Data in Brief 67 (2026) 112945

Contents lists available at ScienceDirect

Data in Brief

journal homepage: www.elsevier.com/locate/dib

Data Article

A multi-source remote sensing dataset for large-scale forest monitoring

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A R T I C L E I N F O

Article history:
Received 11 March 2026
Revised 3 June 2026
Accepted 5 June 2026
Available online 6 June 2026

Dataset link: Multi-source remote sensing data for forest monitoring (Original data)

Keywords:
Copernicus
Forest multifunctionality
Google earth engine
Landsat

A B S T R A C T

This data article presents a multi-source dataset of satellite-based auxiliary data designed for forest modelling and monitoring. The dataset integrates annual medoid composites derived from Sentinel-1, Sentinel-2, and Landsat imagery, together with spectral indices, Landsat-based 3I3D change metrics, forest mask and forest type layers, and terrain variables derived from the Copernicus GLO-30 DEM, offering comprehensive information on forest cover, spectral behavior, and change metrics. It provides harmonized predictors across seven European countries, ensuring consistency, scalability, and ease of use for researchers developing or validating models to understand forest dynamics and estimate forest-related variables such as biomass or canopy recovery. A curated subset of the dataset is distributed via Zenodo, along with direct public access links to the complete multi-terabyte archive.

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https://doi.org/10.1016/j.dib.2026.112945

The data support applications in forest biodiversity conservation, carbon monitoring, biomass modelling, and climate-change impact assessment.

Specifications Table

Subject	Earth & Environmental Sciences
Specific subject area	Remote sensing, Big Data analytics, and forestry applications for large-scale monitoring and assessment
Type of data	Remote sensing multiband images (GeoTiff format)
Data collection	Data were processed and exported from the Google Earth Engine (GEE) cloud platform using filtered Sentinel-1, Sentinel-2, Landsat, and Copernicus products, along with Landsat-based change metrics. Annual medoid composites were generated for Sentinel-2 (2017–2023) and Landsat (1984–2023), and annual Sentinel-1 radar composites were created for 2017–2024 (ascending/descending). Due to the archive's multi-terabyte size, the Zenodo repository hosts a curated subset of the dataset, including wall-to-wall coverage for selected products and years, representative tiles for large-volume layers, and direct public links to the complete country-level archives.
Data source location	Remote sensing data cover seven European countries (Norway, Sweden, Finland, Germany, the Czech Republic, Austria, Italy), providing continuous spatial coverage.
Data accessibility	Repository name: Zenodo Data identification number: https://doi.org/10.5281/zenodo.17242538 Direct URL to data: https://zenodo.org/records/20444955 Instructions for access: The Zenodo repository hosts a curated subset of the full dataset. It includes wall-to-wall Landsat medoid composites for the reference year 2023 for all countries, Landsat-derived spectral change metrics, and static auxiliary layers (forest mask and forest type) for all countries. Sentinel-2 medoid composites include multitemporal examples for Austria (2017, 2020, 2023), full national coverage for 2023 for Germany, Italy, and Czech Republic, and spatially representative tiles for Finland, Sweden, and Norway (2023). Sentinel-1 SAR data are provided as representative tiles (ascending and descending) for each country for 2024, plus multitemporal tiles for Austria (2017, 2020, 2024). Terrain variables (DEM, slope, aspect) are provided as representative samples. A supplementary document containing direct public access links to the complete archives, providing unrestricted access to all years, countries, and data products described in this article.
Related research article	[1] Schumacher, J., Cescatti, A., Chirici, G., D'Amico, G., Francini, S., Hertzler, J., Mehtätalo, L., Nabuurs, G.J., Nilsson, M., Pitkanen, J., Breidenbach, J. (under review). Federated Learning in Forest Resource Modelling and Monitoring: Bridging Data Confidentiality and Collaborative Research. *JAG - International Journal of Applied Earth Observation and Geoinformation.*

1. Value of the Data

- These data provide harmonized annual optical composites from Landsat (5, 7, 8, and 9) and Sentinel-2, along with Sentinel-1 radar layers. The data are distributed as analysis-ready raster layers, enabling researchers to inspect derived predictors and incorporate them into workflows for assessing forest structure, condition, and ecosystem services.
- The dataset supports large-scale forest monitoring by offering consistent predictors suitable for photointerpretation, automated classification, spectral feature extraction, and change detection. The combination of optical, radar, photosynthetic activity change metrics, and thematic variables enables users to test and develop analytical approaches across ecological and management contexts.

- The dataset is consistent across seven European countries, and it allows for cross-border and cross-scale comparisons of forest conditions using a standardized set of variables. This supports common forest monitoring efforts and applications – such as those related to federated learning – and facilitates European and international assessment frameworks.
- Researchers can reuse this data to develop, calibrate, and validate predictive models for biomass estimation, disturbance detection, and post-disturbance recovery analysis. The multi-source composition provides representative input variables for machine learning, spatial modeling, and time-series analyses.
- Combining multitemporal examples with long-term Landsat-based change metrics facilitates the study of forest dynamics and historical change processes. These data can be integrated with field observations, forest inventories, or other geospatial datasets to evaluate modeling approaches and methodological workflows.

2. Background

The dataset was created to address the growing need for consistent and accessible remote sensing predictors to support large-scale forest monitoring across multiple European countries [2]. Although extensive satellite data from Landsat and the Copernicus Sentinel missions are freely available, their operational use often requires substantial preprocessing, including cloud and shadow masking, radiometric harmonization, and temporal aggregation [3,4]. These steps can pose technical barriers for researchers or institutions with limited experience in processing large volumes of satellite data.

The work builds on well-established methodological advances in remote sensing, particularly pixel-based compositing and multi-sensor time series analysis. These methods provide a robust basis for generating spatially and temporally consistent representations of forest conditions using optical and radar data. Their implementation within the Google Earth Engine (GEE) cloud platform enabled the integration of diverse datasets (Sentinel-1, Sentinel-2, Landsat, and Copernicus land products) and the systematic generation of standardized annual composites and spectral change metrics over extended time periods [5].

The dataset was developed to provide a standardized collection of ready-to-use geospatial variables to support modelling, monitoring, and further methodological development [6]. By compiling these predictors into a unified structure, the data provide a common reference framework for a wide range of forest-related analyses.

3. Data Description

The dataset presented here offers comprehensive nationwide information for seven European countries: Austria, Czech Republic, Finland, Germany, Italy, Norway, and Sweden. It includes long-term time series of Landsat optical data from 1984 to 2023, recent high-resolution data from the Sentinel-1/2 missions covering 2017 to 2024, and static layers related to topographic and forest-type variables. The Zenodo repository hosts a curated subset of the dataset, including reference-year wall-to-wall products and representative samples of large-volume layers. A supplementary document included in the record provides direct public access links to the complete country-level archives.

All layers were delivered in GeoTIFF format, ensuring compatibility with standard GIS software and platforms. The dataset uses the European Terrestrial Reference System 1989 (ETRS89) and the Lambert Azimuthal Equal Area (LAEA) projection (EPSG: 3035). The repository is organized into country-level folders, each containing subfolders corresponding to the available data types. Annual products include the corresponding year in their filenames; spatial tiles are used for countries where complete mosaics exceed the file size limit.

The available layers comprise: Forest mask (binary raster);

– Topographic variables, DEM (elevation, slope, aspect);
– Forest type classification (broadleaved, coniferous, mixed);
– Annual multispectral medoid composites from Sentinel-2, including reflectance bands and spectral indices;
– Annual radar composites from Sentinel-1, from ascending and descending orbits;
– Annual multispectral medoid composites from Landsat, including reflectance bands and spectral indices;
– Landsat spectral change and recovery 3I3D metrics [7].

Table 1 provides a complete summary of the dataset layers, including their spatial resolution, temporal extent, and source data.

4. Materials and Methods

The first step in managing large volumes of remote sensing data is generating composite images. Considering the multispectral satellite data (i.e., Landsat and Sentinel-2), composite images are multi-band representations created by combining multiple satellite scenes over time. Pixel computing algorithms aim to reduce noise, fill data gaps, and improve the interpretability of land surface features. The resulting composites are typically generated using temporal aggregation techniques, median reflectance, or cloud-free mosaicking to ensure spatial and spectral consistency, as demonstrated by global composite products based on Sentinel-2 and multi-sensor data [8,9]. Among various methods for creating composite images through remote sensing, the medoid composite method selects the observed pixel that is most spectrally representative among all valid observations for a specific period and has emerged as the preferred method for Sentinel-2 data [5]. The Medoid compositing approach is scalable, portable to different satellite missions and datasets, and – crucially - maintains the physical consistency of reflectance values without introducing temporal blending [3,10].

For the Sentinel-1 radar data, annual backscatter composites were created by averaging observations within a consistent seasonal window. After applying a speckle filter [10], we calculated the per-pixel median of VV (vertical transmit and vertical receive), and VH (vertical transmit and horizontal receive) backscatter values from mid-summer (e.g., July–August) for each year, separately for ascending and descending orbits.

In addition to satellite data, the dataset includes spectral change metrics derived from analyses of Landsat multitemporal photosynthetic activity indices. Time series analysis has become a cornerstone in forest monitoring, enabling the identification of both abrupt and gradual changes in forest cover using dense satellite image archives [11]. In this study, annual medoid composites are combined with 3I3D to extract reliable spectral change metrics from Landsat time series [7]. These predictors are suitable for developing and validating models related to forest dynamics, such as biomass estimation or canopy recovery analysis [3,12].

In forest remote sensing, spectral vegetation indices are commonly used to assess ecosystem condition, monitor dynamics, and identify spectral changes [7,13]. The most frequently used is the Normalized Difference Vegetation Index (NDVI), which measures vegetation "greenness" and correlates with chlorophyll content and photosynthetic activity. The Normalized Difference Moisture Index (NDMI), derived from near-infrared and shortwave-infrared bands, detects vegetation water content and effectively monitors drought stress and canopy moisture dynamics. Among these indices, the Normalized Burn Ratio (NBR) is especially useful for identifying changes caused by wildfires, logging, and storms, due to its sensitivity to both vegetation and soil conditions. NBR is widely used in photosynthetic decrease evaluations and as an indicator of vegetation recovery following spectral change [4]. Beyond these specific indices, we also utilize the Tasselled Cap Transformation components Brightness, Greenness, and Wetness, which offer combined measures of soil reflectance, plant vigour, and surface moisture, respectively [13].

Table 1
Dataset predictors summary.

Data Layer	Source	Complete Temporal Coverage	Spatial Resolution	Description	Bands/Values
Forest Mask	ESA WorldCover 2020 & 2021, Copernicus FT 2018	2020–2021	10 m	Binary mask based on ESA and Copernicus Forests products	Forest No_forest
DEM (elevation, slope, aspect)	Copernicus GLO-30 DEM	Static	30 m	Topographic variables derived from elevation model; consistent GEE integration	DEM Slope Aspect
Copernicus Forest Type	Copernicus FT 2018	2018	10 m	Forest type classification	Non_forest Broadleaved_forest Coniferus_forest
Sentinel-2 Medoid	Sentinel-2 Level-2A MSI	2017–2023	10 m	Annual medoid composite June-October	MSI NDMI NDVI EVI NBR TCB TCG TCW red green blue nir swir2
Sentinel-1 Ascending	Sentinel-1 SAR GRD	2017–2024	10 m	Annual VV/VH composites from ascending orbits	VV VH
Sentinel-1 Descending	Sentinel-1 SAR GRD	2017–2024	10 m	Annual VV/VH composites from descending orbits	VV VH

(*continued on next page*)

Table 1 (*continued*)

Data Layer	Source	Complete Temporal Coverage	Spatial Resolution	Description	Bands/Values
Landsat Medoid	Landsat 5, 7, 8, 9	1984–2023	30 m	Annual medoid composite	blue green red nir swir1 swir2 NDVI EVI NBR NDWI NDBI EMVI TCB TCG TCW TCA
Spectral Change & Recovery Metrics	Derived from Landsat Medoid	1984–2023	30 m	Metrics from 3I3D algorithm	Modul_a p_theta_a p_phi_a Modul_b p_theta_b p_phi_b nbr nbr_pre nbr_recovered mode_year mode_change mode_yearOfRecovery rs_year

These indices are integrated into our annual Landsat and Sentinel-2 composites to leverage their complementary strengths: NDVI and NDMI for assessing vegetation health and water status, NBR for detecting and quantifying photosynthetic fluctuation and the Tasselled Cap components for capturing structural and hydrological forest properties. Their combined use enhances our capacity to monitor forest conditions and change across diverse ecological gradients.

4.1. Forest mask. A harmonized 10 m forest mask integrating multiple sources to maximize forest pixel detection

A binary forest cover mask at 10 m resolution was created by combining the ESA WorldCover land cover maps for 2020 and 2021 [14] with the Copernicus European Forest Type map (2018) [15]. Areas classified as forests ('tree cover') in either the ESA WorldCover 2020 or 2021 datasets were combined with forested areas from the 2018 forest type layer using a logical OR operation. This inclusive approach prioritizes omission error reduction, ensuring subsequent analyses focus on forested pixels, but may introduce commission errors where permanent forest loss occurred between reference dataset acquisition dates.

4.2. Terrain (digital elevation model - DEM) data. Elevation, slope, and aspect derived from GLO-30 multiresolution and projection DEM

Topographic variables from the Copernicus Global Digital Elevation Model at 30 m resolution (GLO-30) [16] were used to derive elevation (meters above sea level), slope (degrees), and aspect (degrees) for each location.

Terrain attributes influence microclimate, soil properties, and forest growth, and are widely used for modelling forest dynamics and susceptibility to change metrics (e.g., steeper slopes may increase erosion risk or windthrow incidence). Topographic variables were derived from the Copernicus Global Digital Elevation Model (GLO-30), which is based on the WorldDEM product generated from TanDEM-X radar data. A key characteristic of the GLO-30 dataset is that it is distributed as multiple tiles with differing native projections and spatial resolutions. As a result, direct mosaicking without harmonization may lead to inconsistencies in slope and aspect calculations across regions. To ensure spatial comparability and analytical consistency across countries, all GLO-30 tiles were harmonized by reprojecting to a common reference system (ETRS89/LAEA, EPSG:3035) and standardized to a consistent 30 m spatial resolution prior to mosaicking. Geometry-based clipping and controlled resampling procedures were applied to preserve elevation integrity while ensuring seamless coverage. In addition to providing consistent terrain predictors (elevation, slope, and aspect), the GLO-30 DEM was also used as the reference surface for terrain correction during Sentinel-1 preprocessing. By integrating a projection-consistent, resolution-standardized DEM directly into the dataset, the need for additional end-user preprocessing is eliminated, ensuring reproducibility and cross-country comparability.

4.3. Forest type classification. broadleaved, coniferous, and non-forest categories from copernicus forest type map

The Copernicus Pan-European Forest Type map (2018) offers a 10 m resolution categorical classification of forests into broadleaf (deciduous) or coniferous types and identifies non-forest areas. This layer distinguishes between broadleaved and coniferous forests to support analyses of the effects of spectral change across various forest types. To focus on natural and semi-natural forests, agricultural plantations and urban trees were excluded from the Copernicus data. It is also important to note that in some regions marked as forest by the mask, the 2018 forest type classification might be missing due to its static year and exclusion criteria.

4.4. Sentinel-2 annual medoid composite. Medoid-based reflectance and spectral index composites from 2017 to 2023

For each year from 2017 to 2023, an annual optical composite at a 10 m resolution was created from Sentinel-2 MultiSpectral Instrument (MSI) Level-2A imagery. All available images from June 1 to October 31 of each year were used to capture the growing season and reduce snow or bare ground conditions in temperate forests.

Only images with a cloud cover of 70% or less were included. From the remaining observations, a per-pixel medoid composite was calculated. The medoid is defined as the single observation (among the time series for that year) whose multi-band reflectance vector is most centrally located (minimum sum of distances) relative to all observations in spectral feature space [5]. This produces a representative pixel value that is less affected by outliers or residual clouds compared to a mean or median composite. Each yearly Sentinel-2 composite includes 16 bands. Five of these are spectral bands (the four visible/NIR bands at 10 m resolution – Blue, Green, Red, Near-Infrared – plus the SWIR2 band resampled to 10 m). Eight bands are spectral indices calculated from the source bands, such as the Normalized Difference Vegetation Index (NDVI), NBR, Normalized Difference Moisture Index (NDMI), Enhanced Vegetation Index (EVI) (Fig. 1), and other vegetation metrics (specific indices follow the definitions in [7]). The remaining three bands are quality and provenance metrics: (i) the Euclidean Distance (ED) of the selected medoid pixel to the mean of all observations (a smaller ED indicates the chosen pixel is very typical of that year's observations), (ii) the number of images n used in the composite at that pixel, and (iii) the day-of-year (DOY) of the selected observation. All bands were scaled to the 0–255 (8-bit) range for storage efficiency.

4.5. Sentinel-1 SAR composite (Ascending and descending). backscatter-based radar metrics for forest structure and moisture from 2017 to 2024

Annual radar backscatter composites at a 10 m resolution were generated from Sentinel-1 C-band Synthetic Aperture Radar (SAR) Ground Range Detected (GRD) data. Sentinel-1 offers dual-polarization data (VV and VH), which are sensitive to forest structure and moisture [17]. For each year from 2017 to 2024, we processed all Sentinel-1 observations within a mid-summer window (July 1 to August 31) to minimize phenological variation and avoid seasonal extremes. A standard de-speckling filter (11 $\times$ 11 kernel) was applied to reduce SAR speckle noise. We then calculated a per-pixel median of the backscatter values over the summer period to produce a stable representation of forest conditions. Additionally, to minimize terrain-induced radiometric distortion, an angular-based slope correction was applied using DEM-derived incidence angles, following the approach proposed by Vollrath et al. [18]. This method produces stable annual radar metrics that complement the optical composites with structural and moisture-related information. Two separate composites were created each year: one using ascending orbit passes and another using descending orbit passes, as the look direction can influence backscatter. Each composite image includes two bands (VV and VH), each stored in decibel. These SAR layers complement optical data by providing information on forest biomass and structure, even under cloudy conditions.

4.6. Landsat annual medoid composite. consistent long-term optical composites for multi-decadal forest monitoring

Annual composites from the Landsat archive were created for each year from 1984 to 2023 at 30 m resolution, providing valuable data to monitor forests over an extensive historical period. We used surface reflectance data from Landsat 5 TM, Landsat 7 ETM+, Landsat 8 OLI/TIRS, and Landsat 9 OLI-2 sensors. For each year, images from May 1 to September 1 were selected,

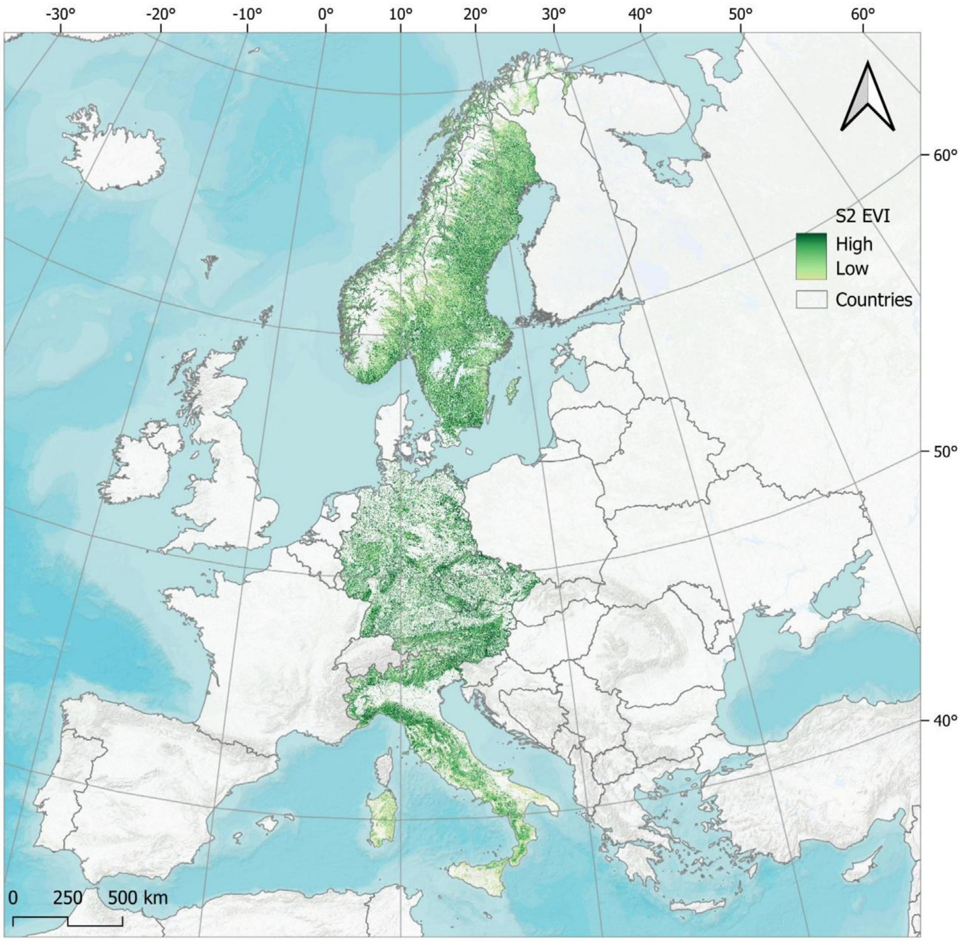

Fig. 1. Enhanced vegetation indices from the 2023 Sentinel-2 medoid composite for the study countries.

covering the main growing season in many regions while maximizing observations. A cloud cover threshold of 70% per scene was applied to exclude overly cloudy images. In line with the Sentinel-2 process, we employed a medoid compositing approach to select a representative annual observation for each pixel, with additional temporal gap filling. Specifically, to handle years with sparse, clear observations or anomalies, we applied de-spiking (removal of obvious outliers) and linear interpolation (infill) using neighbouring years when needed. This method, inspired by prior studies [10], results in a consistent annual time series with minimal missing data. Each Landsat composite includes 17 bands: six core reflective bands (Blue, Green, Red, Near-IR, Shortwave-IR1, Shortwave-IR2), six spectral indices (e.g., NDVI, NBR, NDMI, etc., similar to those used in Sentinel-2 composites) [13], four Tasselled Cap components (Brightness, Greenness, Wetness, and an additional 'angle' component) computed from reflectance bands, and one band indicating the number of valid observations (nValidObs) used for medoid selection per pixel. These Landsat composites provide a long-term record to analyse changes in forest cover and condition over nearly four decades (Fig. 2).

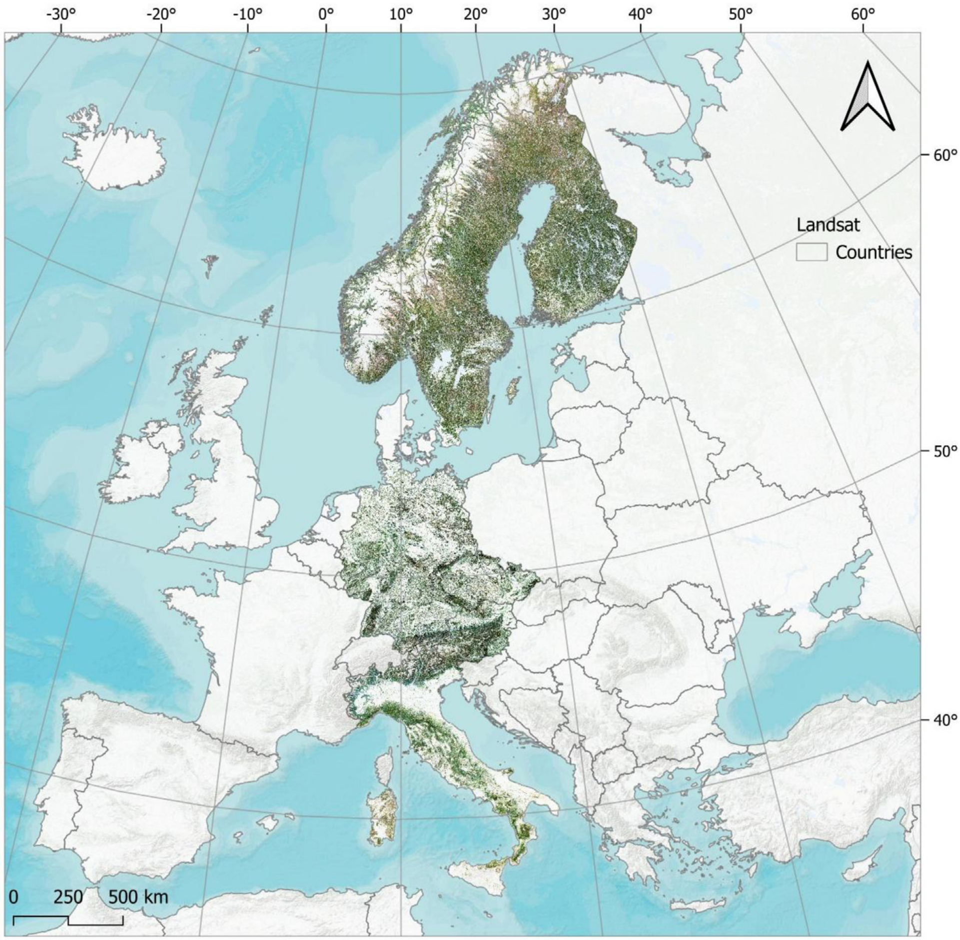

Fig. 2. RGB images for the 2023 Landsat medoid composites over the study countries.

4.7. Photosynthetic fluctuation metrics. 3I3D-derived indicators of photosynthetic increase and decrease magnitude, timing, and regrowth

The dataset includes a layer that captures the timing and magnitude of the most recent change per pixel, derived from time-series analysis of the Landsat medoid composites. The Three Indices Three Dimensions (3I3D) [7] change detection algorithm is applied to the annual Landsat composites, identifying significant spectral change. The 3I3D algorithm works by analysing trajectories of spectral indices in three dimensions over time to detect sudden drops that indicate photosynthetic decrease. To increase sensitivity to real forest changes and reduce noise, the analysis was conducted on a subset of Landsat data focusing on peak summer (July–August) medoid composites, which minimizes phenological variation. A minimum mapping unit of five Landsat pixels (0.45 ha) was applied to reduce noise and remove spectral changes smaller than this threshold. The algorithm produced annual spectral change maps, from which we extracted the year of the most recent photometric fluctuation and related metrics for each pixel. These disturbance metrics include: (1) Year – the year when the latest spectral change occurred; (2) Magnitude – a measure of the spectral change (e.g., the NBR drop) associated with that fluctuation; (3) Pre-Disturbance NBR – the NBR value before change; (4) photosynthetic increase NBR – the immediate NBR value after fluctuation; (5) Year of recovery – the year when the NBR recovered to at least 80% of its initial level; and (6) Recovered NBR – the NBR value in the recovery year when it reached the 80% threshold. The 80% recovery threshold of pre-change NBR is based on studies indicating this level of spectral recovery reflects significant canopy regrowth [4]. If a pixel has not yet recovered to the 80% level, the recovery year remains undefined. Together, these metrics allow users to understand not only when and where spectral changes happened, but also their severity and how quickly the forest recovered (if at all). All metrics were compiled into a single multi-band image that represents the most recent variation at each pixel.

Limitations

While the dataset provides harmonized, multi-source remote sensing predictors, several limitations must be considered when applying it to forest monitoring. First, its spatial resolution (10 m for Sentinel-1 and Sentinel-2; 30 m for Landsat) constrains the detection of fine-scale forest dynamics, such as small canopy gaps or sub-stand features below approximately 0.5 ha [19]. Single-pixel values may be affected by residual noise, geolocation differences, and local spectral variability; therefore, analyses are more reliable when conducted at aggregated spatial scales, such as stands or management units, particularly for change metrics [3].

The dataset uses annual temporal compositing, which is suitable for identifying abrupt disturbances, including clearcuts, storms, or wildfires [12], but may be insufficient for detecting gradual processes such as drought-induced decline, slow pest outbreaks, or subtle structural degradation. These phenomena typically require higher temporal frequency or specialized time-series algorithms [20].

Spectral change metrics included in the dataset represent only one dimension of forest dynamics and do not capture all ecological processes. Users should also consider uncertainties arising from sensor differences, compositing strategies, and the effects of persistent cloud cover on optical time series [1].

Ethics Statement

The authors have read and follow the ethical requirements for publication in Data in Brief and confirm that the current work does not involve human subjects, animal experiments, or any data collected from social media platforms.

CRediT Author Statement

Giovanni D'Amico: Data curation, Investigation, Original draft preparation, Writing- Reviewing and Editing; **Davide Botticelli:** Original draft preparation, Writing- Reviewing and Editing; **Giacomo Marcelli:** Original draft preparation, Writing- Reviewing and Editing; **Elia Vangi**: Investigation, Writing - Review & Editing; **Walter Mattioli:** Methodology, Writing - Review & Editing; **Gherardo Chirici:** Methodology, Writing - Review & Editing; **Costanza Borghi**: Investigation, Writing - Review & Editing; **Piermaria Corona:** Writing - Review & Editing; **Johannes Schumacher:** Data curation, Investigation, Writing- Reviewing and Editing; **Johannes Breidenbach:** Writing- Reviewing and Editing; **Yang Su:** Investigation, Writing- Reviewing and Editing; **Lauri Mehtätalo**: Writing- Reviewing and Editing; **Saverio Francini:** Conceptualization, Data curation, Investigation, Software, Supervision, Original draft preparation, Writing- Reviewing and Editing.

Data Availability

Multi-source remote sensing data for forest monitoring (Original data) (Zenodo)

Acknowledgements

This study was partially supported via the following projects: 1. MONIFUN. H2020 project funded by the European Commission, number 101134991 call HORIZON-CL6-2023-CircBio-01-14. 2. FORWARDS "The ForestWard Observatory to Secure Resilience of European Forests", HORIZON project funded by the European Commission, number 101084481 call HORIZON-CL6-2022-CLIMATE-01. 3. NextGenCarbon. H2020 project funded by the European Commission, number 101184989 call HORIZON-CL5-2024-D1-01-07.

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.

References

[1] J, Schumacher, A, Cescatti, G, Chirici, G, D'Amico, S, Francini, J, Hertzler, L, Mehtätalo, GJ, Nabuurs, M, Nilsson, J, Pitkanen, J, Breidenbach (under review). Federated learning in forest resource modelling and monitoring: bridging data confidentiality and collaborative research. JAG - Int. J. Appl. Earth Obs. Geoinf.
[2] N.C. Coops, P. Tompalski, T.R. Goodbody, A. Achim, C. Mulverhill, Framework for near real-time forest inventory using multi source remote sensing data, Forestry 96 (1) (2023) 1–19, doi:10.1093/forestry/cpac015.
[3] S. Francini, C. Borghi, G. D'Amico, L.T. Waser, M. Lisiewicz, K. Stereńczak, … G. Chirici, Bridging spatio-temporal gaps in ALS data using Landsat time series and forest disturbance-recovery metrics via multi-task neural networks, Sci. Remote Sens. (2025) 100318, doi:10.1016/j.srs.2025.100318.
[4] J.C. White, M.A. Wulder, T. Hermosilla, N.C. Coops, D.K. Bolton, Regional detection, characterization, and attribution of annual forest change from 1984 to 2012 using Landsat-derived time series metrics, Remote Sens Env. 194 (2017) 320–334, doi:10.1016/j.rse.2017.03.029.
[5] S. Francini, T. Hermosilla, N.C. Coops, M.A. Wulder, J.C. White, G. Chirici, An assessment approach for pixel-based image composites, ISPRS. J. Photogramm. Remote Sens. 202 (2023) 1–12, doi:10.1016/j.isprsjprs.2023.06.002.
[6] P. Corona, Integrating artificial intelligence to support systemic advances in silviculture, Ann. Silvic. Res. 50 (2) (2025) 32–35, doi:10.12899/asr-2681.
[7] S. Francini, R.E. McRoberts, F. Giannetti, M. Marchetti, G. Scarascia Mugnozza, G. Chirici, The three Indices three Dimensions (3I3D) algorithm: a new method for forest disturbance mapping and area estimation based on optical remotely sensed imagery, Int. J. Remote Sens. 42 (12) (2021) 4693–4711, doi:10.1080/01431161.2021.1899334.
[8] C. Corbane, et al., A global cloud-free pixel-based image composite from Sentinel-2 data, Data Br. 31 (2020) 105737, doi:10.1016/j.dib.2020.105737.
[9] S. Chen, et al., Global 30 m seamless data cube (2000–2022) of land surface reflectance generated from Landsat 5, 7, 8, and 9 and MODIS Terra constellations, Earth. Syst. Sci. Data 16 (2024) 5449–5475, doi:10.5194/essd-16-5449-2024.
[10] R.E. Kennedy, Z. Yang, N. Gorelick, J. Braaten, L. Cavalcante, W.B. Cohen, S. Healey, Implementation of the LandTrendr algorithm on, Google Earth Engine, Remote Sens. 10 (5) (2018) 691, doi:10.3390/rs10050691.
[11] T. Hermosilla, M.A. Wulder, J.C. White, N.C. Coops, G.W. Hobart, Towards a polyalgorithm for land use change detection, ISPRS. J. Photogramm. Remote Sens. 147 (2018) 132–143, doi:10.1016/j.isprsjprs.2018.01.010.
[12] S. Francini, R.E. McRoberts, G. D'Amico, N.C. Coops, T. Hermosilla, J.C. White, … G. Chirici, An open science and open data approach for the statistically robust estimation of forest disturbance areas, Int. J. Appl. Earth. Obs. Geoinf. 106 (2022) 102663, doi:10.1016/j.jag.2021.102663.
[13] F. Parisi, E. Vangi, S. Francini, G. D'Amico, G. Chirici, M. Marchetti, … R. Tognetti, Sentinel-2 time series analysis for monitoring multi-taxon biodiversity in mountain beech forests, Front. For. Glob. Chang. 6 (2023) 1020477, doi:10.3389/ffgc.2023.1020477.
[14] D. Zanaga, R. Van De Kerchove, D. Daems, W. De Keersmaecker, C. Brockmann, G. Kirches, J. Wevers, O. Cartus, M. Santoro, S. Fritz, M. Lesiv, M. Herold, N.E. Tsendbazar, P. Xu, F. Ramoino, O. Arino, ESA WorldCover 10 m 2021 v200 [Data set], Zenodo (2022), doi:10.5281/zenodo.7254221.
[15] European Environment Agency, High resolution layer forest type 2018 (raster 10 m), Europe, 3-yearly, Copernic. Land Monit. Serv. (2020), doi:10.2909/59b0620c-7bb4-4c82-b3ce-f16715573137.

[16] European Space Agency. (2021). Copernicus global digital elevation model (GLO-30). https://doi.org/10.5270/ESA-c5d3d65
[17] A. Mullissa, A. Vollrath, C. Odongo-Braun, B. Slagter, J. Balling, Y. Gou, … J. Reiche, Sentinel-1 sar backscatter analysis ready data preparation in google earth engine, Remote Sens. 13 (10) (2021) 1954, doi:10.3390/rs13101954.
[18] A. Vollrath, A. Mullissa, J. Reiche, Angular-based radiometric slope correction for Sentinel-1 on Google Earth Engine, Remote Sens. 12 (11) (2020) 1867.
[19] F.E. Fassnacht, J.C. White, M.A. Wulder, E. Næsset, Remote sensing in forestry: current challenges, considerations and directions, Int. J. For. Res. 97 (1) (2024) 11–37, doi:10.1093/forestry/cpad024.
[20] R. Seidl, C. Senf, Changes in planned and unplanned canopy openings are linked in Europe's forests, Nat. Commun. 15 (1) (2024) 4741, doi:10.1038/s41467-024-49116-0.