leaved forests” (CLC code 311 - 16,16%) (Table 1). Among those, the faster post fire vegetation regrowth dynamic was observed for natural grasslands (dLAI= -0.2), followed by woodland-shrubs (dLAI= -0.3) and broad-leaved forests (dLAI= -0.5) (Figure 2).

Table 1. Statistics on the distribution of burned pixels for the various Corine Land Cover 2012 classes.

CLC CODE	Samples	%	Description
223	5047	3.45	Olive groves
242	2161	1.48	Complex cultivation patterns
243	3160	2.16	Land principally occupied by agriculture with significant areas of natural vegetation
311	23629	16.16	Broad-leaved forest
312	562	0.38	Coniferous fores
313	3582	2.45	Mixed forest
321	40753	27.87	Natural grasslands
323	8887	6.08	Sclerophyllous vegetation
324	47495	32.48	Transitional woodland-shrub
333	4189	2.86	Sparsely vegetated area

Figure 3 (left panels) shows average LAI time series profiles representative for specific land use classes along the pre fire (2016) fire (2017) and post fire (2018) 3-years-period. A well marked decrease in LAI values can be easily appreciated in 2017 due to fire events in the three selected land use classes (panel a, c and e). Faster restoration processes, with lower dLAI values, was found for the classes corresponding to medium and moderate landslides hazards, suggesting that the restoration dynamics are slower in areas with higher landslides susceptibility (Figure 3).

No significant relation between vegetation recovery and terrain slope could be detected one year after wildfire occurrence.

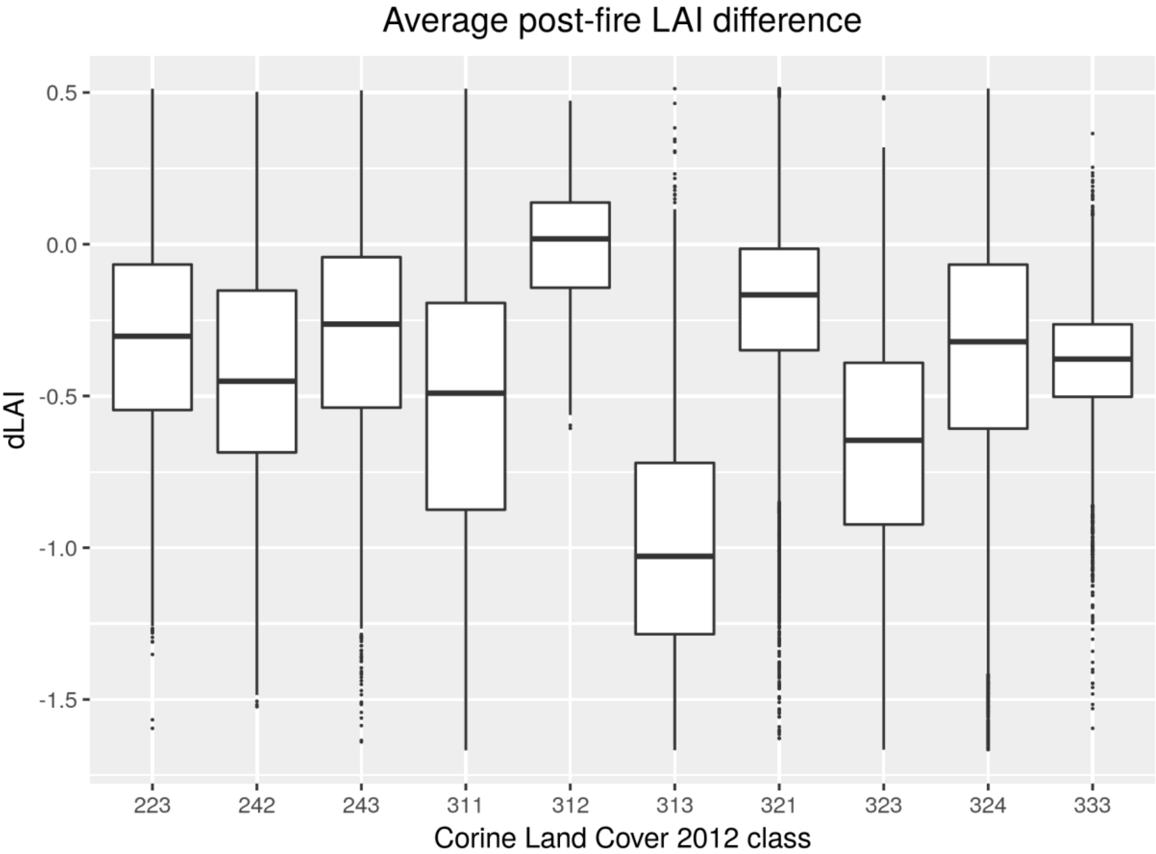

Figure 2. Distribution of dLAI values for the various Corine Land Cover 2012 classes corresponding to burned area pixels.

4. Conclusions

The exploitation of biophysiacal indicators derived from Sentinel-2 satellite observations demonstrated to be a suitable tool to identify, describe and monitor vegetation recovery in wildfire affected areas. Phenological metrics computed from multitemporal LAI series allowed to depict and interpret post firerestoration dynamics featuring various land cover types. A faster restoration of natural grasslands ecosystems was found, when compared against the transitional woodland-shrubs and broad-leaved forests. Areas corresponding to medium and moderate landslides hazard classes showed faster vegetation regrowth, suggesting that the restoration dynamics are slower in areas with higher landslides susceptibility.

Future perspectives of this research study lies in the development of automatic approaches to classify Sentinel-2 time series and operatively derive map of vegetation restoration typologies over burn-affected areas. For example, the application of advanced classification algorithms, as Convolutional Neural Networks (CNNs), Random Forest (RF) or Support Vector Machines (SVM) should be tested and compared each other in order to identify which of those could better cope with the experimental case study, and moreover, benchmarched with well known algorithm (e. g. maximum likelihood) in order to appreciate the added value carried by state-of-the art classifiers.

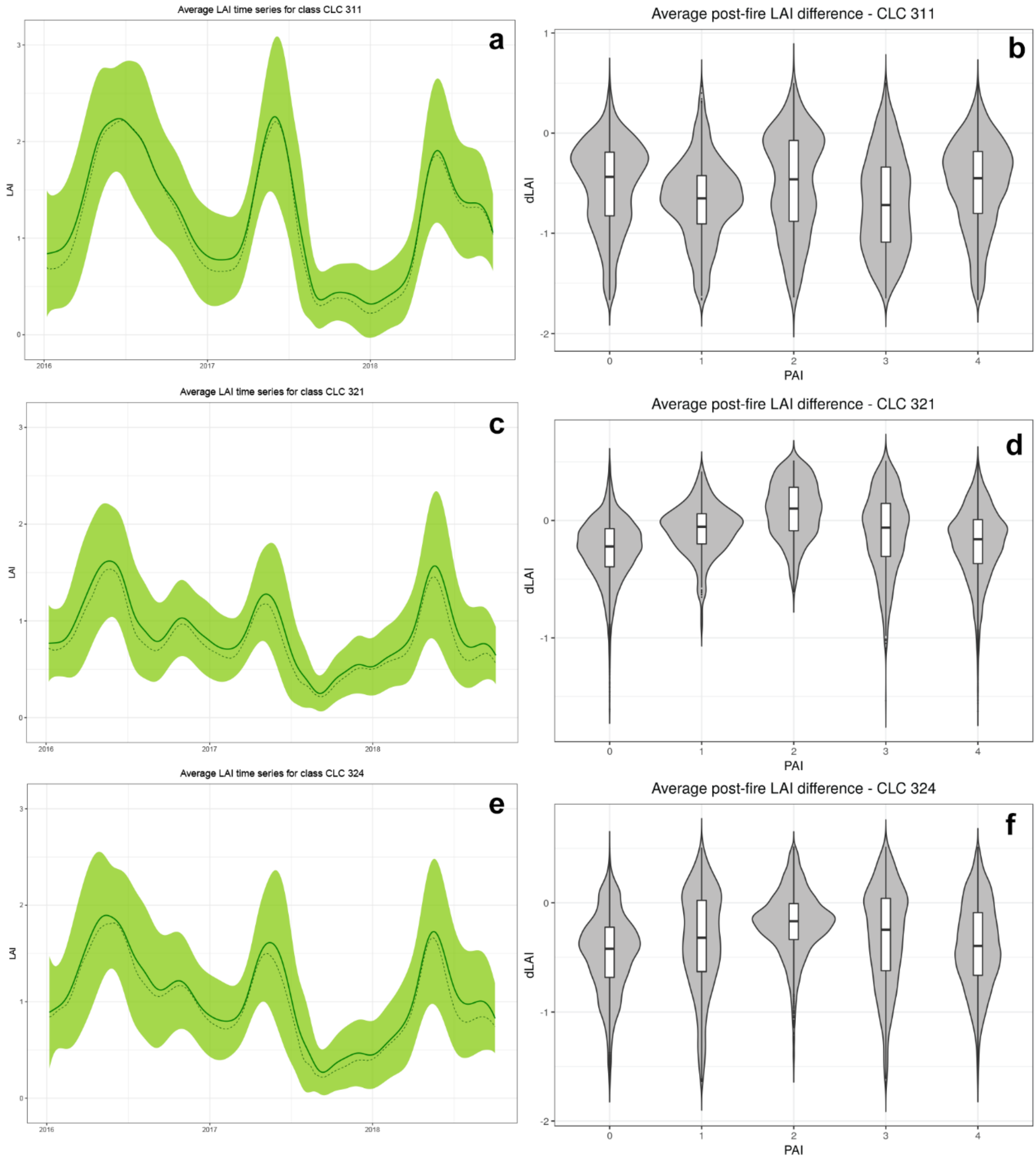

Figure 3. (**a**) Multitemporal series of LAI for burned area pixels corresponding to CLC class 311; (**b**) Distribution of dLAI values over the different PAI classes for CLC class 311; (**c**) Multitemporal series of LAI for burned area pixels corresponding to CLC class 321; (**d**) Distribution of dLAI values over the different PAI classes for CLC class 321; (**e**) Multitemporal series of LAI for burned area pixels corresponding to CLC class 324; (**f**) Distribution of dLAI values over the different PAI classes for CLC class 324.

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Author Contributions: F.F. and G.M. equally contributed to this work.

Conflicts of Interest: The authors declare no conflict of interest.

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