https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

Earth System Science Data
Open Access Discussions

Dense labelled time-series for mapping European forest disturbance agents

Jonas Viehweger[1,2], Manuela Hirschmugl[1,2], Martin Puhm[1], Raphael Burtscher[1,2], Heinz Gallaun[1], Janik Deutscher[1]

[1]Institute for Digital Technologies, Joanneum Research, Graz, 8010, Austria
[2]Department of Geography and Regional Science, University of Graz, Graz, 8010, Austria

Correspondence to: Jonas Viehweger (jonas.viehweger@joanneum.at)

Abstract. Attributing disturbance agents to canopy mortality in European forests remains difficult due to sparse, heterogeneous, and often single-agent reference data. We present DISFOR (Viehweger et al., 2026), a uniformly re-interpreted ground-truth dataset of forest disturbance agents, designed to serve as training data for multi-temporal classification and analysis of disturbance agents with Sentinel-2 time-series. The dataset comprises 3,822 unique sample points, each defined at the 10×10 m pixel level, labelled by disturbance event and agent and fully temporally segmented into consecutive events and forest states for the years 2015-2024. Labels follow a three-level hierarchical scheme that supports analyses from broad "alive vs. disturbed" partitions to specific agents such as bark beetle, windthrow, wildfire, and salvage logging. Samples were drawn from multi-source ancillary data (e.g. EFFIS, FORWIND, Copernicus EMS, and regional forestry datasets) and consistently re-interpreted using an open-source interface and generally available primary data like Sentinel-2 and very high resolution imagery. For each sample we provide interpreter confidence, cluster identifiers to capture spatio-temporal auto-correlation, and additional metadata. Alongside interpreted samples, we release two Sentinel-2 data products tailored to complementary use cases: (i) a tabular single pixel reflectance time series between 2015-2024 and (ii) georeferenced 32×32-pixel image chips centred on the sampled points suitable for computer vision applications, with Python utilities for reproducible data loading and filtering. The dataset is suited for training and calibration of both change detection and agent attribution algorithms at sub-annual resolution, it supports training on single timestamps as well as on time-series, and facilitates studies that integrate spectral dynamics with spatial context. By harmonizing multiple first-level disturbance agent products and providing dense, temporally explicit labels, this resource lowers a major barrier to developing European forest disturbance and recovery monitoring.

1 Introduction

Forests outside the tropics face increasing canopy mortality (Senf et al., 2021; Senf and Seidl, 2021a). Using satellite imagery, we can map forest disturbances accurately in near-real time using various algorithms of temporal analysis (Dutrieux and Viehweger, 2024; Puhm et al., 2020; Verbesselt et al., 2012; Zhu et al., 2020; Zhu and Woodcock, 2014). However, using models to attribute a disturbance agent like wildfire, bark beetle or windthrow to a disturbance event still proves difficult

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

(Rodríguez Paulino et al., 2024; Viana-Soto and Senf, 2024; Zhu et al., 2022). One reason for this gap between model capabilities of disturbance detection versus disturbance attribution is the lack of available ground truth data (Rodríguez Paulino et al., 2024; Viana-Soto and Senf, 2024). It is difficult, using only widely available satellite imagery as provided by Sentinel-2 or Landsat, to visually interpret disturbance agents with sufficient confidence (Senf et al., 2018, 2021; Viana-Soto and Senf, 2024). This makes different data sources necessary to build ground truth datasets mapping forest disturbance agents. First-level disturbance agent products, which provide agent attribution for spatially explicit polygons, derive agents from primary sources like scientific field surveys, by mapping campaigns using very high resolution imagery, or from purpose built sensors like thermal imaging for wildfire detection. These first-level products often only provide information on a single disturbance agent and can vary in their overall quality, spatial extent and temporal resolution.

First-level disturbance agent data sources, mapping forest disturbance agents in Europe exist, but they are difficult to combine due to different metadata formats, considered disturbance agents and response designs as well as quality. DEFID2 (Forzieri et al., 2023) aggregates insect disturbance polygons and points from multiple sources. It homogeneously records metadata about methodology and mapped disturbances for each included source. Due to the different applied methodologies the quality and accuracy of the spatial data itself can vary substantially between the aggregated data providers. EFFIS (San-Miguel-Ayanz et al., 2012) provides areas affected by wildfire but has a coarse resolution and isn't restricted to forested areas. FORWIND (Forzieri et al., 2020) collects geospatial data on areas affected by windthrow, but the overall mapping accuracy varies substantially between different mapped storm events, due to variations in the primary data used for interpretation and the applied mapping methodologies. Besides these multi-national collated data sources there also exist a multitude of data sources collected by local field campaigns and published through scientific articles or by regional forestry departments (Giambelluca et al., 2025; Langner and Oehmichen, 2024). These diverse formats and methodologies make the use of different data sources difficult when developing classification algorithms for disturbance agents. Because of this there already exist some "second-level" disturbance agent products. These second-level products strive to combine multiple first-level products so that they can be used together. One of these available second-level products (Senf and Seidl, 2021b) maps fire and windthrow events for all of Europe in the time between 1986 and 2016. To provide a homogeneous spatial and temporal context they use disturbance polygons from their own forest disturbance detection algorithm which uses Landsat as the primary data. They then assign agents to automatically detected disturbance polygons by checking if disturbances described in FORWIND and EFFIS are visible in their disturbance map. The dataset was later extended with bark beetle areas using the DEFID2 dataset, however this additional data is not available publicly (Seidl and Senf, 2024). However, due to the considered time-frame of the dataset from 1986 to 2016, only few samples intersect the Sentinel-2 time-series starting at the end of 2015. The dataset also only provides polygons on stand-replacing disturbances at a yearly temporal resolution.

DISFOR, the dataset presented here, is also a second-level disturbance agent product and contains homogeneous point samples, with each point sample containing a fully segmented dense time-series describing the state of the forest (e.g. undisturbed, decline, clear cut, revegetation, ...). The disturbance agent is derived from first-level disturbance agent products or other suitable primary data. The disturbance timing is derived from the full Sentinel-2 time series. This sub-annual temporal

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

accuracy of labelled disturbance events and their progression enables the recording of complex disturbance patterns and short-duration disturbances which are characteristic of European forest disturbance regimes.

The research gaps addressed in this study are:

- Lack of training data with precise intra-annual disturbance timing for disturbance agent classification
- Limited data sources to capture and characterize complex, short-duration disturbance events
- Harmonization of heterogeneous first-level disturbance agent data sources

2 Methodology

The aim of DISFOR is to provide homogeneous ground-truth labels of different forest disturbance agents. In this chapter we describe the applied methodology to construct this dataset. We first outline the applied process of homogenizing heterogeneous source material. We then detail the work carried out in different labelling campaigns to construct the full dataset. Finally we outline the applied response design and the structure of the final dataset.

To address the research gaps laid out in the introduction, three different distinct challenges need to be addressed in the methodology. These are: (i) capturing disturbance timing, (ii) disturbance agent attribution and (iii) harmonization of first-level disturbance agent data sources. Different data sources are necessary to address these issues. We categorize the data sources used to construct DISFOR into three categories (see Fig. 1). The first category is primary data. This is uninterpreted sensor data or grey literature data which has not been further interpreted. The second category are first-level disturbance agent products which apply some methodology to primary data to interpret disturbance agents. These first-level data products usually offer spatially explicit points or polygons with interpreted disturbance agents. The third category are second-level disturbance agent products. These products aim to combine multiple first-level products into a homogeneous product. DISFOR and the data available through Senf and Seidl (2021b) belong to this second level.

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

Open Access Earth System Science Data Discussions

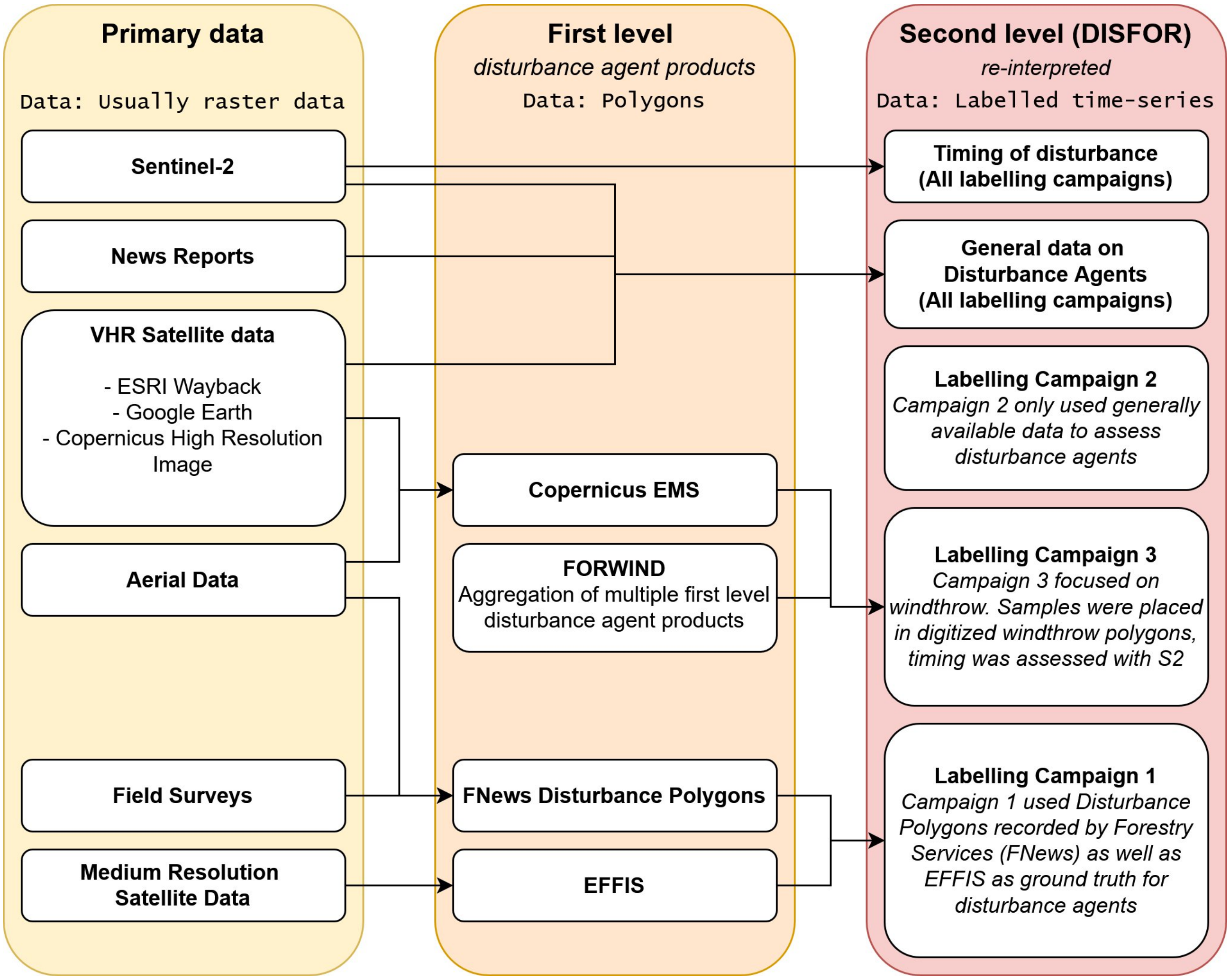

Figure 1: Categorization of data sources. Data categories are coloured boxes, data sources are white boxes, arrows signify which data is used to derive each data source

We considered different aspects to be homogenized: (1) timing of disturbance, (2) disturbance severity, (3) minimum mapping unit, (4) quality of labels. The main approach to homogenize the dataset, is the use of Sentinel-2 to re-interpret first-level products. The minimum mapping unit is consistently defined as a single Sentinel-2 10x10m pixel. The minimum disturbance severity is defined as disturbances that affect the canopy and are visible in the Sentinel-2 spectral signal, this includes both stand-replacing and non stand-replacing disturbances. It however does not include disturbance occurring in the understory or only affecting very small areas of the canopy. The timing of the disturbance is consistently derived from the Sentinel-2 time-series. The disturbance agents are assessed using first-level products and confirmed through visual re-interpretation using the Sentinel-2 time-series and generally available suitable primary data, namely very high resolution imagery from ESRI Wayback (Esri, 2025), Copernicus European Image Mosaic (CLMS, 2021) and Google Earth (Google Earth,

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

2026). This also ensures a consistent quality of labels, since possible commission errors or mapped low-severity disturbances in the first-level dataset are excluded during re-interpretation. Details on the interpretation response design are available in section 2.2. Following is a description of the different labelling campaigns, which used different first-level data to interpret disturbance agents.

2.1 Labelling campaigns

The entire DISFOR dataset was constructed in 3 distinct labelling campaigns. While all campaigns used the Sentinel-2 time-series to assess the disturbance timing, each campaign used different first-level disturbance agent data as ground truth for the disturbance agents (see Fig. 1). The related research projects in which the labelling was carried out are: Evoland, developing dynamic land cover products for future Copernicus services; FNEWs, focussing on annual and near real-time forest disturbance detection products for Germany; CLMS HR-VPP2, where calibration data for disturbance timing was recorded for a pan-European tree cover disturbance product; and FUTUREFOR, where disturbance agent information was recorded (see section Financial support).

2.1.1 Campaign 1

This labelling campaign mainly labelled wildfire, windthrow and bark beetle areas in Germany, Sweden and Spain. It is also the only campaign which included areas affected by gypsy moth. The majority of the used first-level disturbance agent data is provided by regional forest services and research institutes in Germany (Langner and Oehmichen, 2024). This data is augmented with wildfire areas in Sweden and Spain extracted from EFFIS (San-Miguel-Ayanz et al., 2012). For this labelling campaign the first-level disturbance agent data provides disturbed forest areas, assessed disturbance agents and dates of disturbances. 1006 unique points were sampled within these polygons and interpreted for the years 2015-2024. The original polygons which are available in the first-level disturbance data correspond to the cluster IDs which are available in the dataset. This means that if multiple sample points were placed in the same disturbance polygon, they can be grouped through the column *cluster_id* (see section 3.1).

2.1.2 Campaign 2

This labelling campaign is focused on a European-scale sampling of undisturbed and disturbed forest areas and focused on capturing routine forest management practices like thinning and clear cuts. For this campaign, we used a two-stage stratified sampling design. In the first stage, 13 Sentinel-2 tiles covering various biogeographic regions of Europe were selected. In the second stage, we selected a total of 2728 sample points by applying a stratified random sampling approach. This approach used information on forest disturbances from the European Disturbance Atlas (Viana-Soto and Senf, 2024) as strata to increase the amount of samples in disturbed forest areas.

We did not use a first-level disturbance product in this campaign, since there does not exist a product on European scale capturing routine forest management practices. Not knowing the disturbance agent based on first-level data doesn't change the

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

assessment of the disturbance timing during re-interpretation which still only uses the Sentinel-2 time-series. However, it does change the assessment of forest disturbance agents since we could only use suitable primary data. This mainly included multi-temporal VHR data like ESRI Wayback Imagery (Esri, 2025) and the Copernicus European Image Mosaics (CLMS, 2021). Some agents were additionally confirmed using Google Earth (Google Earth, 2026), EFFIS (San-Miguel-Ayanz et al., 2012) and local news reports.

The most frequent classes provided by this campaign are undisturbed forest and routine, planned forestry practices which aren't present in this amount in campaigns 1 and 3. The disturbance agents were interpreted from 2015-2024.

2.1.3 Campaign 3

The third labelling campaign focused on areas affected by windthrow. We used the FORWIND (Forzieri et al., 2020) database as well as emergency mapping activations in response to windstorms in the Copernicus Emergency Management Service (EMS) (EC JRC, 2019) as first-level disturbance agent data. With this approach we were able to identify 12 unique mapped windstorm events between August 2017 and August 2022. We extracted and filtered available damage polygons to only include polygons with a maximum inscribed circle radius greater than 5 meters in order to exclude very small damage polygons. To keep the amount of manually interpreted samples reasonable, a maximum of 50 polygon centroids per unique windstorm event were randomly sampled and interpreted. This resulted in a total of 572 samples which were re-interpreted between 2015 and 2024.

2.2 Labelling interface and response design

All samples were interpreted by the same group of interpreters using the same labelling interface. This labelling interface is available open-source at https://jr-digital.github.io/tsbrowser/.

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

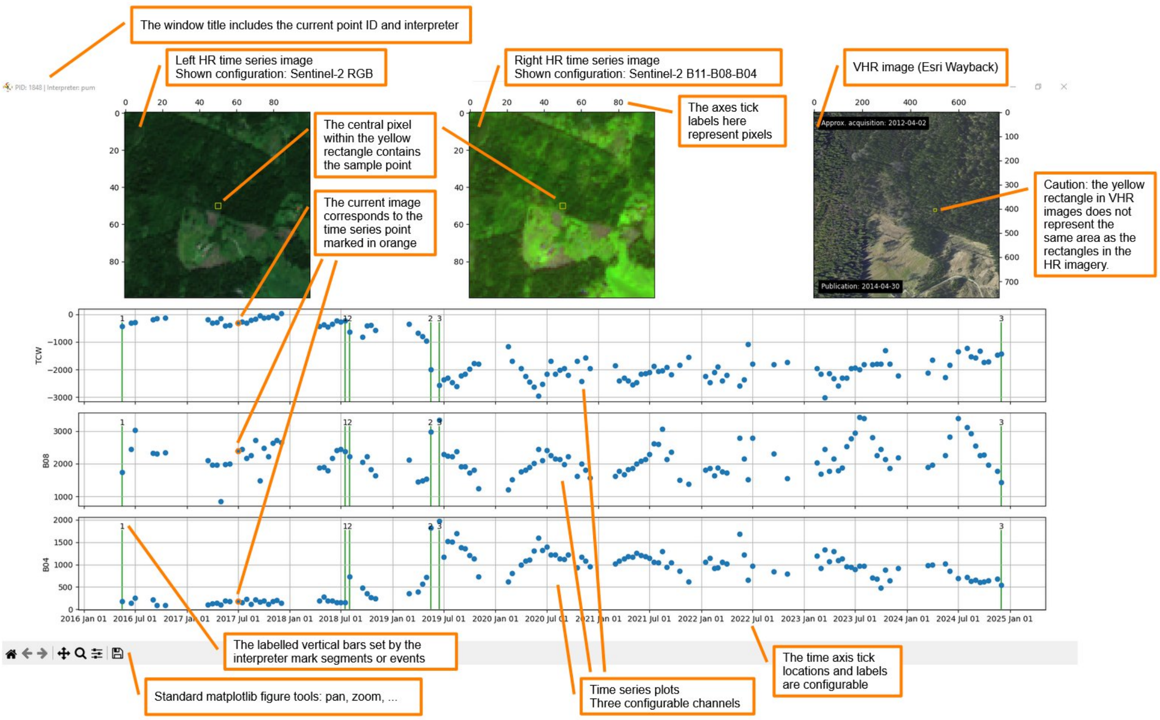

Figure 2: Overview of used time-series interpretation interface

The lower half of the labelling interface shows time-series of multiple spectral bands or indices to aid in the temporal segmentation. We chose a selection of spectral bands and indices based on their sensitivity to changes in forest vitality (Jin and Sader, 2005; Schultz et al., 2016). They include the Tasseled Cap Transform Wetness (TCW), the Normalized Difference Moisture Index (NDMI), as well as Sentinel-2 spectral bands 4 (Red) and 11 (SWIR).

On the top half of the interface the spatial context of the currently selected timestamp is displayed as true colour and false colour (B11 SWIR, B08 NIR, B04 Red) image chips. The rightmost image in the interface displays historic VHR time-series from the ESRI Wayback service to aid in the disturbance agent interpretation.

Each sample time-series was temporally labelled using the entire cloud-free Sentinel-2 time series. For the assignment of reference labels a distinction is made between segments and events. Temporal segments are periods of a distinct condition of the forest (Cohen et al., 2010). This can include stable undisturbed forest, re-vegetation or bark beetle decline. Events on the other hand are singular changes of short duration. This includes most other disturbances like clear cutting, wildfire and windthrow events. In practice this distinction means that a single label is set for events, while two labels are set for segments, one for the start of the segment and one for the end. The assigned reference labels are following a hierarchical classification schema as laid out in Table 1 below.

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

Table 1: Hierarchical classification scheme with three levels ([1] for Segment, [2] for Event)

Level 1	Level 2	Level 3
100 - Healthy Vegetation	110 - Undisturbed Forest	
	120 - Revegetation	121 - With Trees (after clear cut)[1]
		122 - Canopy closing (after thinning/defoliation)[1]
		123 - Without Trees (shrubs and grasses, no reforestation visible)[1]
200 - Disturbed	210 - Planned	211 - Clear Cut[2]
		212 - Thinning[2]
		213 - Non Forest Vegetation Removal (e.g. Forestry Mulching)[2]
	220 - Salvage	221 - After Biotic Disturbances[2]
		222 - After Abiotic Disturbances[2]
	230 - Biotic	231 - Bark Beetle (decline)[1]
		232 - Gypsy Moth (short duration)[1]
	240 - Abiotic	241 - Drought[1]
		242 - Wildfire[2]
		243 - Wind[2]
		244 - Avalanche[2]
		245 - Flood[2]

The hierarchical classification scheme is loosely based on the scheme defined by ICP Forests for assessing tree damage at a forest inventory plot (Schwärzel and Wohlgemuth, 2024). It has to be noted that not all detailed third level classes are available in the dataset. For example there are no samples present in the data which are affected by avalanches or floods.

Is is often not possible to tell from the time-series if revegetation after a clear cut is happening with trees (class 121) or the revegetation is only with shrubs and grasses (class 123). In these unclear cases, we assigned the broader class 120. Using hierarchical classes also makes modelling of coarser classes easier. If a model should only split samples into healthy and disturbed forest, only the first digit of the label can be used for classification.

During interpretation, primary data and first-level disturbance agent data is the main source for the assignment of agents to segments and events. However since many first-level disturbance agent datasets do not have exact dates available on when the disturbance occurred, the pixel time-series is the main source to assign the timing (start and end) of events and segments. In cases where the first-level disturbance agent dataset provides an exact timing of the disturbance, the timing of the disturbance in the satellite signal is double checked. This is especially important for windthrow events. Here the exact day of the disturbance is usually known. If the sample was disturbed before that day or did not show signs of disturbance on the first satellite acquisition after the storm event, the disturbance is unlikely to have been caused by that particular storm event.

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

In cases where no first-level disturbance agent data is available, we use VHR imagery to assign an agent. The displayed Sentinel-2 image chips are used to further confirm the interpretation. The spatial context of the Sentinel-2 image chips can provide additional information making the agent classification more accurate. An example would be a salvage logged area where the specific sampled pixel is in the green attack stage of a bark beetle infestation and does not yet show signs of the infestation in the spectral signal. The spectral signal would look like a clear cut but the spatial context can show neighbouring areas in the red or gray attack stages confirming the interpretation as salvage logging.

The interpreter also provides the confidence of interpretation in three categories: high, medium or low. High is assigned if the timing and the agent were confidently assessed. Medium is assigned in cases where the timing is clear, but the agent could not be assessed with full confidence. Low is assigned in cases where both timing and agent could not be assessed with satisfactory confidence. For each sample a comment can also be provided. Comments serve to give more context on the sample, pointing out possible imagery artifacts, doubts in the classification and reasoning for low confidence. A typical comment would for example point out that the sampled point is a mixed pixel on the border between disturbed and undisturbed areas and thus does not show a typical spectral return.

3 Dataset

This section describes the provided DISFOR dataset (Viehweger et al., 2026). The full dataset provides both metadata and labels for all samples as well as prepared Sentinel-2 data and Python data loading utilities specific for machine and deep learning tasks. The metadata and labels are described in section 3.1. The provided Sentinel-2 data and the data loading utilities are described in section 3.2. Overall characteristics and statistics of the available data are described in section 3.3.

3.1 Metadata and Label Description

The metadata of the samples is available in the dataset *samples.parquet*. The interpreted labels for each sample are available in a separate table *labels.parquet*. The samples table is a geoparquet file. The parquet file format was chosen due to it being well supported by different software and programming languages, due to its strict data types per column and due to its streaming capability. The table is structured as follows:

Table 2: Column names in the table *samples.parquet* and description of content

Column name	Description
sample_id	Unique sample ID for each sample point
original_sample_id	Sample ID of the point in the original publication of the dataset
interpreter	Shorthand code for the interpreter who labelled this sample
dataset	The original sampling campaign in which this point was labelled
source	The first-level disturbance agent product used to interpret the agent
source_description	A long text description of the used source. Link to the original data if available
s2_tile	If available, which Sentinel-2 tile the sample intersects
cluster_id	Unique ID to group samples which are spatio-temporally autocorrelated
cluster_description	What type of cluster it is

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

comment	Free text comment about the interpretation of the sampled point
confidence	Confidence of labelling: high where both timing and agent are confident, medium were only the timing is confident
geometry	Coordinates of the sampled point. In Coordinate Reference System EPSG:4326

For each sample point the column *source* specifies which first-level disturbance agent product was used for interpretation. If the used first-level disturbance agent product is spatio-temporally autocorrelated (for example a mapping campaign for a single storm event, where all samples show similar timing and spectral signature of disturbance) this is recorded in the column *cluster_id*. It was also recorded how confident the interpretation is. All interpretations which were of low confidence were already discarded from the dataset. A high confidence means that both timing and cause of disturbance are confidently assessed. For medium confidence the timing of the disturbance has high confidence, but the assessed disturbance agent is of low confidence. Additionally, a comment about the interpretation is recorded. This comment can give more context on the sampled point.

Every single sampled point is divided into segments and events. All of these segments and events are available in a separate parquet file called *labels.parquet*. Each label is structured as follows:

Table 3: Column names in the table *labels.parquet* and description of content

Column name	Description
sample_id	Taken from sample table
original_sample_id	Taken from sample table
dataset	Taken from sample table
label	Interpreted class of the segment (see table 1)
original_label	The label which was originally assigned and remapped to *label*
start	Start date of the segment
end	End date of the segment
start_next_label	Start date of the next label. Some labels are encoded as events (Clear cuts for example) and are not immediately followed by another label, this column allows a full segmentation of the time-series

Some labels like clear cut or thinning are defined as events. In this context it means that the start and end are on the same day since the change is not gradual (compared to gradual events like regrowth or bark beetle decline). To enable a full segmentation of the timeline, the *start_next_label* column is computed. This column provides the date when the next label starts, making a full segmentation of the time-series possible. Since the three different labelling campaigns did not map all agents, each one used a slightly different label classification scheme, the original labels were captured in the column *original_label.* The detailed re-mapping from the original labels per dataset is available in the dataset repository (see section 5).

A single segmented point might then look like this:

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

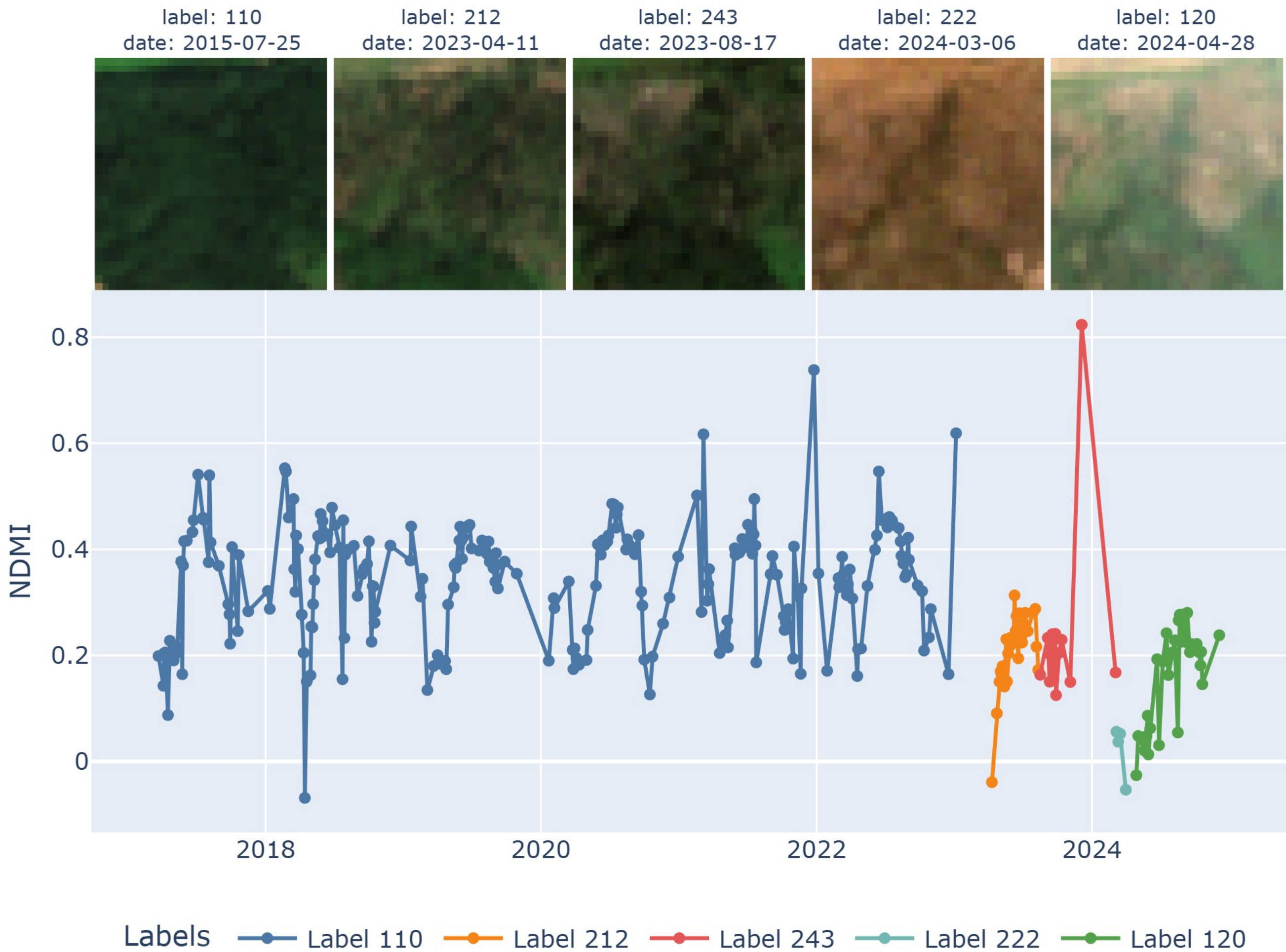

Figure 3: Example of a segmented sample point. Sentinel-2 image chips showing images of different labelled states of the forest are shown on the top. The segmented NDMI pixel time-series of the point is shown on the bottom

Figure 3 shows a sample with a complex disturbance pattern, where an area is thinned (early 2023, label 212) before being affected by windthrow (Summer 2023, label 243), with subsequent salvage logging (early 2024, label 222) and revegetation (since April 2024, label 120).

The dataset also contains two lists of non-overlapping sample IDs to optionally split the dataset into a training and validation set. For the validation set 10% of the full dataset was held out. The dataset was constructed by drawing a random sample of the defined clusters to reduce spatio-temporal correlation between the training and test set. However, it is important to note that since all the data was labelled using the same data sources and methodology, the validation data will still be very similar to the training data. For a rigorous study a fully independent validation dataset is necessary to assess model performance (Olofsson et al., 2014; Reinosch et al., 2024).

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

3.2 Sentinel-2 Data Description

The Sentinel-2 data which was used to interpret the time-series is available for each sampled point. We provide two datasets of different format optimized for various applications: One dataset called *pixel_data.parquet* provides raw single pixel L2A Sentinel-2 time-series reflectance data in a tabular format without any spatial context. The other dataset is available as a compressed archive and provides 32x32 pixel Sentinel-2 image chips at 10 meter resolution per pixel. For each dataset Python data loading utility classes are available to aid in the use of the data in machine learning workflows. These two datasets and the utility classes are described here in more detail.

The file *pixel_data.parquet* provides the following columns:

Table 4: Column names, data types and description of column content in the table *pixel_data.parquet*

Column name	Data type	Description
sample_id	UINT16	Taken from sample table
timestamp	DATE	UTC date of the S2 acquisition
label	UINT16	Interpreted class of the segment (see table 1)
clear	BOOL	True if the pixel is clear (SCL value any of 2,4,5,6)
percent_clear_4x4 [8x8, 16x16, 32x32]	UINT8	The percentage of clear pixels (SCL in 2,4,5,6) within a 4x4, 8x8, 16x16 or 32x32 pixel image chip
B02, B03, B04, B05, B06, B07, B08, B8A, B11, B12	UINT16	DN value for the spectral band
SCL	UINT8	Sentinel-2 Scene Classification Value

The collected spectral data represents Digital Numbers (DN) as provided before Sentinel-2 processing baseline 4, as UINT16 without the offset introduced with baseline 4 (Processor Releases Timeline, 2025). The columns *percent_clear_*.. provide information on the percentage of clear pixels in the centre pixel's neighbourhood. These columns can also be used for filtering of the provided image chips without having to load the image chips themselves to inspect the quality of a single chip.

This tabular dataset can be queried through a Python data loading class called *TabularDataset*. This class provides arguments to filter the data and return machine learning ready collections. This class provides data for per pixel machine learning tasks, but it is not suitable to extract data to use in time-series based classifications. The data loading utility transforms the raw tabular data into ML-ready formats. This means that the spectral input data is converted into numeric arrays and the target labels are encoded into classes starting from 0 and increasing sequentially. Additionally, a validation set is held out from the training data, to be able to validate trained models on unseen data. The full and up to date parameter documentation is available in the open source GitHub repository https://github.com/JR-DIGITAL/DISFOR.

For machine learning tasks that also take the spatial dimension into account, we provide Sentinel-2 image chips as 32x32 pixel cloud optimized GeoTIFFs (COGs), with a 10 meter resolution. We upsampled all 20m spectral bands to 10m resol-

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

ution using nearest neighbour resampling. The chips are available in their local UTM projection. The file structure in which the chips are provided follows this pattern:

<Sample Id> / <YYYY-MM-DD>.tif

For this dataset there also exists a Python data loading utility called *MonoTemporalClassification*. It is implemented to support data loading specifically for deep learning tasks, using the widely supported PyTorch package (Paszke et al., 2019). The image chip loading utility offers the same filtering capabilities as the one for the tabular pixel-level data. It returns tensors and labels which are compatible with the torchvision package. With this, data augmentations and deep learning model architectures which work on generic image data can be easily adapted to the provided training data.

3.3 Dataset Characteristics

In total 3822 unique points are included in the dataset.

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

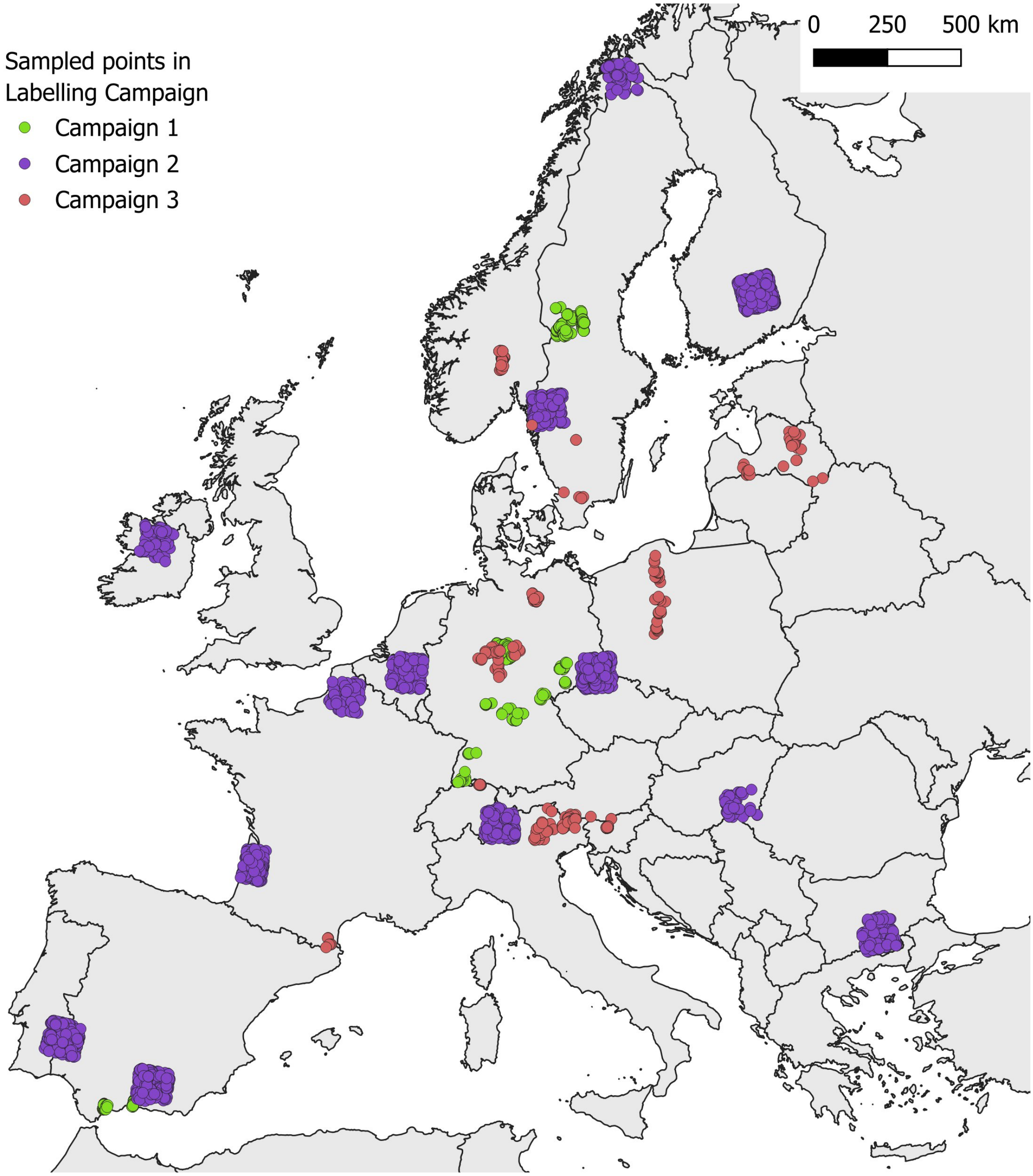

Figure 4: Distribution of sampled points from described labelling campaigns within Europe

Figure 4 shows the spatial distribution of sampled points. The dataset contains sampled points in each major ecological zone in Europe.

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

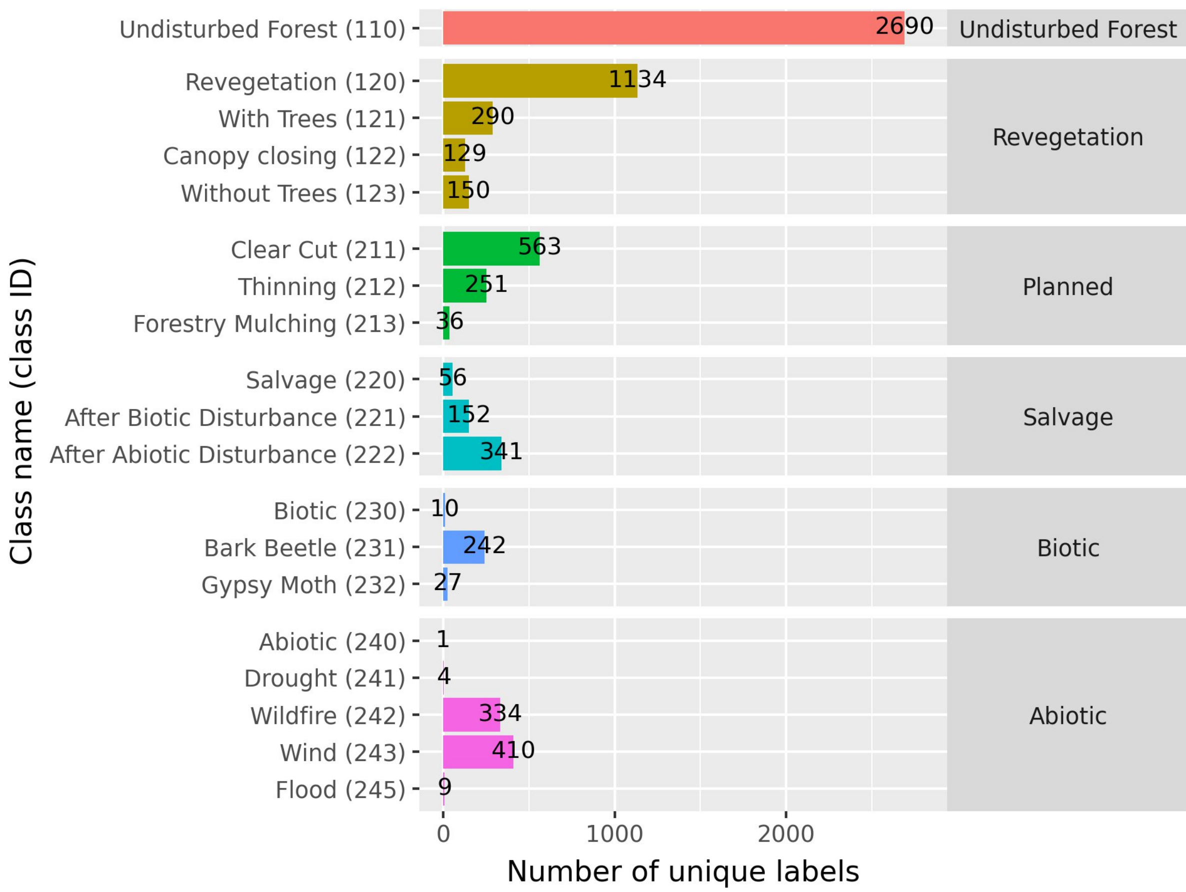

Figure 5: Counts of unique segments and events split into classes

Counting the number of unique labelled segments (Fig. 5) shows that the majority of segments are undisturbed forest. The second most common segment is the broad revegetation class. The most common disturbed class is clear cut, followed by windthrow, wildfire, salvage after abiotic disturbance and bark beetle.

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

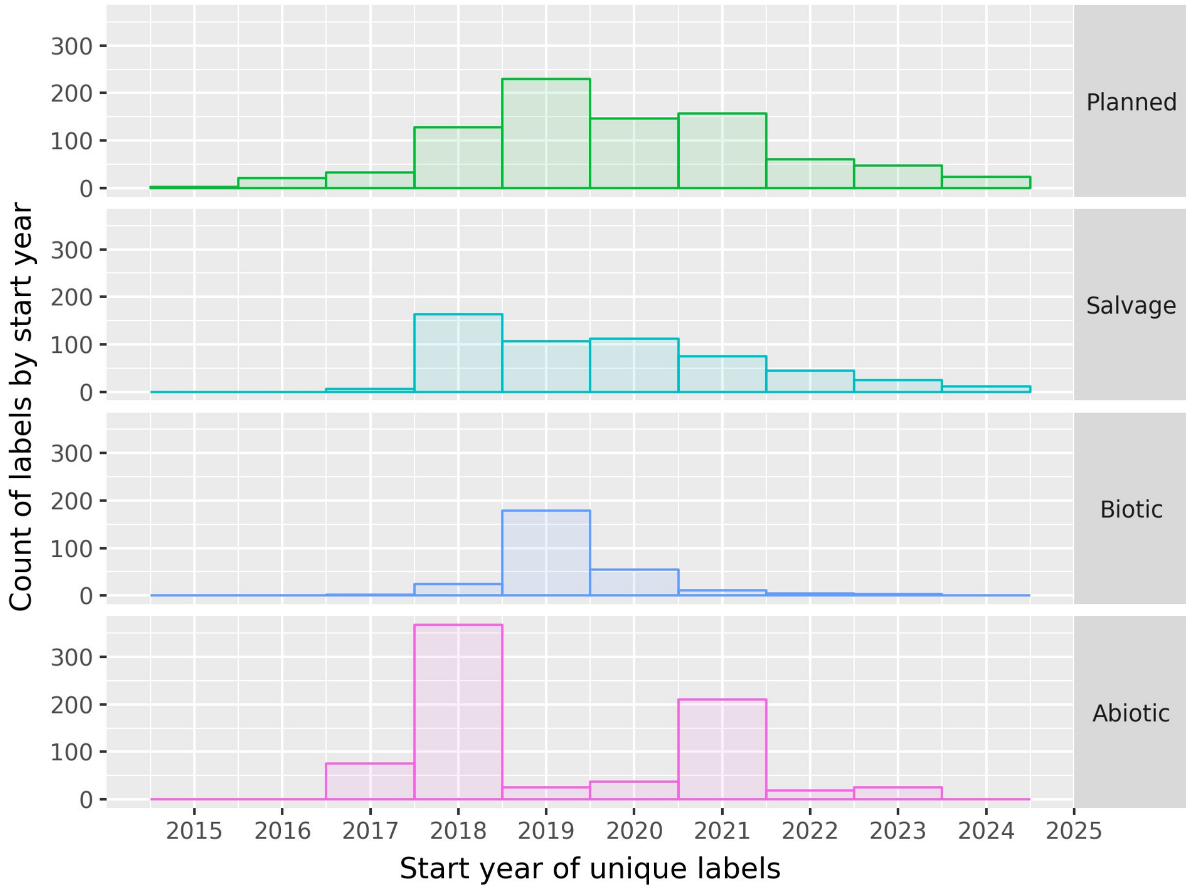

Figure 6: Distribution of start years of labelled disturbances, split into broad categories

The temporal distribution of labels (Fig. 6) is influenced by the data collection method and underlying disturbance dynamics. A clear peak of disturbances can be observed for the period 2018 to 2022. One reason for this accumulation of events in the classes salvage and biotic are the drought years in central and western Europe 2018 and 2019 (Buras et al., 2019) which caused large scale bark-beetle outbreaks with subsequent salvage logging (Schuldt et al., 2020; Thonfeld et al., 2022). For all classes, factors inherent to the data collection process also shape the temporal pattern of labels. Reliable attribution of disturbance agents requires both Sentinel-2 imagery and suitable first-level disturbance agent data. Consequently, fewer disturbances were recorded between 2015 and 2017 because the Sentinel-2 time series was still sparse. A similar decline appears between 2022 and 2025, which is mainly due to the timing of the labelling campaigns and the typical delay between the occurrence of a disturbance and the publication of corresponding first-level disturbance-agent polygons.

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

5 Code and Data Availability

The DISFOR reference data is available at https://doi.org/10.57967/hf/7983 (Viehweger et al., 2026). The code for the data loading utilities is available at https://github.com/JR-DIGITAL/DISFOR, with comprehensive library and usage documentation at https://jr-digital.github.io/DISFOR/. The interpretation tool which was used for the interpretation of the Sentinel-2 time-series is available at https://github.com/JR-DIGITAL/tsbrowser.

6 Conclusion

We introduce DISFOR, a dense, hierarchically labelled, sub-annual ground-truth dataset for European forest disturbance agents. The resource fills a key gap between operational disturbance detection and robust agent attribution by (i) unifying heterogeneous first-level disturbance agent data through consistent re-interpretation, (ii) providing complete time-series segmentation at the pixel level, and (iii) packaging data and loaders for both machine learning and deep learning on single images.

While the dataset provides temporal detail and spatial consistency, several limitations remain. First, the labels are provided at the pixel level, without object-based segmentation of contiguous disturbance patches. This fact restricts the direct application of segmentation-based convolutional architectures such as U-Net without additional pre-processing. Second, the current Python utilities primarily support per-pixel and image-based tasks. Dedicated data loaders for temporal models such as LSTMs will further expand usability for diverse model architectures. Third, temporary or subtle disturbance processes (e.g., gypsy moth defoliation, short-term drought stress or thinning) are currently under-represented due to the scarcity of reliable first-level disturbance agent data.

Future work will focus on extending and refining this resource. Planned developments include increasing the number and diversity of samples and increasing the accuracy of already existing labels. Additional efforts will address the integration of object-based labels and the release of utilities for time-series deep learning. Beyond its immediate application in training and benchmarking algorithms, the dataset provides a reproducible foundation for research into disturbance dynamics, cascading impacts, and recovery processes.

By combining multiple data sources into a harmonized, dense, annotated reference, DISFOR facilitates the improvement of disturbance agent modelling which should allow for more accurate, rapid classification of disturbance agents from satellite data.

Author contributions

JV: Writing – original draft, Software, Visualization, Data Curation. MH: Writing – review and editing, Supervision, Funding acquisition. MP: Writing – review and editing, Visualization, Software, Data Curation. RB: Data Curation. HG: Writing – review and editing, Funding acquisition, Supervision. JD: Writing – review and editing, Funding acquisition, Supervision.

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

Financial support

This research has been supported by funding from the European Union's Horizon Europe Research and Innovation Programme for projects Evoland (grant no. 101082130), FORbEST (grant no. 101181878) and FUTUREFOR (grant no. 101180278), by the EEA funded project Copernicus Land Monitoring Service - Pan European Component - Production and Validation of High Resolution Vegetation Phenology and Productivity 2 (no. EEA/DIS/R0/23/007), and by funds from the German Federal Ministry of Food and Agriculture (BMEL) via the Fachagentur Nachwachsende Rohstoffe e. V. (FNR) for project FNEWs (Fernerkundungsbasiertes Nationales Erfassungssystem Waldschäden, grant no. 2220NR013

Competing interests

The contact author has declared that none of the authors has any competing interests.

References

Viehweger, J., Hirschmugl, M., Puhm, M., Burtscher, R., Gallaun, H., and Deutscher, J.: DISFOR (1453), https://doi.org/10.57967/hf/7983, 2026.

Senf, C. and Seidl, R.: Mapping the forest disturbance regimes of Europe, Nat Sustain, 4, 63–70, https://doi.org/10.1038/s41893-020-00609-y, 2021a.

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

Puhm, M., Deutscher, J., Hirschmugl, M., Wimmer, A., Schmitt, U., and Schardt, M.: A Near Real-Time Method for Forest Change Detection Based on a Structural Time Series Model and the Kalman Filter, Remote Sensing, 12, 3135, https://doi.org/10.3390/rs12193135, 2020.

Verbesselt, J., Zeileis, A., and Herold, M.: Near real-time disturbance detection using satellite image time series, Remote Sensing of Environment, 123, 98–108, https://doi.org/https://doi.org/10.1016/j.rse.2012.02.022, 2012.

Zhu, Z., Zhang, J., Yang, Z., Aljaddani, A. H., Cohen, W. B., Qiu, S., and Zhou, C.: Continuous monitoring of land disturbance based on Landsat time series, Remote Sensing of Environment, 238, 111116, https://doi.org/10.1016/j.rse.2019.03.009, 2020.

Zhu, Z. and Woodcock, C. E.: Continuous change detection and classification of land cover using all available Landsat data, Remote Sensing of Environment, 144, 152–171, https://doi.org/10.1016/j.rse.2014.01.011, 2014.

Dutrieux, L. and Viehweger, J.: nrt: operational monitoring of satellite image time-series in Python, JOSS, 9, 6815, https://doi.org/10.21105/joss.06815, 2024.

Rodríguez Paulino, E., Schlerf, M., Röder, A., Stoffels, J., and Udelhoven, T.: Forest disturbance characterization in the era of earth observation big data: A mapping review, International Journal of Applied Earth Observation and Geoinformation,

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

128, 103755, https://doi.org/10.1016/j.jag.2024.103755, 2024.

Viana-Soto, A. and Senf, C.: The European Forest Disturbance Atlas: a forest disturbance monitoring system using the Landsat archive, https://doi.org/10.5194/essd-2024-361, 21 November 2024.

Zhu, Z., Qiu, S., and Ye, S.: Remote sensing of land change: A multifaceted perspective, Remote Sensing of Environment, 282, 113266, https://doi.org/10.1016/j.rse.2022.113266, 2022.

Senf, C., Pflugmacher, D., Zhiqiang, Y., Sebald, J., Knorn, J., Neumann, M., Hostert, P., and Seidl, R.: Canopy mortality has doubled in Europe's temperate forests over the last three decades, Nat Commun, 9, 4978, https://doi.org/10.1038/s41467-018-07539-6, 2018.

Forzieri, G., Dutrieux, L. P., Elia, A., Eckhardt, B., Caudullo, G., Taboada, F. Á., Andriolo, A., Bălăcenoiu, F., Bastos, A., Buzatu, A., Dorado, F. C., Dobrovolný, L., Duduman, M., Fernandez-Carrillo, A., Hernández-Clemente, R., Hornero, A., Ionuț, S., Lombardero, M. J., Junttila, S., Lukeš, P., Marianelli, L., Mas, H., Mlčoušek, M., Mugnai, F., Nețoiu, C., Nikolov, C., Olenici, N., Olsson, P., Paoli, F., Paraschiv, M., Patočka, Z., Pérez-Laorga, E., Quero, J. L., Rüetschi, M., Stroheker, S., Nardi, D., Ferenčík, J., Battisti, A., Hartmann, H., Nistor, C., Cescatti, A., and Beck, P. S. A.: The Database of European Forest Insect and Disease Disturbances: DEFID2, Global Change Biology, 29, 6040–6065, https://doi.org/10.1111/gcb.16912, 2023.

San-Miguel-Ayanz, J., Schulte, E., Schmuck, G., Camia, A., Strobl, P., Liberta, G., Giovando, C., Boca, R., Sedano, F., Kempeneers, P., McInerney, D., Withmore, C., Oliveira, S. S. de, Rodrigues, M., Durrant, T., Corti, P., Oehler, F., Vilar, L., and Amatulli, G.: Comprehensive Monitoring of Wildfires in Europe: The European Forest Fire Information System (EFFIS), in: Approaches to Managing Disaster, edited by: Tiefenbacher, J., IntechOpen, Rijeka, https://doi.org/10.5772/28441, 2012.

Forzieri, G., Pecchi, M., Girardello, M., Mauri, A., Klaus, M., Nikolov, C., Rüetschi, M., Gardiner, B., Tomaštík, J., Small, D., Nistor, C., Jonikavicius, D., Spinoni, J., Feyen, L., Giannetti, F., Comino, R., Wolynski, A., Pirotti, F., Maistrelli, F., Savulescu, I., Wurpillot-Lucas, S., Karlsson, S., Zieba-Kulawik, K., Strejczek-Jazwinska, P., Mokroš, M., Franz, S., Krejci, L., Haidu, I., Nilsson, M., Wezyk, P., Catani, F., Chen, Y.-Y., Luyssaert, S., Chirici, G., Cescatti, A., and Beck, P. S. A.: A spatially explicit database of wind disturbances in European forests over the period 2000–2018, Earth Syst. Sci. Data, 12, 257–276, https://doi.org/10.5194/essd-12-257-2020, 2020.

Langner, N. and Oehmichen, K.: Referenzdaten aus dem Projekt FNEWS, Johann Heinrich von Thünen Institut, DE, 5 pp., 2024.

Giambelluca, A. L., Hermosilla, T., Álvarez-Mozos, J., and González-Audícana, M.: Identifying forest harvesting practices: Clear-cutting and thinning in diverse tree species using dense Landsat time series, Forest Ecology and Management, 578, 122442, https://doi.org/10.1016/j.foreco.2024.122442, 2025.

Senf, C. and Seidl, R.: Storm and fire disturbances in Europe: Distribution and trends, Global Change Biology, 27, 3605–3619, https://doi.org/10.1111/gcb.15679, 2021b.

Seidl, R. and Senf, C.: Changes in planned and unplanned canopy openings are linked in Europe's forests, Nat Commun,

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

Open Access Earth System Science Data Discussions

15, 4741, https://doi.org/10.1038/s41467-024-49116-0, 2024.

Esri: World Imagery (Wayback), 2025.

CLMS: Very High Resolution Image Mosaic 2021 True Colour (raster 2 m), Europe, 2021.

Google Earth: https://earth.google.com/web/, last access: 9 March 2026.

EC JRC: Copernicus Emergency Management Service (©2019 European Union) EMSR143, 2019.

Jin, S. and Sader, S. A.: Comparison of time series tasseled cap wetness and the normalized difference moisture index in detecting forest disturbances, Remote Sensing of Environment, 94, 364–372, https://doi.org/10.1016/j.rse.2004.10.012, 2005.

Schultz, M., Clevers, J. G. P. W., Carter, S., Verbesselt, J., Avitabile, V., Quang, H. V., and Herold, M.: Performance of vegetation indices from Landsat time series in deforestation monitoring, International Journal of Applied Earth Observation and Geoinformation, 52, 318–327, https://doi.org/10.1016/j.jag.2016.06.020, 2016.

Cohen, W. B., Yang, Z., and Kennedy, R.: Detecting trends in forest disturbance and recovery using yearly Landsat time series: 2. TimeSync — Tools for calibration and validation, Remote Sensing of Environment, 114, 2911–2924, https://doi.org/10.1016/j.rse.2010.07.010, 2010.

Schwärzel, K. and Wohlgemuth, L.: Forest Condition in Europe : The 2024 Assessment, edited by: Michel, A. K., Haggenmüller, K., Kirchner, T., and Prescher, A.-K., Johann Heinrich von Thünen Institut, DE, 99 pp., 2024.

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., and Wulder, M. A.: Good practices for estimating area and assessing accuracy of land change, Remote Sensing of Environment, 148, 42–57, https://doi.org/10.1016/j.rse.2014.02.015, 2014.

Reinosch, E., Backa, J., Adler, P., Deutscher, J., Eisnecker, P., Hoffmann, K., Langner, N., Puhm, M., Rüetschi, M., Straub, C., Waser, L. T., Wiesehahn, J., and Oehmichen, K.: Detailed validation of large-scale Sentinel-2-based forest disturbance maps across Germany, Forestry: An International Journal of Forest Research, cpae038, https://doi.org/10.1093/forestry/cpae038, 2024.

Processor Releases Timeline: https://operations.dashboard.copernicus.eu/processors-viewer.html, last access: 21 November 2025.

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Köpf, A., Yang, E., DeVito, Z., Raison, M., Tejani, A., Chilamkurthy, S., Steiner, B., Fang, L., Bai, J., and Chintala, S.: PyTorch: An Imperative Style, High-Performance Deep Learning Library, https://doi.org/10.48550/ARXIV.1912.01703, 2019.

Buras, A., Rammig, A., and Zang, C. S.: Quantifying impacts of the drought 2018 on European ecosystems in comparison to 2003, Earth System Science/Response to Global Change: Climate Change, https://doi.org/10.5194/bg-2019-286, 2019.

Thonfeld, F., Gessner, U., Holzwarth, S., Kriese, J., da Ponte, E., Huth, J., and Kuenzer, C.: A First Assessment of Canopy Cover Loss in Germany's Forests after the 2018–2020 Drought Years, Remote Sensing, 14, 562, https://doi.org/10.3390/rs14030562, 2022.

Schuldt, B., Buras, A., Arend, M., Vitasse, Y., Beierkuhnlein, C., Damm, A., Gharun, M., Grams, T. E. E., Hauck, M.,

https://doi.org/10.5194/essd-2026-185
Preprint. Discussion started: 12 May 2026

Hajek, P., Hartmann, H., Hiltbrunner, E., Hoch, G., Holloway-Phillips, M., Körner, C., Larysch, E., Lübbe, T., Nelson, D. B., Rammig, A., Rigling, A., Rose, L., Ruehr, N. K., Schumann, K., Weiser, F., Werner, C., Wohlgemuth, T., Zang, C. S., and Kahmen, A.: A first assessment of the impact of the extreme 2018 summer drought on Central European forests, Basic and Applied Ecology, 45, 86–103, https://doi.org/10.1016/j.baae.2020.04.003, 2020.