MONITORING THIRTY-FIVE YEARS OF ITALIAN FOREST DISTURBANCE USING LANDSAT TIME SERIES

C. Borghi[1], S. Francini[1,2,3*], M. Pollastrini[1], F. Bussotti[1], D. Travaglini[1], M. Marchetti[2], M. Munafò[4], G. Scarascia-Mugnozza[3], D. Tonti[2], M. Ottaviano[2], C. Giuliani[4], A. Cavalli[3], E. Vangi[1,2], G. D'Amico[1], F. Giannetti[1], G. Chirici[1]

1. Department of Agriculture, Food, Environment and Forestry, Università degli Studi di Firenze. Via San Bonaventura, 13, 50145 Firenze, Italy – (costanza.borghi, saverio.francini,, martina.pollastrini, filippo.bussotti, davide.travaglini, elia.vangi, giovanni.damico, francesca.giannetti, gherardo.chirici)@unifi.it

2. Dipartimento di Bioscienze e Territorio, Università degli Studi del Molise, Pesche, Isernia, Italy – (marchettimarco, daniela.tonti, ottaviano)@unimol.it

3. Dipartimento per l'Innovazione dei sistemi Biologici, Agroalimentari e Forestali, Università degli Studi della Tuscia, Via San Camillo de Lellis, Viterbo, Italy – (gscaras@unitus.it, alice.cavalli@studenti.unitus.it)

4. ISPRA - Italian National Institute for Environmental Protection and Research - (michele.munafo, chiara.giuliani)@isprambiente.it

*Corresponding author: saverio.francini@unifi.it

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ABSTRACT:

Forest ecosystems have a crucial role for biodiversity conservation, providing a large set of ecosystem services. Understanding and assessing forest disturbance regimes on a large spatial and temporal scale is a prerequisite setting up sustainable forest management solutions. In this context, Remote Sensing is an efficient tool frequently used in land-use change detection. The present work is aimed at spatially estimating forest disturbing events occurred in Italy in the period 1985-2019. Using Landsat time series and the 3I3D forest disturbance detection algorithm, we analyzed "extreme" forest disturbance patterns and their evolution in the last 35 years. We found a total of 472 events, with the highest incidence (96) in the period 1990 - 1994. The accuracy of the 3I3D algorithm was estimated using a photo-interpreted dataset of nine random-sampled squared cells of 225 km^2 each, distributed in the Italian region. Omission error for the 3I3D map ranged from a minimum of 37.43% to a maximum of 64.62% (mean value of 47.07%) while the commission error between 36.80% and 83.92%, with an average of 49.60%. Results suggest that occurrence of severe disturbance events do not seem to increase over time in the study period.

1. INTRODUCTION

Forest ecosystems cover approximately one-third of Earth's land surface (Hansen et al., 2013). They supply water, provide livelihoods, mitigate climate change, and are essential for sustainable food production (MEA, 2005). However, deforestation and forest degradation continue at alarming rates (Senf & Seidl, 2021). FAO defines forest degradation as "the reduction of the capacity of a forest to provide goods and services" (FAO, 2011), while the Intergovernmental Panel on Climate Change (IPCC) introduces the notion of timescale, as a loss of a state persisting for a certain period (Penman, 2003).

Natural disturbances, such as fires, insect outbreaks, and windthrows are an integral part of ecosystem dynamics in forests around the globe. They occur as relatively discrete events and form characteristic regimes of typical disturbance frequency, sizes, and severity over extended spatial and temporal scales (Seidl et al., 2017). Nevertheless, forests nowadays must also cope with the anthropogenic intensification of stressors that affect their condition, either directly or indirectly through climate change, pollution, and invasive species (Trumbore et al., 2015).

Forest disturbance regimes have changed thoroughly in many ecosystems in recent years, with climate change being the major driver of disturbance changes (Seidl et al., 2011). Indeed, severe and wide-ranging negative impacts may be expected in most European regions over the next few years (Linder et al., 2010). Such alterations have the potential to impact forests profoundly due to their lack of rapid adaptation (Seidl et al., 2017). Therefore, understanding and quantifying the forest vulnerability to disturbances is crucial to assess climate change impacts and to develop effective mitigation and adaptation strategies. In this scenario, Remote Sensing (RS) offers an effective way to monitor and mapping forest disturbance. Nowadays, the union of open access data and cloud computing platforms, such as Google Earth Engine (Gorelick et al., 2007), makes it possible to monitor large areas timely (Francini et al., 2020) and in a cost-effective manner (Gomes et al. 2020). In a recent paper, Francini et al. (2021) presented an unsupervised algorithm (3I3D) that detects forest changes by analyzing the trends of three vegetation indices used as axes for a three-dimensional space; 3I3D was then successfully used for the whole Italy, with an accuracy of 97% (Francini et al., 2021 in review).

In this work, we apply the 3I3D algorithm using Landsat Best Available Pixel (BAP) composites (White et al., 2014) to predict forest disturbances in Italy over the period 1985-2019. The aim of this study was to identify the incidence of particularly large disturbance events in the Italian forests and evaluate how this pattern varied over time. The accuracy of the forest disturbance map was then determined through the photointerpretation of nine random-sampled square cells. Then, the map's omission and commission errors were assessed through a confusion matrix.

2. MATERIALS AND METHODS

The study area coincides with the Italian forested area, defined using a fine-resolution forest/non-forest mask (D'Amico et al., 2021; Vangi et al., 2021). According to the last Italian NFI (INFC, 2007), forest vegetation and other wooded lands occupy approximately 10 mln ha, about 34% of the Italian national territory. Employing Landsat time-series imagery as input data, we applied BAP composite procedure, as described in White et al. (2014), and the 3I3D algorithm proposed by Francini et al.

* Corresponding author

(2021), to create 35 forest disturbance maps at 30 m spatial resolution, one for each year of the analysis.
Utilizing the 3I3D-derived maps, we calculated the area of forest disturbances for each province (NUTS3 are called Provinces in Italy) over the study period. Then, the data were aggregated at the regional (NUTS2) and national levels (NUTS1). Additional analyses were performed in order to identify extreme forest disturbance events. First, we estimated for each Province the "standard disturbed area" as the average of the 35 disturbed areas registered for that Province by the 3I3D map. Then, we identified for each Province Extreme Events (EEs) as forest disturbances which were 80% greater than the standard.
The performance of 3I3D used with Sentinel-2 imagery was assessed in Francini et al. (2021) and Francini et al. (in review). Here we assessed the algorithm's accuracy when applied to Landsat images using a reference dataset. Nine 15-km side square areas (225 km^2 each), were chosen around Italy using simple random sampling and analyzed through photointerpretation of high-resolution multi temporal orthophotos and satellite images. The location of the reference areas is shown in Figure 3. The same reference dataset was then used to assess the accuracy of the forest disturbance map proposed by Senf & Seidl (2021), aiming at comparing the performance of both approaches.
To evaluate maps' accuracy, we calculated (i) the number of true positives, corresponding to pixels correctly classified as disturbed forest, (ii) the number of true negatives, corresponding to pixels correctly classified as undisturbed forest, (iii) the number of false positives, corresponding to pixels incorrectly classified as disturbed, and (iv) the number of false negatives, corresponding to pixels incorrectly classified as undisturbed. Subsequently, those parameters were used to evaluate the maps' omission and commission errors through a confusion matrix (Kubat et al.1998).

3. RESULTS

Figure 1 illustrates the annual disturbed forest area in Italy during the period 1985-2019. The results show that the greatest events were detected in 1991 and 2016 with respectively 110591.30 and 100022.90 hectares of disturbed forest, respectively. In percentage, the most affected Region was Umbria with 22.43% of its total forest area disturbed during the 35-years study period, while the least was Emilia Romagna with 3.26%.

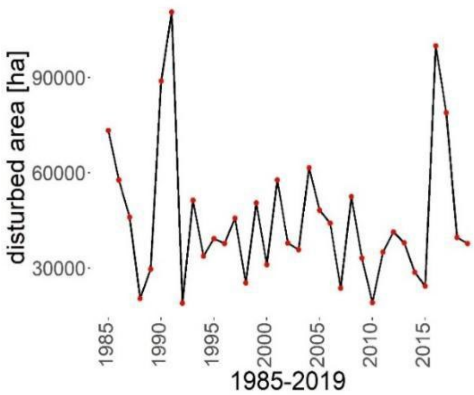

Figure 1. The trend of disturbed forest area in Italy during the period 1985-2019

The number of EEs over the 35 years was 472. As shown in Table 1, the occurrence of EEs does not increase over the time.

Table 1. Number of extreme events that occurred over the analysis period 1985-2019

	1985 - 1989	*1990 - 1994*	*1995 - 1999*	*2000 - 2004*	*2005 - 2009*	*2010 - 2014*	*2015 - 2019*	**TOT**
n°	76	96	67	66	57	44	66	**472**

The years 1985 and 1991 registered the highest number of EEs, with 28 episodes each, while the lowest number of EEs was 3 in 2000 and 2010 (figure 2).

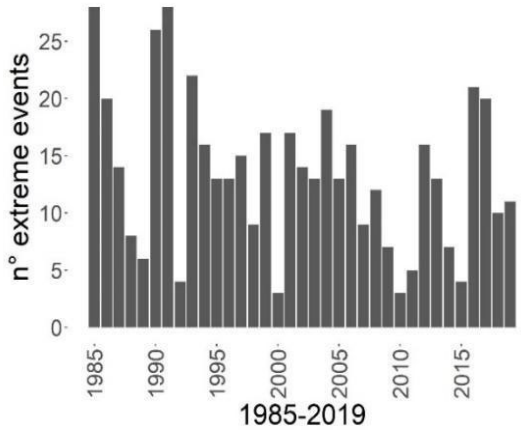

Figure 2. Trend of extreme events occurred in Italy during the period 1985-2019

46% of the EEs occurred over the period 1985-1995 (Figure 3).

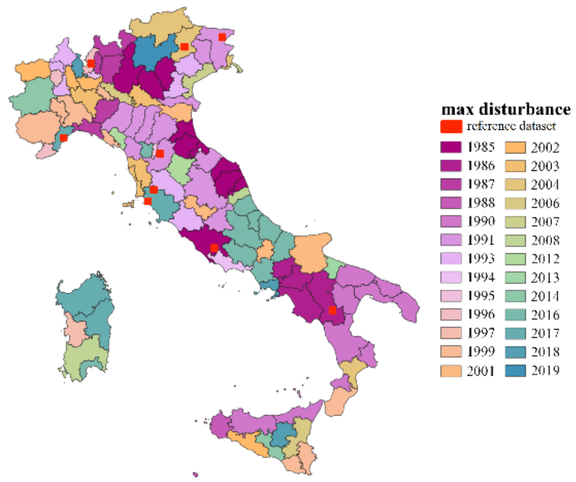

Figure 3. Years when the largest forest disturbance event occurred, per province. In red, the 9 plots of the reference dataset.

Table 2. 3I3D [(1)] and Senf and Seidl' [(2)] maps accuracies.

	Omission Errors		Commission Errors	
Min	37.43 [(1)]	40.72 [(2)]	36.80 [(1)]	34.46 [(2)]
Mean	47.07 [(1)]	58.20 [(2)]	49.60 [(1)]	51.14 [(2)]
Max	64.62 [(1)]	70.94 [(2)]	83.92 [(1)]	78.42 [(2)]

4. DISCUSSION

In the present work, we analyzed the Italian forest disturbance regime over the period 1985-2019. Before this study, available forest disturbance maps detected for each pixel just one disturbance. More specifically, the Global forest change map shows for each pixel the last disturbance that occurred after 2000 (Hansen et al., 2013) while the Senf & Seidl (2021) map shows the disturbance with the largest magnitude. Whereas Hansen and Senf & Seidl's maps contain a single layer, here we analyzed 35 years and maps independently, avoiding the loss of information about multiple events occurring in the same place, in different periods. While their incidence was expected to be increasing over time (Senf & Seidl, 2021), especially harvesting (Ceccherini et al., 2020), our results do not confirm this trend (Figure 1). Differently, the EEs incidence (Figure 2) suggests an overall decrease over time (Table 1).

The highest numbers of EEs, registered in 1985 and 1991, could be correlated to the exceptionally cold weather in Italy in those years, which caused severe damages, even if not permanent (Bartolozzi & Fontanazza, 1999). However, the current climate change effects in the Mediterranean zone suggest an increment in the frequency of hot days, heat waves, heavy precipitation events, and fewer cold days with a lower risk of freezing events. For example, the record-breaking drought that affected Europe during the July 2016–June 2017 period (Garcia et al., 2021), caused extensive stress to Italian forests, especially in *Quercus* sp. and beech forests, with huge defoliation and leaf discoloration. These events were correctly registered using our procedure as shown in Figure 2. Severe drought causes higher vulnerability to forests (Forzieri et al., 2021), especially towards pest outbreaks (McDowell et al., 2011).

The results we obtained confirm the utility of satellite data in forest disturbance detection (Pontius et al., 2020), thanks to the high level of accuracy that can be obtained using forest disturbance detection algorithms.

To calculate the accuracy of the disturbance map based on the 3I3D algorithm (Table 2), we used a reference dataset, as proposed by Francini et al. (2021). We acknowledge that the photo-interpreted dataset is not error-free. Moreover, while disturbed polygons may be correctly classified, a partial identification of larger events could lead to a dwindling accuracy. Thus, the most reliable accuracy evaluation methods of forest disturbance maps are based on a reference dataset selected by stratification of the predicted maps (Olofsson et al., 2014). Furthermore, three out of nine validation plots were in the Alps (Figure 3). In this area, meager accuracy is expected due to (i) larger number of clouds (Hermosilla et al., 2016), (ii) extreme slopes that complicate images geometrical correction (White et al., 2016), (iii) consistent presence of snow and (iv) a prevailing continuous cover forestry with silviculture activities in small patches. For those reasons, accuracy assessment on the presented maps could lead to an error overrate. Nonetheless, the comparison between 3I3D and Senf & Seidl's forest disturbance maps accuracy shows an overall better performance of the former (Table 2). The 3I3D algorithm presented an average of 11.13% on omission and 3.54% on commission errors less than Senf & Seidl's forest disturbance map. Moreover, the 3I3D algorithm is easily tunable using Google Earth Engine, and, depending on the task, omission or commission error rates can be tuned. Evidently, as the omission errors decrease, the commission errors increase, as the commission errors decrease, omission errors increase.

5. CONCLUSIONS

Using Landsat BAP composites, Google Earth Engine, and the 3I3D algorithm, we mapped forest disturbances in Italy over the period 1985-2019 detecting 472 EEs in 107 Italian provinces. The rate of EEs was quite stable during the investigated period.

The distribution of EEs has significant implications for understanding how large forest disturbance events change their pattern over the years. The awareness of variations in disturbance regimes is also crucial to evaluate forests' stress response.

The present work contributes to existing knowledge on how climate change interferes with forest disturbance regimes and how events' magnitude and frequency change in a long time series. However, further analysis are needed to identify forest disturbance drivers and how their incidence varied over the time.

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