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Remote sensing techniques to assess post-fire vegetation recovery

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Abstract

Wildfires substantially disrupt and reshape the structure, composition and functioning of ecosystems. Monitoring post-fire recovery dynamics is crucial for evaluating resilience and securing the relevant information that will enhance management and support ecosystem restoration after fires. Compared to the extensive and labour-intensive field campaigns, remote sensing provides a time- and cost-effective tool to monitor post-fire vegetation recovery (PVR). This concise literature review presents tools and recent advances in remote sensing techniques, focusing on the most commonly used sensors and indicators/metrics. It also provides recommendations on the use of these tools for assessing vegetation recovery and on existing gaps regarding technical limitations that could guide future research.

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Keywords

Wildfire, Vegetation regrowth, Satellite imagery, Change detection, Time series, Spectral variables.

Introduction

Wildfires are an important modelling agent in terrestrial ecosystems, influencing the dynamics and interaction of soil and vegetation components [1]. In the immediate aftermath, the most significant impact on the landscape is the total or partial combustion of vegetation cover. The intensity of the subsequent regrowth process (often called recovery [2]) is heavily dependent on the following: the effectiveness of the anatomical and physiological regeneration strategies of the affected species, the degree of alteration of the other elements of the soil—vegetation complex, and their interactions in light of environmental factors and post-fire temporal conditions [3]. Monitoring post-fire vegetation recovery (PVR) is crucial, as it provides valuable information for analysing ecosystem resilience, for determining landscape dynamics, and for forest management purposes.

Compared to extensive and labour-intensive field campaigns, remote sensing (RS) techniques are a time- and cost-effective way to monitor post-fire ecosystem recovery [4]. Numerous studies have affirmed the capacity of satellite imagery to quantify fire impacts over vast zones and different ecosystems. In this sense, RS has been identified as an effective tool for understanding how ecosystems respond to fire, which can provide an enhanced understanding of vegetation recovery patterns and make a positive contribution to sustainable forest management [5]. Spectral trajectories (considered a proxy for vegetation recovery) are usually used to analyse the spatial—temporal dynamics of vegetation cover following wildfires, using different indices, metrics, and temporal perspectives.

A concise and nonsystematic review of different publications on the trends in RS applications for analysis of PVR is presented in this article. The emphasis is on contextualizing the use of the different temporal perspectives applied, and the most commonly used sensors, indicators, and metrics. It is important to highlight that there are a large number of reviews on change detection techniques and trend analysis using RS products. For example, Gitas et al. [6] and Chu & Guo [5] provided one of the first systematic reviews of post-fire monitoring methods and techniques. Banskota et al. [7], Zhu [8], Tewkesbury et al. [9] and Hirschmugl et al. [10] addressed a complete revision of the different algorithms developed to analyse imagery time series, including applications for monitoring areas affected by wildfires. Bartels et al. [11] undertook a quantitative review of the literature, to determine recovery times following wildfire, whereas Cohen et al. [12] conducted a comparative analysis of the main algorithms used to map the full range of magnitudes of forest disturbance. Martínez et al. [13] and Szpakowski and Jensen [14] are two of the most recent and up-to-date studies that deal with RS techniques for post-fire monitoring. All these reviews provide insightful contributions on the topics summarized in the present paper (sensors, indicators and metrics used in PVR).

Sensors and RS products

For decades, PVR has been mainly analysed through multispectral optical satellite imagery, both with coarse spatial resolution instruments—Advanced Very High Resolution Radiometer, *Système pour l'observation de la Terre* and Moderate Resolution Imaging Spectroradiometer (MODIS)—as well as with tools that provide a finer resolution—Thematic Mapper, Enhanced Thematic Mapper Plus, Operational Land Imager and MultiSpectral Instrument (MSI). These sensors generate images that go beyond simply capturing vertical views of the Earth's surface; they provide information on spectral regions that capture vegetation conditions, such as near- and mid-infrared, and thereby support detailed monitoring of post-fire dynamics.

Among the finer spatial resolution RS data sets, the Landsat program (NASA-USGS) is the main source of time-series data for monitoring vegetation at regional scales because of the following advantages: (1) good temporal, spectral and spatial characteristics (30 m spatial resolution and 16 days of revisiting time); (2) long time span coverage (from 1980s to today); and (3) the derived data sets can be easily accessed free of charge [15−18]. Moreover, the RS data sets derived from the MSI sensors onboard the Sentinel-2 satellites of the European Space Agency have grown in importance since the start of the mission in 2015. Their information is also freely available and provides greater spatial and temporal resolution than Landsat (10−20 m and up to a 5-day revisiting cycle). More recently, the development of harmonized Landsat and Sentinel-2 products has received special attention in the RS community [19]. By providing more frequent acquisitions, they enable the detailed monitoring that is necessary to uncover the short-term, post-fire dynamics in ecosystems that recover quickly, like tropical savannas and grasslands. Regarding the coarse spatial resolution products, the MODIS series stands out. With an almost daily temporal resolution (1−2 days, with a spatial resolution of up to 250 m), it allows broader spatial scales, which can explore in more detail the effects of seasonality and land surface phenology (LSP) associated with the vegetation's response to fire.

Concurrently with the recent development and availability of collections of dense time series of optical satellites, other sensors and technologies, such as RADAR (Radio Detection and Ranging) and LIDAR (Light Detection and Ranging), are being deployed. Unlike optical sensors, active sensors can retrieve information below the tree canopies, allowing access to variables associated with the vertical structure of the vegetation recovery after fire [20−22]. Although LIDAR data are largely acquired via aircraft missions, especially in certain areas, NASA's Global Ecosystem Dynamics Investigation (GEDI) programme has delivered significant advances. GEDI data are derived from an LIDAR sensor on board of a satellite platform, providing access to data on biomass dynamics and diversity of canopy structure [23,24] with outstanding potential for PVR monitoring. At the same time, the growing application of unmanned aerial vehicles (UAVs) for generating RS data sets provides more flexible access to multitemporal data and allows for the deployment of sensors with ultra-high spatial resolution [25−27].

Furthermore, a growing number of investigations combine optical and active RS data sets, both as complementary data and in an integrated way through fusion processes. For example, Bolton et al. [22] fused Landsat time series data and airborne (LIDAR) to assess changes in forest structure; Meng et al. [28] linked multispectral satellite imagery, airborne imaging spectroscopy and LIDAR, with the aim to quantify post-fire forest recovery rates by differentiating canopy recovery from understory recovery. In the same way, Voleger et al. [29] explored the combination of LIDAR data and multitemporal Landsat series (calibrated with field data), to produce maps of post-fire wildlife habitats.

Indicators, metrics and algorithms

Spectral variables and indicators

From an RS perspective, the vegetation processes that follow disturbances can be mainly analysed by reflectance values and spectral indices [30]. In relation to PVR, these indicators generally rely on greenness measurements of red−near-infrared (R−NIR) vegetation indices [31,32], based on different algebraic combinations between original spectral bands. These indices are used to determine (1) whether postdisturbance values correspond to the previously recorded state (i.e. post-fire resilience) and (2) how long it costs to reach the previous state [33].

Among the NIR-based spectral indices derived from RS imagery, the Normalized Difference Vegetation Index (NDVI), the Enhanced Vegetation Index (EVI) and the Normalized Burn Ratio (NBR) are the ones used most frequently to monitor PVR. NDVI and EVI are very sensitive to seasonal and biophysical variations of vegetation changes and are, thus, used where natural variability is important [34]. Although they tend to saturate over dense forests and are not effective in measuring forest structure or species composition, they still provide a good proxy for vegetative regrowth [35]. NBR is usually used to evaluate burn severity levels; however, it also delivers good results in assessing long-term vegetation regeneration [36] and is being reconceptualized as an indicator for the scope of post-fire recovery (e.g. burn recovery ratio) [33] (Table 1). Other indices used as variables in PVR are the Soil Adjusted Total Vegetation Index [31], an effective way to capture temporal changes in grassland vegetation; the Anthocyanin Reflectance Index 2 and the Transformed Chlorophyll Absorption Reflectance Index [37], very resistant to the changes of Leaf Area Index and solar zenith angle; the Tasseled Cap Transformation−based indices [38], sensitive for monitoring the canopy moisture and structure; the Forest Recovery Index 2, that is, the reciprocal of Integrated Forest Z-score, a threshold-based index developed as a part of the Vegetation Change Tracker algorithm [32], or variables derived from texture analysis, especially useful in areas of heterogeneous vegetation because they consider the spatial adjacency relationships of pixels [37].

Variables derived from traditional classification, spectral mixture analysis (SMA) techniques, Geographic object-based image analysis (GEOBIA) and active microwave RS are also important alternatives. SMA considers that each type of ground cover is represented by its mean spectral signature, deriving endmember proportions using spectral unmixing procedures. In this sense, some outstanding examples in the generation of indicators are the shade normalized green vegetation fraction image obtained by applying Multiple Endmember Spectral Mixture Analysis [39], or the Normalized Degradation Fraction Index for monitoring forest degradation [40], both using Landsat time series. GEOBIA are techniques that use both spectral response and contextual information to assess post-fire vegetation characteristics in groups of pixels (geographic objects generated by image segmentation) [25]. Regarding active microwave RS, advanced applications that stand out include the use of L-band HV-polarized SAR backscatter in the monitoring of post-fire changes (e.g. tree survival in eucalyptus forests of Western Australia [20] or the use of airborne LIDAR in the Boreal Shield West Ecozone of Canada [22]).

Metrics and algorithms

Within the field of change detection methods, in which PVR studies are integrated, two types of temporal approaches are usually considered: (1) bitemporal change detection methods, a comparison between states at different moments (i.e. pre- and post-fire) and (2) spectral trajectories of land surface change, in which recovery processes are considered as a continuous process [13]. An example of the first approach is the Multi-Index Integrated Change Analysis, which was applied in the context of the Fire and Resource Management Planning Tools programme (LANDFIRE) [41]. This metric integrates different spectral indices—differenced Normalized Burn Ratio, differenced Normalized Difference Vegetation Index, the Change Vector, and the Relative Change Vector Maximum—to identify the magnitude of the spectral changes between pre- and postdisturbance events [42]. Similarly, Torres et al. [43] proposed the Cumulative Relative Recovery Index, a long-term recovery indicator using the product MOD13Q1 (MODIS) (Table 1); and White et al. [44] readapted the Recovery Indicator of Kennedy et al. [45] (Table 1). Recently, Du et al. [46] proposed the Tri-Temporal Logic-verified Change Vector Analysis, an unsupervised method for improving bitemporal methods, which introduces an additional image to form a mutual validation logic.

There is an ongoing shift from bitemporal to continuous approaches [47], because of the improved access to continuous RS series and the opportunity they provide to assess post-fire dynamics in detail [48]. Long satellite time series can capture the complexity of vegetation regeneration processes in fire-affected areas, allowing the analysis of both short duration phenomena and the smoothing of long-term trends with high consistency [8]. Thus, the open access to satellite image archives, especially MODIS or USGS Landsat, has led to the development of many techniques and applications to describing vegetation regrowth patterns in fire-affected forest [8,18]. One of the most widely used tools is the Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr) [49], a trajectory segmentation method that applies a temporal and spatial normalization process for extracting spectral trajectories of land surface change. The technique consists of decomposing the time series curve into a sequence of straight-line segments [30]. In the case of burnt areas, three segments would be obtained: (1) a flat line before the fire event, (2) a declining line following the disturbance and (3) a segment line with a positive slope throughout the recovery. Recently, this method has been used to map snag hazard for fire responders in disturbed forests [50] or to record the disturbance and recovery history in pine forests [30,38,48,51].

Other spectral trajectory methods are based on curves and trajectory fitting (i.e. methods that assume a linear relationship between time and spectral bands or indices [8]). Torres et al. [43] proposed the Half Recovery Time (HRT), a post-fire recovery indicator, using nonlinear model fitting of the post-fire NDVI anomalies to identify the number of days needed to reach a 50% level of recovery. Looking through a 5-year window, Frazier et al. [52] used different indicators based on predisturbance NBR to detect trends in post-fire spectral recovery; Wang and Zhang [53] calculated LSP trends from MODIS time series of about 1000 fires that occurred from 2002 to 2014 in the western USA. Vogelmann et al. [54] proposed the Image Trends from Regression

Table 1

Examples of spectral variables recently used for monitoring post-fire changes vegetation.

Index	Source	Applied or Adapted by	Expression
NDFI	Souza CM, Roberts DA, Cochrane MA: Combining spectral and spatial information to map canopy damage from selective logging and forest fires. *Remote Sensing of Environment* 2005, 98:329–343	Bullock et al. (2020) [40] To detect tropical forest canopy damage and degradation processes	$NDFI = \frac{GV_{\mathrm{Shade}} - (NPV + Soil)}{GV_{\mathrm{Shade}} + (NPV + Soil)}$ NPV = nonphotosynthetic vegetation GV = green vegetation $GV_{Shade} = \frac{GV}{1 - Shade}$
EVI	Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG: Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment* 2002, 83:195–213	Vo & Kinoshita (2020) [35] To assess the effects of post-fire treatment (wood and straw mulch) on vegetation	$EVI = \frac{\rho NIR - \rho Red}{\rho NIR + C1 \times \rho Red - C2 \times \rho Blue + 1}$
NDMI	Gao BC: NDWI - A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment* 1996, 58:257–266	Hamunyela et al. (2020) [55] To determine vegetation water content on regeneration monitoring of montane forests of Eastern Tanzania	$NDMI = \frac{NIR - SWIR}{NIR + SWIR}$
RI	[44]	White et al. (2017) [44] To measure spatial and temporal patterns in post-disturbance vegetation recovery (harvest and wildfire) in Canada's forested ecosystems)	$RI = \frac{\Delta NBRregrowth}{\Delta NBRdisturbance}$ $\Delta NBR_{\mathrm{regrowth}} = NBR_{\mathrm{postfire}}$- $NBR_{\text{year of the disturbance}}$ $\Delta NBR_{\mathrm{disturbance}} = NBR_{\mathrm{prefire}}$- $NBR_{\text{at the end of disturb.}}$
VRR	Lin WT, Chou WC, Lin CY, Huang PH, Tsai JS: Vegetation recovery monitoring and assessment at landslides caused by earthquake in Central Taiwan. *Forest Ecology and Management* 2005, 210:55–66	Adagbasa et al. (2020) [36] To validate vegetation response-ability models on grassland, integrating environmental factor and adaptive vegetation strategies	$NDVI = \frac{\rho NIR - \rho Red}{\rho NIR + \rho Red}$ $VRR = \frac{NDVI_2 - NDVI_1}{NDVI_0 + NDVI_1}$ $NDVI_0 = prefire$ $NDVI_1 = disturbance$ $NDVI_2 = postfire$
CRRI	[43]	Torres et al. (2018) [43] An integrative indicator to measure long-term recovery and to rank the main drivers in northern Portugal using high-temporal resolution satellites	$CRRI = \frac{1}{N}\sum_{i=1}^{N}\frac{\lvert NDVI_{post,i} - minNDVI_{fire}\rvert}{NDVI_{pre}}$
HRT	[43]	Torres et al. (2018) [43] To measure short-term recovery velocity using high-temporal resolution satellites	Number of days necessary to reach the 50% level of recovery from the minimum NDVI value observed

			during the year of fire to the pre-fire median.
RTI	[43]	Torres et al. (2018) [43] To capture temporal patterns of PVR process after the first phases of regrowth using high-temporal resolution satellites	The slope of the trend in the NDVI data for the post-fire period using the Theil–Sen estimator.
SATVI	[31]	Villarreal et al. (2016) [31] To characterize long-term recovery trajectories of desert grassland	$SATVI = \frac{\rho SWIR5 - \rho Red}{\rho SWIR5 + \rho Red + L}(1+L) - \frac{\rho SWIR7}{2}$
ARI	Gitelson AA, Merzlyak MN, Chivkunova OB: Optical Properties and Nondestructive Estimation of Anthocyanin Content in Plant Leaves. *Photochemistry and Photobiology* 2001, 74:38–45	Fernández-Guisuraga et al. (2019) [37] To assess quantitative variables of vegetation recovery (density seedlings and woody species cover) in fire-prone ecosystems using fine-grained satellite imagery	$ARI = B7\left[\left(\frac{1}{B3}\right) - \left(\frac{1}{B6}\right)\right]$
TCARI	Haboudane D, Miller JR, Pattey E, Zarco-Tejada PJ, Strachan IB: Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. *Remote Sensing of Environment* 2002, 90:337–352	Fernández-Guisuraga et al. (2019) [37] To assess variable quantifying vegetation recovery (density seedlings and woody species cover) in fire-prone ecosystems using fine-grained satellite imagery	$TCARI = 3\left[(B6 - B5) - 0.2(B6 - B3)\left(\frac{B6}{B5}\right)\right]$ *B3 = green (510–580 nm)* *B5 = red (630–690 nm)* *B6 = red edge (705–745 nm)*
BRR	Lin WT, Lin CY, Chou, WC: Assessment of vegetation recovery and soil erosion at landslides caused by a catastrophic earthquake: a case study in Central Taiwan. *Ecol. Eng.* 2006, 28: 79–89.	Chompuchan and Lin (2017) [33] To evaluate the forest recovery considering the concept of resilience and the magnitude of fire damage	$BRR = \frac{NBR_{ta} - NBR_{td}}{NBR_{to} + NBR_{td}}$ *to = prefire event* *td = time when delay mortality existed* *ta = time of assessment*
TCT-TCA	Powell SL, Cohen WB, Healey SP, Kennedy RE, Moisen GG, Pierce KB, Ohmann JL: Quantification of live aboveground forest biomass dynamics with Landsat time-series and field inventory data: A comparison of empirical modeling approaches. *Remote Sensing of Environment* 2010, 114:1053–1068	Viana-soto et al. (2020) [38] To characterize postfire trajectories in Mediterranean pine forests	$TCA = \tan^{-1}\frac{TCG}{TCB}$ *TCB = Tasseled Cap: Brightness* *TCG = Tasseled Cap: Greenness*
FRI2	Huang, C.; Goward, S·N.; Masek, J.G.; Thomas, N.; Zhu, Z.; Vogelmann, J.E. An automated approach for reconstructing recent forest disturbance history using dense Landsat time series stacks. *Remote Sens. Environ.* 2010, 114, 183–198	Morresi et al. (2019) [32] To track long-term forest regeneration and to monitor the development of tree canopy cover	$IFZ = \sqrt{\frac{1}{NB}\sum_{i=1}^{N}\frac{(b_i + \overline{b_i})}{SD_i}}$ $FRI2 = \frac{1}{(IFZ + 1)}$ b_i *= spectral value of the pixel in band*$_i$*,* $\overline{b_i}$ *and* SD_i*= mean and standard deviation obtained from forest samples* *NB = number of spectral bands*

ARI, Anthocyanin Reflectance Index; BRR, Burn Recovery Ratio; CRRI, Cumulative Relative Recovery Index; EVI, Enhanced Vegetation Index; FRI2, Forest Recovery Index 2; HRT, Half Recovery Time index; NDFI, Normalized Difference Fraction Index; NDMI, Normalized difference moisture (water) index; RI, Recovery Indicator at short-term; RTI, Recovery Trend Index; SATVI, Soil Adjusted Total Vegetation Index; TCARI, Transformed Chlorophyll Absorption Reflectance Index; TCT-TCA, Tasseled Cap Transformations–Tasseled Cap Angle; VRR, Vegetation Recovery Rate.

Analysis (ITRA), which is based on NDVI and SWIR/NIR index, to assess gradual changes; Chompuchan and Lin [33] identified time of recovery using a curve-fitting of forest recovery trajectories to the exponential decay function. Hamunyela et al. [55] used the STEF algorithm (Space-Time Extremes and Features) based on space-time features—such as magnitude of change, temporal linear trend in spatial variability (using NDWI as indicator)—to track forest disturbances and detected forest gains (i.e. regeneration) in Tanzania. Cunha et al. [56] applied the Time Series Segmentation and RESidual TREND method [57], implemented in the Breaks For Additive Seasonal and Trend method [58], to differentiate structural change (breakpoint) and trends happening over a longer period in seasonally tropical dry forests. Furthermore, nonparametric tests such as Mann—Kendall and the Theil—Sen slope estimator have also been widely used. For example, Morresi et al. [32] assessed the significance of the SVIs trends and calculated the rate of change and the direction of NDVI trends. Torres et al. [43] proposed the Recovery Trend Index, computed as the slope of the trend in the NDVI data for the post-fire period using the Theil—Sen estimator.

Alternatively, metrics based on digital classification processes applied to time series data have also been used. For example, Cardille and Fortin (2016) used Bayesian Updating of Land Cover, an algorithm designed to allow continuous updating of classifications using image collections, applied for tracking a fast-growing forest fire from Landsat-8 images [59,60]; Savage et al. [61] used Landsat imagery to predict species composition of vegetation growing from a disturbance ecology point of view, using the zero-inflated regression to map percent canopy cover by species and subcanopy species. However, despite the large number of algorithms and changes detection techniques, Heiley et al. [62] demonstrated that an ensemble of change detection algorithms could be more effective and accurate than maps from any single automated algorithm. In this sense, examples of other more complex algorithms from the literature on detecting and monitoring land disturbance using Landsat time series include COntinuous monitoring of Land Disturbance providing large-scale detection of land disturbance [63]; Vegetation Regeneration and Disturbance Estimates Through Time, a segmentation algorithm to track forest changes (patch-based approach) [64]; or Ecosystem Disturbance and Recovery Tracker, a highly automated system to detect disturbances such us wildfire burn, tree mortality or forest treatments, processing Landsat images time series [65].

Final remarks

A deep understanding of PVR is critical for elucidating ecosystem processes and for the elaboration of effective management strategies, especially in the context of global climate change. The most practical way to monitor changes over large areas and periods is through image-processing techniques based on change detection or classification techniques [40]. These approaches are especially fitting because wildfires, and the following vegetation recovery processes, substantially alter the land surface's spectral signature. Metrics and techniques to track vegetation changes and trends following fire using satellite time series provide information at different spatiotemporal and spectral resolutions. The last years have seen a proliferation of research efforts, published in various specialized journals; however, several key gaps concerning the use of RS for the analysis of PVR remain. From the literature review presented in this paper, the following key considerations have emerged:

1) According to Pickell et al. [2], along with the numerous studies in which post-fire recovery trends are analysed, it is necessary to highlight the importance of properly interpreting the use of spectral indicators with the recovery in ecological terms, taking into account data on the structure, composition and ecological functions of the colonizing plant communities. In this context, Bartels et al. [11] point out that there is a lack of clarity in the definition of the term 'recovery' and that a connection should be set up between spectral indicators and ecological understanding of forest recovery. For example, the classification of plant associations, combined with measures such as canopy cover, tree height or stand basal area, are fundamental for understanding the effects of fire on vegetation recovery and elaborating fitting conservation strategies [66]. In this sense, according to Szpakowski & Jensen [14], owing to the specific nature of the vegetation's spectral response and the different components of forest recovery, using a single method may not be the best option, requiring multiple methods to be deployed in each ecosystem. Moreover, ground-based validations are necessary, to determine how a recovery component is being displayed by the metrics.
2) The effects of temporal mismatch issues should be minimized; it is essential to secure adequate imaging data sets in relation to the fire occurrence date. Image date discrepancies may introduce more noise than algorithms or metrics [62], thereby hindering the establishment of consistent connections between ecological meaning and RS information. Each type of ecosystem has specific post-fire vegetation cover responses, requiring an adequate time scale approach that can strike a compromise between immediate and long-term fire effects. Moreover, several factors can hinder post-fire RS monitoring, such as phenology, topography, vegetation characteristics and the consistency of spectral responses. All these issues still

need to be carefully considered and addressed to generate a consistent PVR monitoring.

3) The use of RS to analyse vegetation recovery is expected to grow even further in application and prominence as new sensors become available (i.e. UAVs and new satellites) and bring enhanced spatial, spectral and temporal resolutions to the observations. In this sense, the great challenge lies in the development of methodologies that combine the potential of different sensors, with particular emphasis on studies that integrate data from active and passive sensors (e.g. integrating LIDAR with UAS imagery [14] or GEDI data with time-series optical imagery to enable historic analysis of forest height [67]). The availability of open high-capacity analysis software has enhanced the potential to access and analyse combined data sets (e.g. via Google Earth Engine, a cloud-based storage and processing platform [68]). Moreover, the growing expansion of sensors has to go hand-in-hand with the development of algorithms that can monitor changes through time irrespective of the characteristics of each platform [69].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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