ForestPaths

Co-designing holistic forest-based policy pathways for climate change mitigation

D2.1 Next generation European forest disturbance map

29/09/2023

Author(s): Alba Viana-Soto & Cornelius Senf

Funded by the European Union

This project receives funding from the European Union's Horizon Europe Research and Innovation Programme (ID No 101056755), as well as from the United Kingdom Research and Innovation Council (UKRI). Views and opinions expressed are those of the author(s) only and do not necessarily reflect those of the European Union or the European Commission. Neither the EU nor the EC can be held responsible for them.

Prepared under contract from the European Commission and the United Kingdom Research and Innovation Council.
Grant agreement No. 101056755
EU Horizon Europe Research and Innovation Action

Project acronym:	**ForestPaths**
Project full title:	**Co-designing Holistic Forest-based Policy Pathways for Climate Change Mitigation**
Project duration:	01.09.2022 – 28.02.2027 (54 months)
Project coordinator:	Dr. Hans Verkerk, European Forest Institute (EFI)
Call:	HORIZON-CL5-2021-D1-01
Deliverable title:	Next generation European forest disturbance map
Deliverable n°:	D2.1
WP responsible:	WP2
Nature of the deliverable:	Data
Dissemination level:	Public
Lead partner:	TUM
Recommended citation:	Viana-Soto, Alba & Senf, Cornelius (2023). ***Next generation European forest disturbance map***. ForestPaths project deliverable D2.1.
Due date of deliverable:	Month 12
Actual submission date:	29.9.2023

Deliverable status:

Version	**Status**	**Date**	**Author(s)**
1.0	Draft	15 September 2023	Alba Viana-Soto & Cornelius Senf, TUM
	Review	19 Sep 2023	Mikko Peltoniemi, Luke & Hans Verkerk, EFI
2.0	Final	29 Sep 2023	Alba Viana-Soto & Cornelius Senf, TUM

Table of contents

Key takeaway messages

- Up-to-date forest disturbance maps depicting the timing, number and agent of disturbances at a spatial resolution of 30 m from 1985 onwards.
- Maps distributed through a fully accessible web-mapping application.
- Significantly reduced omission errors compared to previous maps.
- Multiple disturbance events detected per pixel, improving the representation of fire disturbance regimes and plantation forests.
- Causal agents of disturbance attributed at the agent level for all disturbances mapped.

Summary

This document presents the Next Generation European Forest Disturbance Map (version 2.0.0.). The map product includes a set of layers characterizing forest disturbances from 1985 onwards, including the year of the greatest and latest disturbance, the number of disturbances and the predominant agent. The document includes a summary of the data and methods and technical details on the map layers.

1 Introduction

Forest canopy disturbances are climate and land use change related risks to Europe's forests and have strong impacts on forest carbon pools through determining forest structure and composition for decades. Forest canopy disturbances can be related to natural causes, such as caused by bark beetle, fire or windthrow, but they can be also caused by e.g., timber harvest. Both natural and human disturbances have increased in the past three decades and are expected to increase further in response to climate and land use change (Senf et al. 2021). Consistent information on forest disturbances is therefore essential to understanding changes in forest dynamics, structure and demography over time and space, as well as to calibrate and validate models simulating future forest development and forest climate change mitigation potential.

Satellite data allow for a seamless monitoring of forest disturbances and developments in recent years have produced annual wall-to-wall European forest disturbance maps (Senf & Seidl 2021, Hansen et al. 2013). That said, existing products have important shortcomings, including relatively high omission errors (i.e., not detecting disturbances that are present in reality), no possibility to detect multiple disturbances per pixel time series (i.e., omitting disturbances in short-rotation plantation systems and areas prone to reburns), and insufficient attribution of disturbance events to causal agents.

The next generation European forest disturbance map presented in this deliverable aims at filling those shortcomings by developing a new approach for mapping forest disturbances from spaceborne satellite data. The data product is the longest time series of spatially explicit information on disturbances in Europe and is designed for operational use such as annual updates. In the following, we will briefly summarize the salient methodological details behind the data product and outline the individual layers produced. A full report of the final map product with best-practice examples on how to use it will be made available in Deliverable 2.5.

2 Summary of the underlying data & methods

The data basis for the next generation European forest disturbance map is the Landsat archive, which is the longest running civilian satellite archive extending back to 1972. We downloaded all available Landsat 4/5/7/8 data covering Europe, having cloud cover <50%, and representing approximately summer growing season conditions (here defined as the period from 1st June to 30th September representing the period around maximum vegetation greenness). The Landsat data was processed using the Framework for Operational Radiometric Correction for Environmental Monitoring (FORCE version 3.6.5, Frantz, 2019). FORCE is an all-in-one software that enables to efficiently process large datasets by organizing data in regular, non-overlapping tiles and applying atmospheric and topographic corrections and cloud masking. A total of 106,429 images (50 TBs; Figure 1) were processed to obtain a so-called ***European Data Cube*** consisting of harmonized, standardized, geometrically and radiometrically consistent surface reflectance images organised in a regular grid of 150 x 150 km tiles. The number of images available per tile varies from a minimum of 49 to a maximum of 663 (152 on average). For detailed information on processing steps about atmospheric and topographic correction, adjacency effect and bidirectional reflectance distribution function corrections, as well as cloud and cloud shadow see the FORCE documentation (https://force-eo.readthedocs.io/en/latest/index.html). The workflow was implemented on an internal server infrastructure and is independent of cloud providers, allowing for operational use. The whole processing of the 106,429 images took approximately three months.

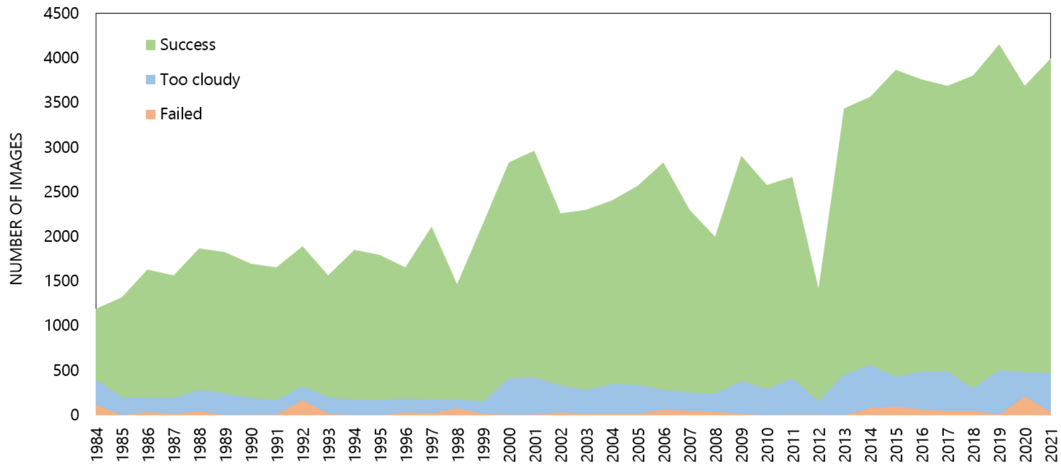

Figure 1: Image processing statistics for building the European Data Cube of Landsat data.

The surface reflectance images were temporally aggregated to obtain annual, seamless and gap free composites representing summer conditions. This was done, because individual images might contain gaps due to clouds or other artefacts masks during the initial processing. The aggregation was performed using a parametric weighting scheme described in Griffiths et al. (2013). For each year, the “best” observation from all available observations is selected per pixel based on a set of weighting functions, which rank each observation based on the temporal proximity to a target date (the 1st of August in our case), the distance to clouds or cloud shadows, as well as atmospheric opacity. The resulting product is called best available pixel composite (BAP; see Figure 2) and recent research has shown their superiority in detecting disturbances compared to other temporal aggregation methods (Francini et al. 2023). As there were still remaining gaps in the BAPs (i.e., areas where no high-quality observation could be found during the summer season, 1.45% of the total area on average), we applied a linear gap-filling algorithm extrapolating the previous year’s spectral value to all missing observations remaining in the BAPs.

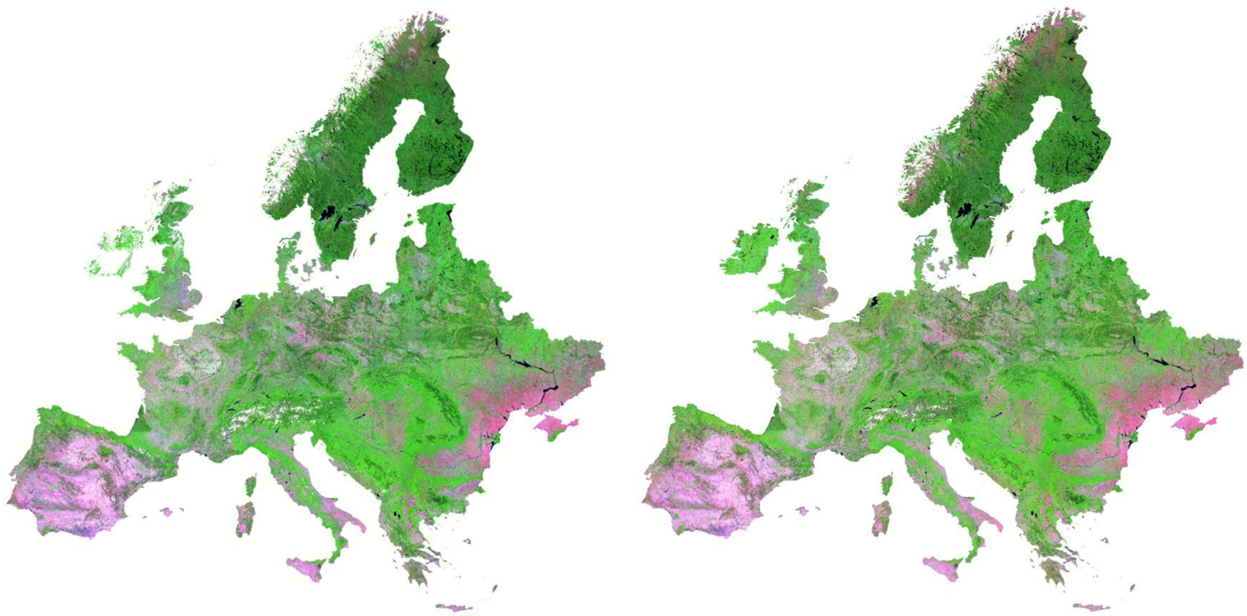

Figure 2: Best Available Pixel composite Europe 2020 (RGB composite: SWIR2/NIR/Red). The left side shows the unfilled BAP and the right side the filled BAP with missing pixels interpolated (e.g. Ireland).

As reference data for disturbance classification, we used a set of nearly 20,000 pixels with labels on disturbance occurrence available through the TimeSync-Europe database (Senf, 2021). As this database only covers forest areas, but classification and masking of non-forest areas was necessary, we supplemented the reference database by land cover data available from European Land Use/Cover Area frame Survey (LUCAS, Eurostat). For classifying disturbances annually (i.e., from each year to the following year), we trained a random forest model (Breiman, 2001) implemented in Python scikit-learn v1.2.1 (Pedregosa et al., 2011) using the reference dataset and a set of predictors derived from the Landsat BAPs: the individual Landsat Bands, the Normalised Burn Ratio (NBR), the Normalized Difference Vegetation Index (NDVI), the Tasselled Cap Transformations (Brightness, Greenness and Wetness) and the Disturbance Index (Healey et al. 2005). A hierarchical classification is applied to obtain 3 levels of information, from the more general to the more detailed:

- Level 1. A forest mask is created by classifying forest and non-forest pixels annually. A Minimum Mapping Unit is applied so that forest patches smaller than 0.5 ha are removed (minimum area according to FAO forest definition).
- Level 2. Forest disturbances are classified annually based on the spectral changes between a target year and the previous year. The output is a binary classification of disturbed and undisturbed pixels.
- Level 3. The disturbed pixels are grouped to patches and a minimum mapping unit of three pixels (0.27 ha) is applied. The disturbance patches are then assigned to the most likely agent, including wind/bark beetle, fire and harvest.

The agent attribution follows methods described in Sebald et al. 2021 and Senf and Seidl 2021 and includes a recent update of the reference database (Seidl and Senf, in review). First model assessments using cross-validation showed a good model performance (Table 1). Most remarkable is the reduction of omission errors (i.e., missing true disturbances in the map) in the level 2 classification with respect to the previous version (Senf, Seidl, 2021), i.e., the ability to detect disturbances has increased while keeping commission errors low. We here note that the numbers reported are model accuracies and not map accuracies, which will be published in the final report (Deliverable 2.5.)

Table 1: Model accuracies for Level-1 and Level-2.

Level 1: Forest, non-forest	Level 2: Disturbed, undisturbed
Class Non-forest Accuracy class: 0.995 Precision: 0.84 Recall: 1.00 F1 Score: 0.91	**Class Undisturbed** Accuracy class: 0.996 Precision: 0.98 Recall: 1.00 F1 Score: 1.00
Class Forest Accuracy class: 0.798 Precision: 0.99 Recall: 0.80 F1 Score: 0.89	**Class Disturbed** Accuracy class: 0.804 Precision: 0.82 Recall: 0.80 F1 Score: 0.85

As a last step we aggregated the annual disturbance maps to summary products, including (1) the year of the greatest disturbances (measured in terms of spectral change), (2) the year of the latest disturbance, the number of disturbances, and the agent (assigned to *mixed* if more than one agent occurred in the past). The individual layers are described in detail in the section below. To reduce noise resulting from remaining errors in the forest classification, we used the CORINE land cover dataset to mask out non-forest areas, including areas classified as artificial surfaces, agricultural areas (arable land, permanent crops and pastures) and water bodies.

3 European forest disturbance map product

We distribute the summary products per country as GeoTIFF files both in a web-mapping app for easy exploration (https://albaviana.users.earthengine.app/view/european-forest-disturbance-map) and in a permanent and open data repository under a Creative Commons Attribution 4.0 International license (https://zenodo.org/record/8389086). The maps currently cover the time period 1985-2021 across 38 countries at a spatial resolution of 30 m. The spatial reference system is EPSG 3035 (pan-European projection system ETRS89 Lambert Azimuthal Equal Area (LAEA).

The *year of disturbance* layers contain the year of the most recent disturbance event in the time-series and the greatest disturbance (see Figure 3).

The *number of disturbances* layer shows the number of disturbance events detected within the time-series. It shows the frequency of disturbances within the time series (1985-2021) and is an important indicator of specific disturbance regimes, such as reburns, short rotation plantation systems and also compound disturbances (e.g., a thinning with subsequent harvest).

The *disturbance agent* layer summarises the attribution of agents over the full time series. The causal agents assigned are wind/bark beetle complex, fire, harvest and mixed agents. If only disturbances of one agent occurred, the agent was taken. If more than one agent occurred, we assigned the pixel to the *mixed class.* The mixed category thus indicates that different agents have been assigned in the time series, for example bark beetle outbreaks followed by salvage logging events, or the removal of timber after a fire.

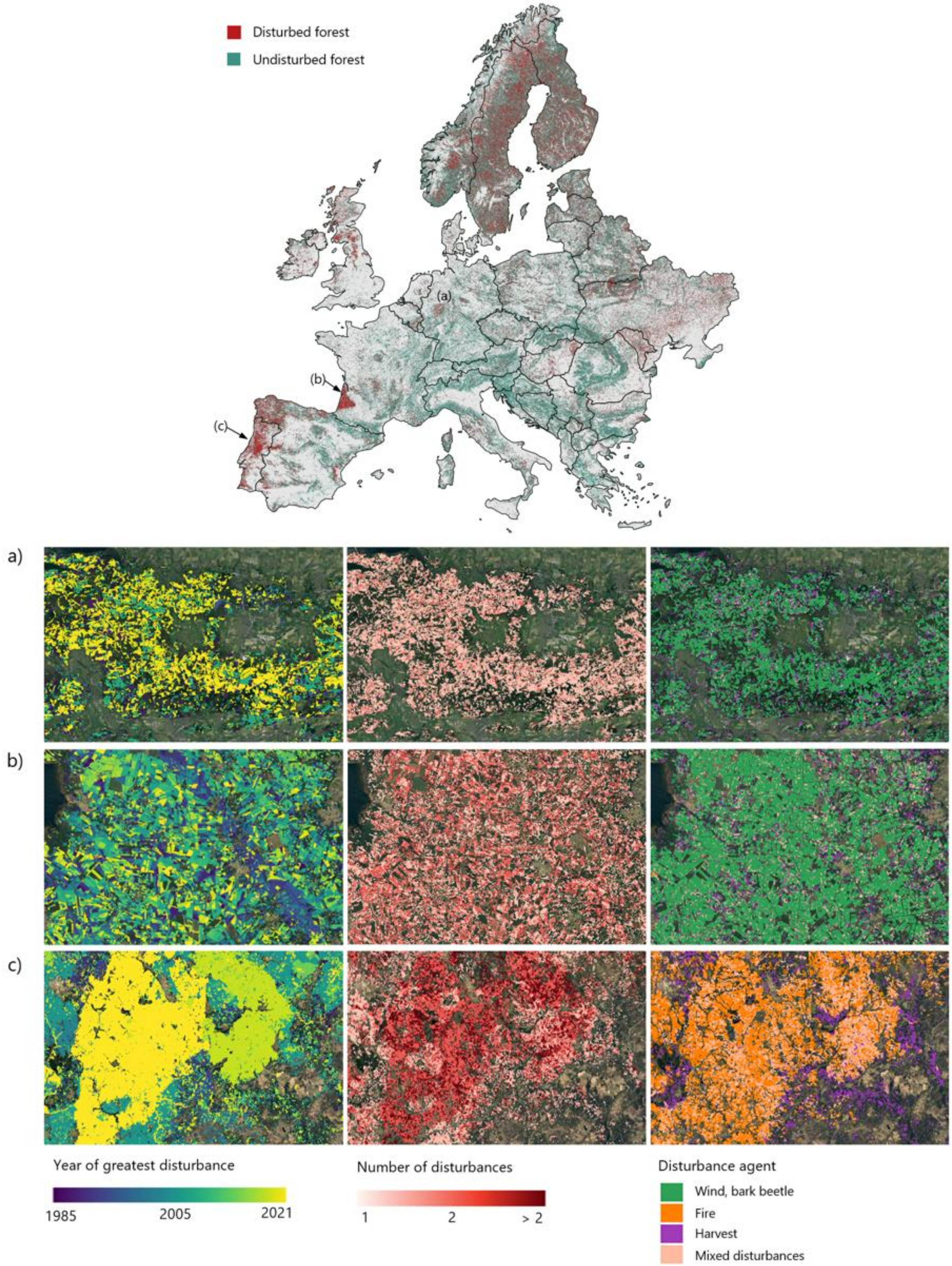

Figure 3: Forest disturbances in Europe (1985-2021). Details show (a) bark beetle outbreaks and windstorm events in north-west Germany; (b) a wind disturbance in an intensively managed forest plantation in Gascony (France); and (c) recurrent fire disturbances in central Portugal.

4 References

Breiman, L., 2001. Random forests. *Machine learning*, *45*, 5-32. https://doi.org/10.1023/A:1010933404324

Francini, S., Hermosilla, T., Coops, N. C., Wulder, M. A., White, J. C., & Chirici, G., 2023. An assessment approach for pixel-based image composites. *ISPRS Journal of Photogrammetry and Remote Sensing*, 202, 1-12. https://doi.org/10.1016/j.isprsjprs.2023.06.002

Frantz, D., 2019. FORCE-Landsat + Sentinel-2 analysis ready data and beyond. *Remote Sensing*, 11 https://doi.org/10.3390/rs11091124.

Frantz, D., Roder, Ä., Stellmes, M., & Hill, J., 2016. An operational radiometric Landsat preprocessing framework for large-area time series applications. *IEEE Transactions on Geoscience and Remote Sensing*, 54, 3928–3943. https://doi.org/10.1109/TGRS.2016.2530856

Griffiths, P., van der Linden, S., Kuemmerle, T., & Hostert, P., 2013. A pixel-based Landsat compositing algorithm for large area land cover mapping. *Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *6*(5), 2088–2101. doi: 10.1109/JSTARS.2012.2228167

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., ... & Townshend, J. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, *342*(6160), 850-853. DOI: 10.1126/science.1244693

Healey, S. P., Cohen, W. B., Zhiqiang, Y., & Krankina, O. N., 2005. Comparison of Tasseled Cap-based Landsat data structures for use in forest disturbance detection. *Remote Sensing of Environment*, *97*(3), 301-310. https://doi.org/10.1016/j.rse.2005.05.009

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, É., 2011. Scikit-learn: Machine learning in Python. *Journal of machine Learning research*, *12*, 2825-2830.

Sebald, J., Senf, C., & Seidl, R., 2021. Human or natural? Landscape context improves the attribution of forest disturbances mapped from Landsat in Central Europe. *Remote Sensing of Environment*, 262, 112502. https://doi.org/10.1016/j.rse.2021.112502

Senf, C. & Seidl, R., 2021. Mapping the forest disturbance regimes of Europe. *Nature Sustainability*, *4*(1), 63-70. https://doi.org/10.1038/s41893-020-00609-y

Senf, C., Sebald, J., & Seidl, R., 2021. Increasing canopy mortality affects the future demographic structure of Europe's forests. *One Earth*, *4*(5), 749-755. https://doi.org/10.1016/j.oneear.2021.04.008

Senf, C., 2021. corneliussenf/TimeSyncEurope: Final data and code of the published paper. (1.0). *Zenodo*. https://doi.org/10.5281/zenodo.4682960