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ForestPaths

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

D2.3 Drivers of forest disturbances in Europe

30/08/2024

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Key takeaway messages

- Statistical hazard models for wind and fire disturbances have been developed from remote sensing data for Europe
- Models simulate disturbance frequency, size, severity and location of disturbances
- Different parts of the hazard models will be incorporated into dynamic forest models developed in Work Package 3

Summary

We here present the development of empirical hazard models of wind and fire disturbances developed from remote sensing-based disturbance maps. The models simulate disturbance frequency (i.e., the number of disturbances per year), size (i.e., the spatial footprint of disturbances), disturbance severity (i.e., the proportion of mortality within a disturbance event) and the location of disturbance across Europe. The spatial prediction is based on a set of environmental and socio-economic variables and climate reanalysis data. It is finally discussed how the fire and wind hazard models can be used to force disturbances in forest models developed in Work Package 3.

1 Introduction

Natural forest disturbances play a crucial role for forest dynamics (McDowell et al., 2020), and it is thus essential to well represent natural disturbances in models of forest dynamics (Seidl et al., 2011). However, many large-scale dynamic vegetation models lack proper disturbance models (Pugh et al., 2020), hampering the projection of future forest dynamics and thus the assessment of future forest carbon potential. Even where such disturbances models are included, they are generally either not parameterized or structurally suitable to be applied at the scale of the European continent (Jönsson et al., 2012; Lagergren et al., 2012). In this deliverable, we aim at filling this gap by providing empirical models of forest disturbances to be included into dynamic vegetation models.

One of the major challenges in developing robust empirical disturbance models is the lack of data on forest disturbances. To calibrate representative and robust disturbance models, disturbance data needs to be (i) spatially explicit, (ii) long-term, and (iii) spatially exhaustive. Spatially explicit data is needed to quantify the spatial characteristics of disturbances, such as patch size distributions, and to match disturbance information to underlying climate drivers. The spatial resolution of the disturbance data thereby needs to be at least at the resolution of the model but ideally higher, which allows for quantifying important disturbance characteristics (e.g. disturbance severity) for each grid cell of the dynamic vegetation model. Long-term data is needed to provide robust quantification of return intervals, which are driven by extreme and thus rare events. Too short time series are liable to misrepresent the frequency of rare events and can thus lead to bias in calculating return intervals. Spatially exhaustive data is needed to cover the full variation and diversity of disturbances and not to build models based on singular or specific events that might have low generalization power.

Remote sensing-based disturbance maps fulfil most of the requirements stated above and thus are ideal data to calibrate robust empirical disturbance models (McDowell et al., 2015). Previous studies have shown the potential of using remote sensing data for model calibration, such as studies combining remote sensing data with meteorological data (Grünig et al., 2022; Senf et al., 2020), vegetation trait and climate data (Pugh et al., 2023) or topographic data (Maroschek et al., 2023). For Deliverable 2.3, we used the next-generation disturbance map created in Deliverable 2.1 to build empirical disturbance models for wind and fire disturbances. Both disturbance models described here were developed as part of a collaborative process that created improved representations of wind and fire disturbances in the EFISCEN-Space European forest model and LPJ-GUESS dynamic vegetation model, drawing on all or parts of the models described herein. Within this deliverable report, we describe the specific models and highlight the components of the disturbance models taken forward to Work Package 3. For the description of how these components are applied in EFISCEN-Space and LPJ-GUESS, please refer to Deliverable 3.1.

2 Methods

2.1 Conceptual framework

During two in-person meetings held in Freising (Germany) and Lund (Sweden) in 2023 and 2024, respectively, we decided to adapt a hazard-vulnerability-exposure modelling framework for developing disturbance models in ForestPaths (Figure 1). The hazard-vulnerability-exposure modelling framework breaks down the model structure into three components: hazard, vulnerability and exposure. Hazard represents the external disturbance event without dynamic feedback to the actual forest state (e.g. the probability that a storm event occurs or that a fire ignites). Vulnerability, in turn, represents the susceptibility of the forest to a disturbance event (a hazard), defined by the forest's composition and structure. Exposure represents the value at risk, such as carbon pools or timber value that could be lost during a disturbance. Overall, this represents the risk of disturbance. The advantage of the framework is that it allows for modelling disturbance hazards irrespectively of the underlying forest population, and thus from remote sensing-based disturbance maps as produced in Deliverable 2.1. The vulnerability is subsequently determined using process-based functions implemented in dynamic forest models, such as in EFISCEN-Space or LPJ-Guess. That way, modelling dynamic feedback between hazard and vulnerability becomes possible. In this deliverable, we focus on the hazard component of the modelling framework, modelling the occurrence and characteristics of natural disturbances irrespectively of the forest state and solely based on stochastic principles. The implementation of vulnerability functions (and the estimation of exposure) is implemented in the forest models and will be described in Deliverable 3.1.

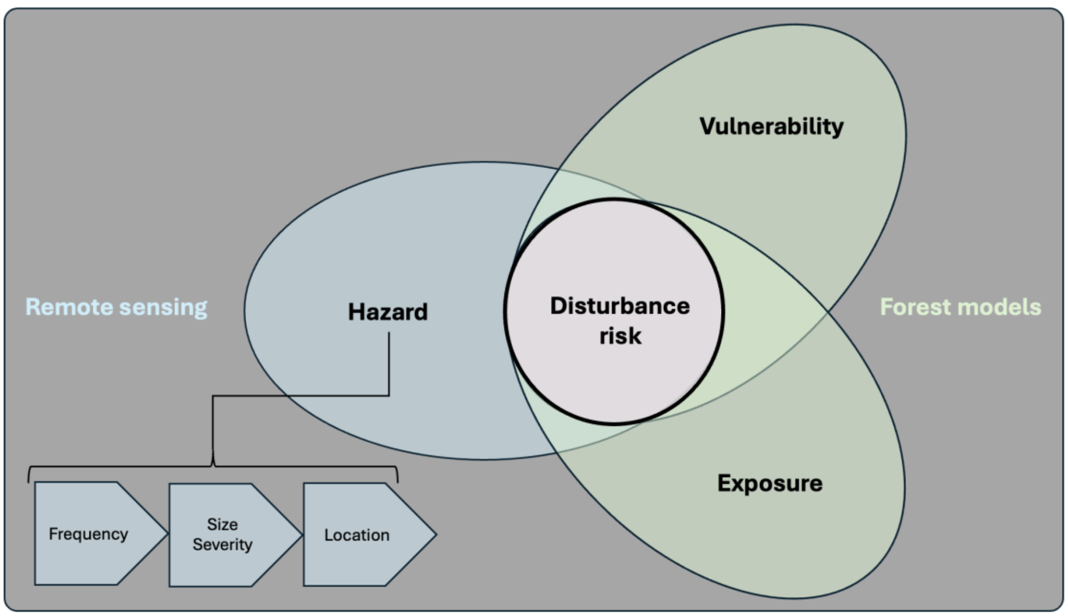

Figure 1: Conceptual representation of the disturbance modeling approach.

The hazard modelling approach consists of three major steps (see also Figure 1): (1) modelling the disturbance frequency, that is the number of disturbance event to occur per year; (2) modelling the size and severity of each disturbance event, that is the spatial area covered and the proportion of forests affected once a disturbance materializes, and (3) modelling the location of each disturbance by a spatially explicit disturbance occurrence probability model. We will describe this process for both fire and wind disturbance in more detail in the following.

2.2 Fire disturbance model

We first aggregated all fire disturbance patches occurring in the next-generation forest disturbance map to fire complexes by combining patches that were <= 150 m apart. This was done to avoid large fires being split into many smaller patches due to fire breaks or forestry roads. We then drew a convex hull around all patches belonging to one complex to calculate the area of the fire complex. We did the aggregation annually, thus creating annual maps of fire disturbance complexes covering 30-year period 1987 to 2016. Based on the annual fire complexes, we fitted a statistical model to represent the distribution of fire frequency (i.e. number of fires per year across Europe), fire size, and fire severity (defined as the relative area within each complex affected by disturbance). We compared multiple statistical models, including normal, log-normal, pareto, gamma, Weibull and logistic distributions and chose the distribution with the smallest Akaike information criteria. The distribution allows for drawing random realizations of fire frequency, size and severity for forcing disturbances in forest models. In a second step, we aggregated all fire complexes to a grid of 10 x 10 km nested within the coarser grid. For each 10 x 10 km grid cell, we obtained the presence or absence of at least one fire, irrespectively of the year the fire occurred in. If a fire occurred in the past, the cell was assigned as presence, and all grid cells without fires were labeled as absences. Using this data, we calibrated a binomial generalized additive model to predict the probability of a fire based on a set of environmental and socio-economic predictors. While many predictors of fire probability have been suggested in the literature, we selected the following predictors that all were available spatially: population density (Klein Goldewijk et al., 2017), distance to roads and summer lightning density (Kaplan and Lau, 2021) as predictors of ignition (through arson and lightning); elevation, slope and aspect as predictors of accessibility (Copernicus Land Monitoring Service); distance to water as predictor of extinction capacities (Copernicus Land Monitoring Service); as well as temperature, precipitation, and seasonality (averaged over 30 years and derived from Copernicus ERA5; Hersbach et al., 2020) as predictors of fire weather. The resulting probabilities were divided by the number of years to obtain annual probabilities of fire occurrence.

2.3 Wind disturbance model

In contrast to fire disturbances, wind disturbances can cover extremely large areas spread across many countries, leaving a distinct footprint at the continental scale. To account for this fact, we first aggregated all wind disturbances from the next-generation forest disturbance map (D2.1) to a grid of 10 x 10 km and assigned each grid cell as zero if no wind disturbances was included and as one if at least one disturbance was included. As wind and bark beetle disturbances are mixed in one category in the disturbance map, we only used disturbances until 2016 (i.e. the same 30-year period as for fire), because disturbances prior to 2016 are mainly related to wind disturbances (see also D2.5). We though acknowledge that some bark beetle disturbances might be included in the reference data, but their relative importance in comparison to wind disturbances is considered minor (Patacca et al., 2023). The aggregation was done at the annual level, resulting in annual grids of wind disturbance presence and absence. For each annual presence/absence map, we connected neighboring presence cells to continuous areas using a queen-contiguity. This converts the individual raster cells into storm events, that is continuous areas affected by storm disturbances in the same year. An example of the processing step in shown in Figure 2. Based on the annual storm events, we derived statistical models to represent the distribution of wind frequency (i.e. number of wind events per year across Europe), wind size, and wind event severity (defined as the relative area within each event affected by disturbance). We tested variable statistical models, including normal, log-normal, pareto, gamma, Weibull and logistic distributions and chose the distribution with the smallest Akaike information criteria. The distribution allows for drawing random realizations of wind event frequency, size and severity for forcing disturbances in process-based models.

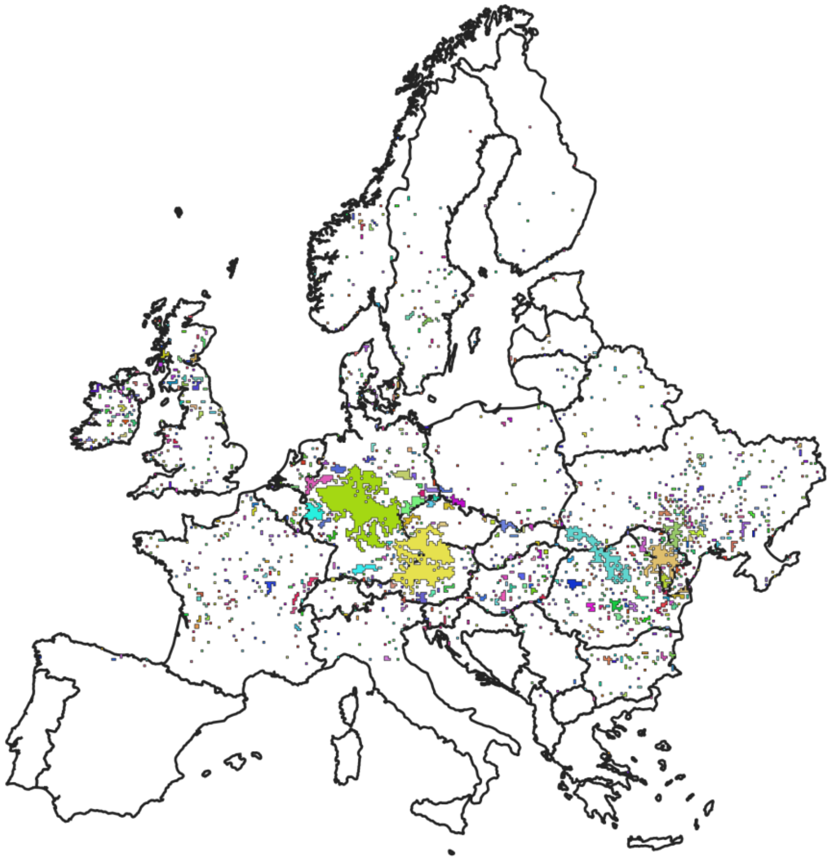

Figure 2: Wind disturbance events derived from the gridded wind disturbance data at 10 x 10 km spatial resolution. The example shows the year 2007, which was characterized by the large-scale storm Kyrill that resulted in several distinct storm events across Europe. The colors indicate different events, which are spatially separated (i.e. at least 10 km between them).

In a second step, we aggregated all wind disturbance events to a 10 x 10 km grid as described for fire disturbances, and following modelled the spatial wind disturbance occurrence probability. For doing so, we calibrated a binomial generalized additive model with 5-year storm wind speed return intervals and maximum storm gusts as predictor variables. That is, we predict the occurrence of a wind disturbance event based on historical storm data, expecting a higher occurrence probability in areas of higher historic storm intensity. The 5-year storm wind speed return intervals and maximum storm gusts (see Figure 3) were obtained from the Copernicus storm database (https://doi.org/10.24381/cds.9b4ea013), which is a pan-European database of storm reanalysis. The database provides the most accurate representation of storm conditions for Europe to date. From the model, we predicted average occurrence probability for each grid cell (i.e. what is the probability that a wind disturbance occurs in this grid cell) and divided the probability by the number of years to obtain an annual wind disturbance probability. We did not use additional topographic predictors, because topographic data was already used for the reanalysis of the storm database.

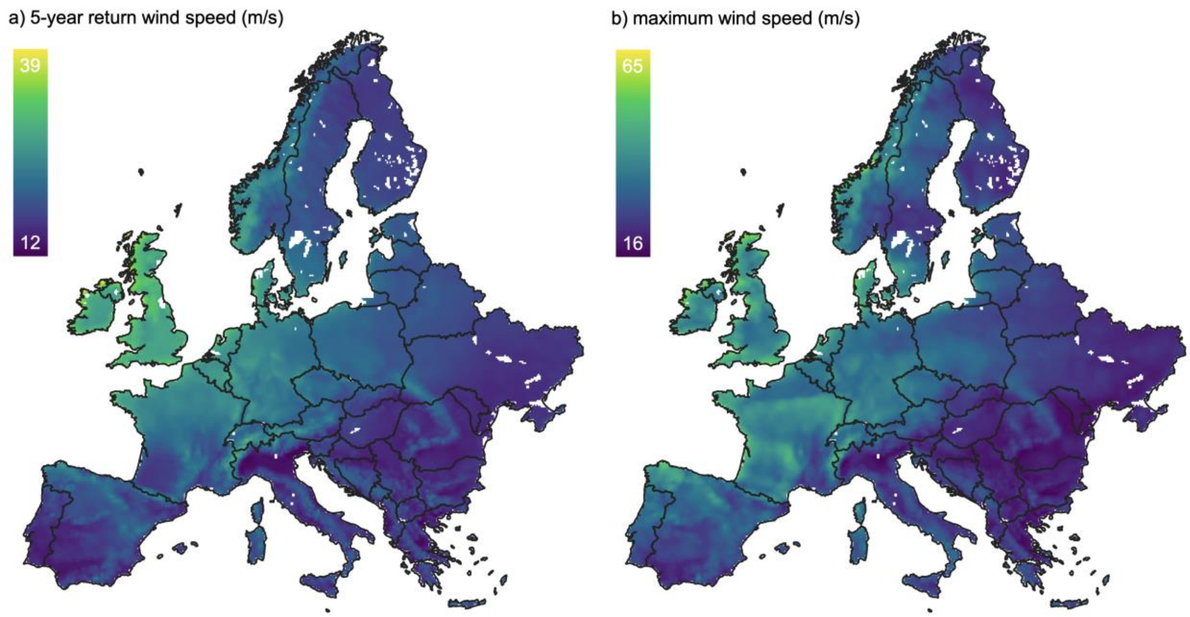

Figure 3: (a) 5-year return maximum wind speed and (b) overall maximum wind speed, both derived from the Copernicus storm database and used as predictor of wind disturbance occurrence probability.

3 Results

3.1 Fire disturbance model

We identified over 70,000 fire complexes across Europe between 1987 and 2016 with an average frequency of 1865 fires per year or 0.005 fires per km^2 (Figure 4). The frequency distribution was right-skewed and best described through a log-normal distribution with parameters given in Table 1. Fire size was also heavily right-skewed and best described through a log-normal distribution (see Table 1), with 90% of the fire complexes being smaller than 150 ha or 1.5 km^2. Fire severity, that is the total area that burned within a fire complex (and not the pixel-wise severity), was left-skewed, with 24% of the complexes showing 100 % severity. The distribution was best described through a logistic model (Table 1). Average severity, i.e. proportion of the complex that burned, was 80 %.

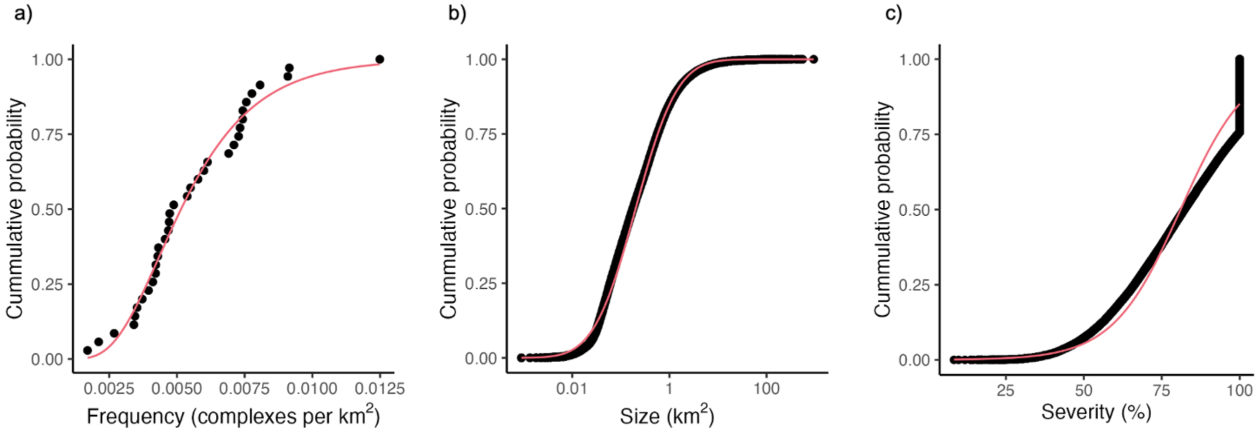

Figure 4: (a) Distribution of fire complex frequencies with the corresponding statistical model (log-normal model), (b) distribution of wind fire complex sizes with the corresponding statistical model (log-normal model), and (c) distribution of wind disturbance severities with the corresponding statistical model (logistic model). Note the $\log_{10}$-scale for (b).

Table 1: Parameters of the statistical models

Model	Unit	Distribution	Parameters
Frequency	Number of complexes	Log-normal	$mean_{log}$ = 7.45; sd_{log} = 0.42
Size	km^2	Log-normal	$mean_{log}$ = -1.60; sd_{log} = 1.56
Severity	%	Logistic	location = 81.02; scale = 10.86

The spatial model of annual fire event probability (Figure 5), including population density from, summer lightning density, elevation, slope, aspect, distance to roads, distance to water and climate as predictors, yielded an R^2 of 0.58 and an AUC of 0.92 and predicted a distinct geographic pattern of disturbance probability across Europe. We note that this occurrence probability is the probability that a randomly chosen fire (i.e. based on the distributions shown in Figure 4) will occur in this grid cell. Highest probability was found in southern Europe (e.g. Spain, Greece), with moderate probability in Eastern Europe (e.g. Ukraine) and the southern Alps, and lowest probabilities in Western- and western Central-Europe (e.g. Northern France, Germany). Occurrence probability was mainly driven by temperature, with increasing probability with increasing average temperature, by lighting, with increasing probability with increasing lightning density, and by population density, with decreasing probability with increasing population density. Average probability ranges from 0.0 to 0.03, meaning an annual probability of 3 % or a return interval of ~33 years.

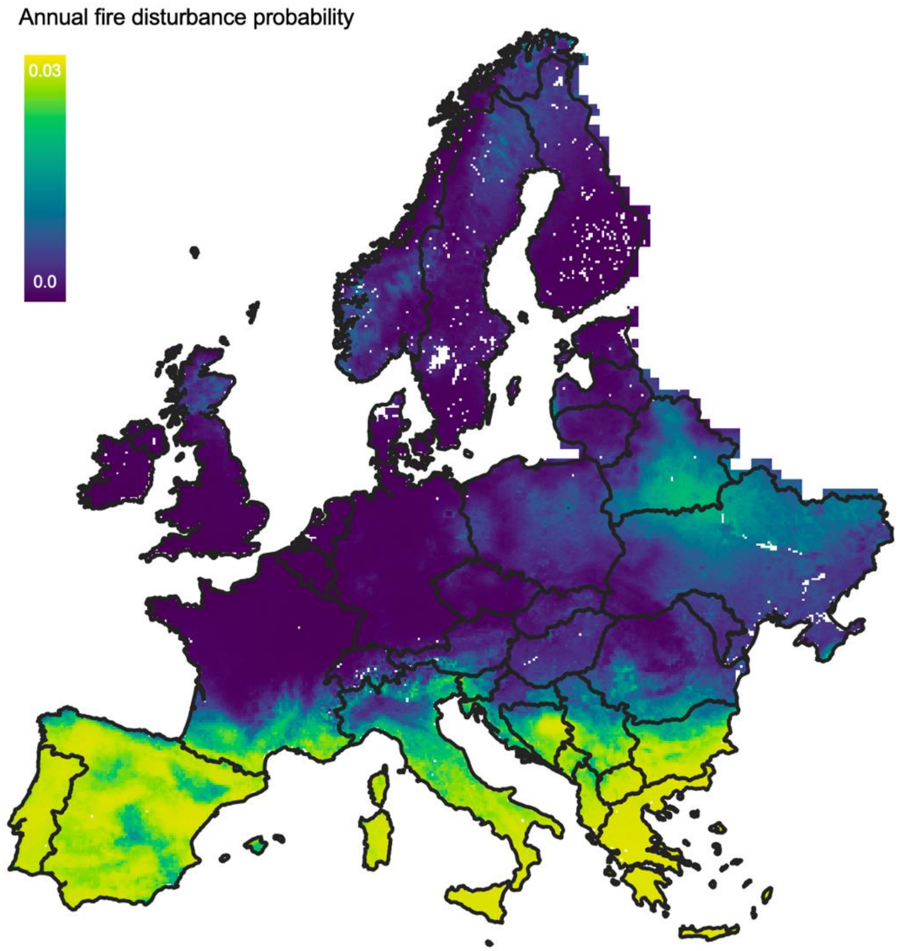

Figure 5: Annual probability of fire disturbance occurrence as predicted from our model.

3.2 Wind disturbance model

We identified over 30,000 wind disturbance events across Europe between 1986 and 2016 with an average frequency of 1003 wind events per year or 0.003 wind events per km^2 (Figure 6). The frequency distribution was best described through a normal distribution (Table 2). Wind events were overall larger than fire complexes but also heavily right-skewed (log-normal distribution, see Table 1), with 90% of the wind events being smaller than 30,000 ha (300 km^2). Wind event severity, that is the total area disturbed within a single wind event, was low and log-normally distributed (Table 1). On average, wind event severity was only 0.9 %, meaning that only a very small fraction of the area affected by a wind event are disturbed. However, due to heavy skewedness, 90 % of the wind events had a severity of 2.1 % and the average is not descriptive of the distribution of severities. This example nicely shows the necessity for proper quantified distributional models instead of relying on simple estimates that might not be proper for the underlying distribution.

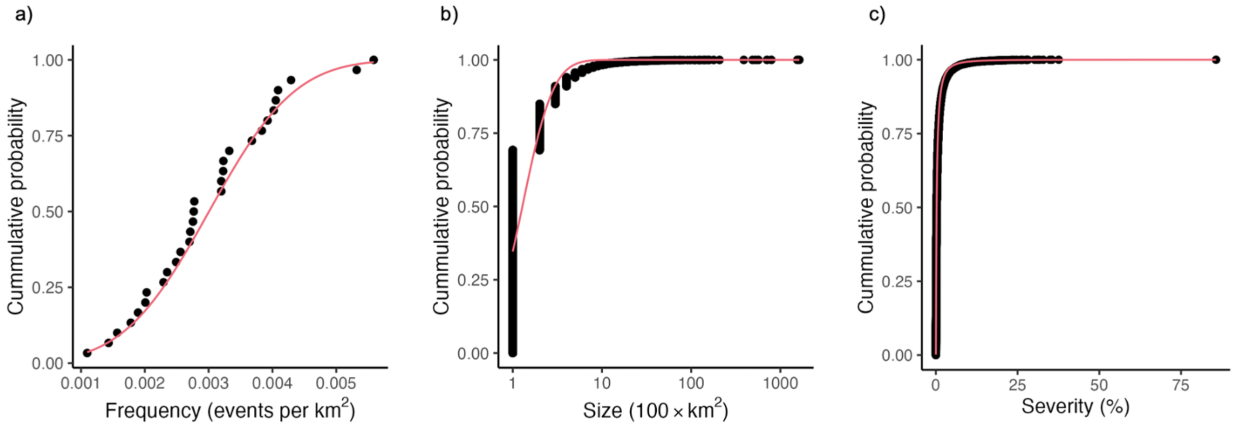

Figure 6: (a) Distribution of wind disturbance frequencies with the corresponding statistical model (normal model), (b) distribution of wind disturbance sizes with the corresponding statistical model (log-normal model), and (c) distribution of wind disturbance severities with the corresponding statistical model (log-normal). Note the $\log_{10}$-scale for (b).

Table 2: Parameters of the statistical models of wind frequency, size and severity.

Model	Unit	Distribution	Parameters
Frequency	Number of events	Normal	mean = 1003.0; sd = 354.4
Size	km^2	Log-normal	$mean_{log}$ = 4.85; sd_{log} = 0.63
Severity	%	Log-normal	$mean_{log}$ = -1.46; sd_{log} = 1.51

The spatial prediction of wind disturbance occurrence probability (Figure 7) yielded an R^2 of 0.17 and AUC of 0.74 and showed again a strong geographical pattern with highest probabilities found in Western Europe (the UK, France, Ireland, the Netherlands, Belgium and Germany) and in mountainous regions such as in the Alps, Carpathians and Pyrenees. Also close to coastlines there was a higher probability. Overall, wind disturbance occurrence probability was strongly driven by high return intervals od wind speeds exceeding 5 m/s, with highest probabilities found in areas with regular winter storm occurrence (i.e. coming from west and moving eastwards). Maximum wind speed, however, showed a negative effect with lower probability found at highest maximum wind speeds, which likely occur in high-mountain regions and very close to the coastline and thus in areas rarely affected by wind disturbances. The south-east of Europe had overall lowest probabilities, due to a lack of large-scale winter storm systems reaching the far south-east of Europe. There are, however, local hotspots in mountainous regions (i.e. Dinaric Alps, Balkan Mountains). Occurrence probability had a similar range than for fires, with highest probabilities indicating an annual 3 % change of experiencing a wind disturbance event (or every ~33 years on average).

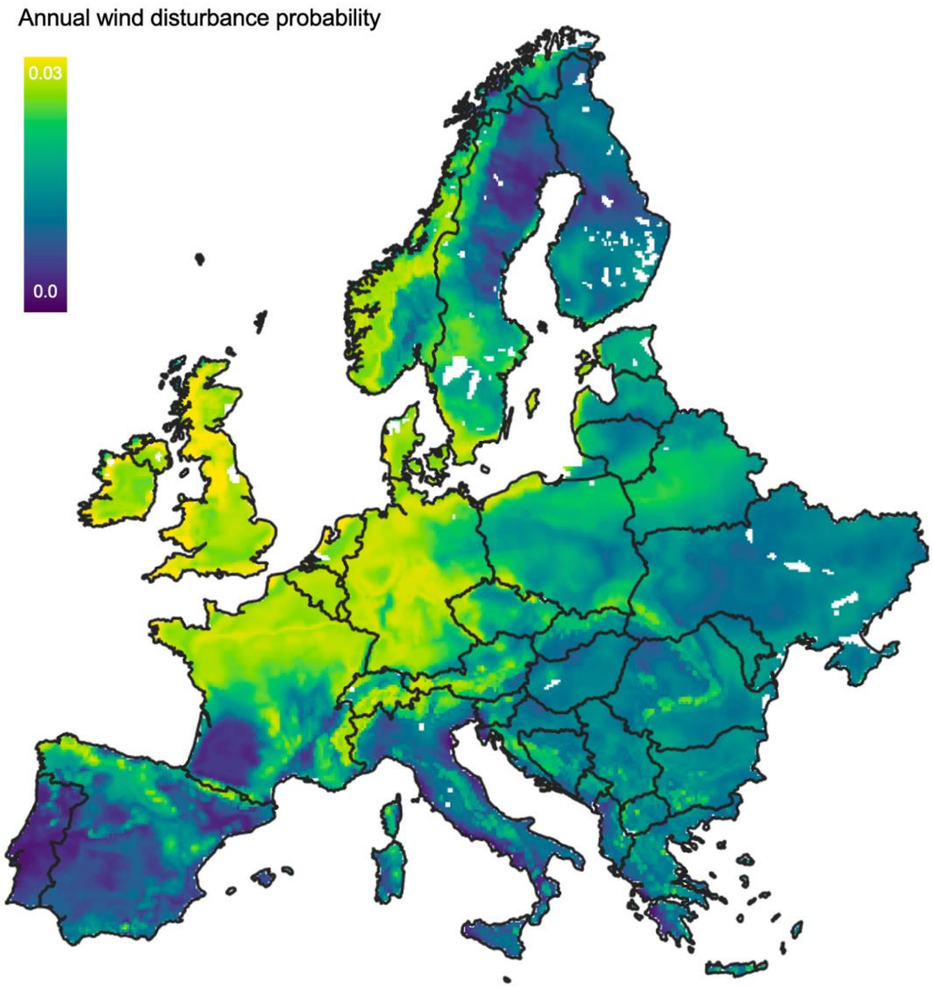

Figure 7: Wind disturbance occurrence probability predicted from our model.

4 Discussion and conclusion

Here, we present statistical hazard models of fire and wind disturbances calibrated from remote sensing data and intended to be included into dynamic forest models. The empirical models allow for simulating the number, size, severity and location of wind and fire disturbances across Europe, which can be used to force disturbances in forest models. Within ForestPaths, we use the disturbance models, their components, or the knowledge gained from implementing them within LPJ-GUESS and EFISCEN-Space (see Table 3 for details). We explicitly did not include forest structure variables into our models, because the vegetation state (e.g. tree height, density, species) will be included within the forest models using process-based or empirical vulnerability functions. Doing so allows for feedback between vegetation state and disturbances (i.e. tree height changes in response to disturbance). This is important to allow for dampening feedback such as declining disturbance risk due to changes in species or forest structure. The different level of disturbance vulnerability representation within different forest models will necessitate different levels of incorporation of the disturbance hazard model components developed in this deliverable. For instance, where advanced calculations of the vulnerability of the existing forest structure to a disturbance is already included in a forest model, then it makes sense to extract the component of the information that is most related to the likelihood that conditions capable of causing disturbance to occur. This is the approach we take in ForestPaths in incorporating wind disturbances into the LPJ-GUESS and EFISCEN-Space models, as described in more detailed in Deliverable 3.1. Similarly, if the forest model benefits from the full breakdown of disturbance frequency, size and severity provided by the disturbance hazard models herein, then it may make sense to include the disturbance model in its entirety (for instance, in the case of fire in EFISCEN-Space). Conversely, if the forest model has a more aggregated representation of disturbance probability, then the information on key drivers that we have generated here can be powerful in helping customise the existing disturbance representations to better reflect the conditions in European forests (for instance, in the case of fire in LPJ-GUESS).

Table 3: Incorporation of components of the hazard models developed herein into forest models developed in Work Package 3 (see Deliverable 3.1).

Hazard model	Component	Forest model
Wind disturbance model	Wind occurrence probability (Figure 7)	LPJ-Guess EFISCEN-Space
Fire disturbance model	Fire occurrence probability (Figure 5)	EFISCEN-Space
	Fire size and frequency (Figure 4)	EFISCEN-Space
	Total area burned per year	LPJ-Guess

We only provide models for wind and fire disturbances, but not bark beetle disturbances. The reason for this were challenges in separating wind and bark beetle disturbances in the disturbance maps in more recent years (after 2016), where wind and bark beetle disturbances showed very similar spatial pattern and were of equal prevalence (Patacca et al., 2023). We hence did not have a reliable reference database for calibrating a bark beetle model from the remote sensing data. We also excluded wind disturbance after 2016 from the modelling approach described herein to not introduce a bias from bark beetle disturbances wrongly assumed to be wind disturbances. We discussed the issue of missing empirical data on bark beetle disturbances during two modelling workshops held in Freising and Lund in 2023 and 2024, and we agreed to proceed with an entirely process-based modelling approach for bark beetle disturbances in Work Package 3.

Overall, we provide first empirical data on the frequency, size, severity and location of wind and fire disturbances across Europe, calibrated based on long-term and consistent remote sensing data. The data will help to improve process models of natural disturbances and allow for assessing changes in disturbances into the future by linking the empirical disturbance models presented herein with predictions of future vegetation states from dynamics forest models.

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