Understanding Europe’s forest harvesting regimes

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Abstract

The functioning and structure of most European forests are actively shaped by intensive human use. Harvesting of wood is one of the key processes of forest management, making it a crucial element to include in any large-scale analysis of forest ecosystems. Yet, our understanding of how forests are harvested across Europe is limited, as the true harvest regimes – a realisation of decisions made by individual forest owners – are not well described by aggregated wood harvest statistics or formal management guidelines. To fill this gap, we analysed recent forest harvest activity, as observed in permanent plots of forest inventories in eleven European countries, totalling to 182,649 plots and covering all major forest types from boreal to Mediterranean forests. We aimed to (1) characterise harvest regimes through the frequency and intensity of harvest events spatially across Europe, and (2) build predictive models for the probability and intensity of harvest events at the plot-level, by linking individual harvests to the pre-harvest forest structure and composition, but also to climatic, topographic and socio-economic factors, as well as past natural disturbances. The results reveal notable variation in harvest regimes across Europe, with different harvest strategies emerging in regions with similar total harvest rates. These include, for example, low-frequency but high-intensity harvest regimes in northern Europe and high-frequency but low-intensity harvest regimes in eastern Central Europe. The harvest regimes were strongly driven by country-level variation, emphasising the role of national level factors in driving harvest patterns. Pre-harvest forest structure and composition was an important driver for the intensity of harvest events, whereas probability of harvest was more related to socio-economic factors and the occurrence of natural disturbances. The empirical quantification of the current forest harvesting regimes across Europe presented in our study provides much needed detail in our understanding of the contemporary forest management practices in Europe, crucial for understanding how human activities shape forests and providing a baseline against which to assess future changes in management.

Keywords: forest, Europe, forest management, land management

1. Introduction

The majority of forests in Europe are under human management and harvest dominates over natural mortality as the main cause of tree death (Schelhaas et al., 2018; Senf and Seidl, 2021a). Harvesting of wood is a major process through which human activities shape forests (Duncker et al., 2012). The applied harvesting strategies fundamentally impact the extent to which forests may act as a carbon sink (Daigneault et al., 2022; Dalmonech et al., 2022; Soimakallio et al., 2022), provide ecosystem services (Gregor et al., 2022; Triviño et al., 2023), maintain or enhance biodiversity (Savilaakso et al., 2021) or be vulnerable to natural disturbances and stress (Manrique-Alba et al., 2022; Pukkala et al., 2016; Wallentin and Nilsson, 2014). These all are key elements of the EU forest strategy (European Commission, 2021). If European-scale assessments of current and future forest-based services are to be accurate, it is essential that they are grounded in the actual harvesting frequencies and intensities applied to these forests.

While it is crucial to understand harvest to understand European forests, a detailed quantification of the contemporary harvest regimes does not currently exist. The quantitative studies of harvest at European level have so far been limited to the total amount of wood harvested (Levers et al., 2014; Verkerk et al., 2015) and contain little detail on the harvest strategies applied. Remote sensing methods provide a promising approach for quantifying harvests, but they have faced challenges in separation of harvest from natural disturbances and identification of less intensive harvest events (e.g. Ceccherini et al., 2020, and responses by Palahí et al., 2021 and Breidenbach et al., 2022). To move beyond the amount of wood or forest area harvested towards understanding management regimes, several efforts have been made to map different management approaches in European or at global scales using remote sensing, forest statistics and expert knowledge – or some combinations of these (Lesiv et al., 2022; Nabuurs et al., 2019; Schulze et al., 2019). However, they describe management through qualitative categories and lack quantifications of how harvests are actually carried out. More detailed information on harvest strategies can be found in forest management plans and guidelines, which are typically available at national or smaller scales. Compilations of these, together with expert knowledge, have been used to describe management across Europe (Aszalós et al., 2022; Cardellini et al., 2018; Mason et al., 2021) and to characterise harvests in modelling efforts (Härkönen et al., 2019; Nabuurs et al., 2001; Vauhkonen et al., 2019). Yet, guidelines and management plans are not always adhered to in reality, which leaves the real world management deviating significantly from the guidebook (Schelhaas et al. 2018). Thus, despite a considerable amount of research attention on European forest management, we are still lacking a quantification of harvest regimes that characterises the variation in harvesting approaches across different countries and is based on direct empirical observations.

The need for a consistent observational basis in describing the harvest regimes in Europe is emphasised by the large variation in harvesting practices between countries and regions (Aszalós et al., 2022; Schelhaas et al., 2018). This spatial variation stems from many factors. The variation of the natural environment, including the climatic, edaphic and topographic conditions, gives the basic framework governing how forests can grow and be managed. Superimposed on this are the nationally and regionally varying legislations, regulations and subsidies, as well as different goals of forest management and forest use. These affect which types of harvest strategies are applied. Harvest also does not occur in isolation, but depends on the dynamic natural and socio-economic environment. Natural disturbances lead to increased harvest rates and different harvest strategies when salvaging damaged wood (Verkerk et al., 2015), and fluctuations in the economy drive harvest levels through the prices and demand for wood (Beach et al., 2005). All these factors lead to diverse patterns of forest harvest across Europe. Yet, the individual contributions of these different factors are not well understood.

To understand how harvest is carried out, national forest inventories (NFIs) provide a powerful source of data, as they systematically and extensively sample Europe's forests. While information from NFIs underlies a lot of national forest statistics (FAO, 2020; FOREST EUROPE, 2020), they contain detail and potential that go far beyond the highly aggregated information reported in these sources. Several studies have used NFI data to give detailed characterisation of harvest regimes at regional and national extents (Antón-Fernández and Astrup, 2012; Kilham et al., 2019; Schelhaas et al., 2018; Thompson et al., 2017), but this approach has not been applied across larger spatial scales. Analysing NFI data consistently across countries would allow going beyond the national scale and thus close a major gap in understanding Europe's harvest regimes.

Here, our goal is to improve the current understanding of contemporary harvest regimes across Europe by extracting information about harvest patterns from re-measured plots of national forest and landscape inventories in eleven European countries, totalling to 182,649 plots and representing 123 million hectares of forest across all major forest types from boreal to Mediterranean forests. Our specific aims are to (1) characterise harvest regimes through the frequency and intensity of harvest events spatially across Europe, and (2) build predictive models for the probability and intensity of harvest events at the plot-level, by linking individual harvests to the pre-harvest forest structure and composition, alongside climatic, topographic and socio-economic factors, and past natural disturbances.

2. Material and methods

2.1 Forest inventory data

We used a collection of data from permanent plots of national forest inventories and landscape inventories from eleven European countries (Table 1). This data set consisted of a total of 182,649 plots and 2,123,952 trees across over 123 million hectares of forest (70% of the EU forest area, plus Norway and Switzerland). From each plot we used two consecutive measurements, recording the species, diameter, and status (alive/dead/harvested) of each tree. The first measurement was used to describe the pre-harvest status of the forest and from the second measurement we took the information about tree status, describing which trees had been harvested between the two measurements. Only trees alive in the first measurement were considered. Each plot came with coordinates accurate to ca. kilometre scale.

***Table 1**. Data set details and years of data used for pre-harvest status (1st measurement) of forests and the harvest information (2nd measurement) and the average measurement interval for each country, including the total number of plots and those with harvest recorded.*

Country	**Data source**	**1st measurement**	**2nd measurement**	**Average interval (years)**	**Number of plots**	**Number of plots with harvest**
Belgium	NFI Wallonia	1994-2003	2008-2011	10.4	1 140	639
Czechia	CzechTerra	2008-2009	2014-2015	5.9	575	267
Finland	NFI	2009-2013	2014-2018	5	9 928	1 884
France	NFI	2010-2014	2015-2019	5	29 730	5 801
Germany	NFI	2000-2003	2011-2013	10.3	45 199	24 663
Netherlands	NFI	2012-2013	2017-2020	5.8	927	300
Norway	NFI	2012-2016	2017-2021	5	11 176	627
Poland	NFI	2010-2014	2015-2019	5	19 061	8 430
Spain	NFI	1985-1999	1997-2008	11.2	45 566	11 049
Sweden	NFI	2008-2012	2013-2017	5	14 977	2 512
Switzerland	NFI	2004-2006	2009-2017	8.1	4 370	1 274
Total					182 649	57 446

2.1.1 Data processing and harmonisation

In Europe, each country conducts their forest inventory independently, and the sampling design and thus measurement interval differ between countries and need to be harmonised. Here, the differing diameter-at-breast-height (DBH, measured at 1.3 m height) threshold for the minimum size of measured trees was harmonised by setting a common threshold of 10 cm, which was used for all countries except for Switzerland, where the threshold in the data was 12 cm. To account for the different sample plot designs, we weighted each tree by the inverse of their sampling probability on a hectare when calculating the plot level variables from the tree data (see details of sampling designs in the Table S1). The sampling probability was calculated by comparing the plot area from which a tree would be measured (which, depending on the sample plot design, can depend on the tree size) to the area of a hectare.

Plots with no trees in the first measurement were excluded, together with plots with a census interval of more than 15 years In total, the data set finally consisted of 182,649 plots (Table 1).

As the time interval between the two measurements varied across the data, we annualised the data by transforming the two observations from each plot into annual data points. This annualised version of the data set was used for calculating the harvest frequencies for the 1 degree grid (see details in section 2.1.2) and for training the random forest predicting the probability of harvest in a plot (see details in section 2.3). The annualisation was done by, first, converting a single plot into data points representing each of the years between the two measurements, and then assigning harvest to the middle year of the measurement interval. Finally, the data points representing years after harvest were updated to represent the post-harvest forest structure at the plot. This update is relevant only for the random forest predicting harvest probability, as it affects the forest structure variables used in the prediction (see section 2.3.2). For example, tree basal area per hectare would be calculated from all trees in the first measurement for the annualised data points before harvest, and only from the non-harvested trees in the first measurement for data points after harvest. These updated post-harvest data points were excluded from further analysis if they did not fit the original inclusion criteria (i.e., did not contain any trees above the 10 cm threshold). For example, in the case of a clear cut occurring between the measurements, the final annualised data set would contain data points for the pre-harvest years and the harvest year, but the post-harvest years would be excluded as they would not have any trees left. The final annualised data set contained 1,430,229 data points.

Sampling density (plots per forest area unit) varied between countries and, in some cases, within countries, if the country was divided into sampling regions with different sampling designs. We therefore calculated weights for each observation based on the forest area represented by the plot. This was either calculated by dividing the forest area in the country (or sampling region) by the number of plots included in the analysis, or in some cases this information was provided with the inventory data (see details in the Supplementary material). The weights were used as observation weights in the random forest training and for calculating the partial dependence plots (section 2.3).

2.1.2 Characterising harvesting regimes

Harvesting regimes were characterised in terms of the frequency and intensity of harvest events and aggregated on a 1-degree grid to explore general spatial patterns of harvest across Europe. A harvest event was defined on plot-level as a case where at least one of the trees alive in the first measurement had been harvested in the second measurement. Harvest therefore includes any event where trees are cut, including thinnings, selective harvests and clear cuts, as well as salvage loggings after natural disturbances.

The frequency of harvest events was calculated for the grid cells from the annualised data (see details in section 2.1.1) as the percentage of annual data points containing harvest in the grid cell. *The intensity of harvest event* was defined as the percentage of the tree basal area removed in harvest between the measurements (i.e., not the annualised data). For the grid cell, we calculated the mean intensity of harvesting in the plots, and also the share of harvest events in different intensity classes (<25%, 25-50%, 50-75% and >75% of basal area removed). In addition, we calculated a *total harvest rate,* which integrates the frequency of harvest events and their intensity. This was defined as the percentage of the total tree basal area in the grid cell that was harvested annually. Additional detail on the calculation of the harvest variables can be found in the Supplementary material.

Grid cells were only included in the results when there were at least 20 inventory plots in the cell. For intensity of harvest, calculated as the average of all harvest events, only grid cells with at least 5 harvest events were included (Fig. S1).

All the analyses were conducted in R (R Core Team, 2021, versions 4.0.4 and 4.1.0).

2.3 Predictive models

2.3.1 Implementation

Predictive modelling was carried out on plot-level using random forest models (RF). Models were built in two steps using the plot-level forest inventory data. In the first step, a random forest model was trained to predict the probability of a harvest event in the annualised data set, with the binary response variable of harvest or no-harvest ($RF_{Probability}$). As the classes were strongly unbalanced, with a lower number of harvest cases compared to non-harvested data points, different resampling methods to balance the classes were tested and evaluated with cross-validation to find the approach leading to best performance of the model (see details in Fig. S5). Based on this, the classes were balanced to a 1:1 ratio prior to model training by undersampling the no-harvest class. The effects of the undersampling were corrected to the predicted probabilities following Pozzolo et al. (2015).

In the second step, a random forest model was trained to predict the intensity of harvest, defined as the percentage of basal area removed in the harvest event, thus having a continuous response variable ranging from 0 to 1 ($RF_{Intensity}$). For this, only the data points where harvest was present were used, and no annualization was needed.

Both models used the same set of predictor features (described in section 2.3.3 and Table 2) and were fitted with the number of trees in the random forests set to 300, the other hyperparameters kept to their default values. For both RFs, the categorical predictors were handled by ordering the classes based on the proportion of observations falling into the harvest class and treating the predictor as an ordered factor, using this order in the binary splits of the regression/classification trees (Hastie et al., 2009; Wright and Ziegler, 2017).

The random forests were trained with the R package *ranger* (Wright and Ziegler, 2017, version 0.12.1), while the overall workflow was constructed with the *mlr3* package (Lang et al., 2019, version 0.13.3).

2.3.2 Features predicting harvest

Harvest is driven by factors relating to the characteristics of the forest, as well as the natural and human environment. We identified variables in these three categories (forest structure and composition, natural environment, and human environment) potentially affecting the probability and intensity of harvest events (Table 2, Figs. S6 and S7).

Forest structure and composition

Harvest depends on the *forest characteristics* as harvest operations are typically planned at certain developmental stages of stand rotation and different species are harvested with different strategies and intensities. We describe the pre-harvest state of the forest using forest structure (quadratic mean diameter, total tree basal area per hectare, tree size structure described with the Gini coefficient of tree diameters) and species composition (dominant species group, the percentage of basal area covered by the dominant species). These variables were calculated using the first census at each plot. The dominant species was defined as the species with the highest basal area in the plot and characterised by species groups modified from the grouping in Verkerk et al. (2015, Table 2).

Natural environment

The *growth conditions* of the site provide the basic framework for how forests can be grown and managed. In our analysis, we used the average net primary production (NPP) from 2000 to 2012 to describe the variety of growth conditions across the study area (Neumann et al., 2016). *Topographic conditions* are also related to growth condition, but it can also affect harvest through increased costs of harvest (Spinelli et al., 2017) and through specific forest management goals, e.g. increasing the need to use forests for protection against rockfall and avalanches (Dorren et al., 2004). Here, elevation and topographic roughness were used for describing the topography. Topographic roughness is an index that describes the variability of local topography and is defined as the largest inter-cell difference between a cell and its eight neighbours in a digital elevation model (DEM). These were extracted from a data set by Amatulli et al. (2018), calculated from the 1 km base resolution, which was itself aggregated as median values of the original 250 m resolution GMTEDmd DEM.

Human environment

The policy environment affects forest harvest regimes through legislation and regulations limiting the management decisions of the forest owner and by subsidies supporting certain types of management operations. To represent these factors, we included administrative unit as a categorical variable. In most cases this was the country, except for Germany (state) and Spain (autonomous community), where significant legislative power also on forest relates issues is on sub-national government levels. The policy environment is also described in our analysis with a variable of country-level share of forest area in public ownership (FOREST EUROPE, 2020). While different types of owners can have different management approaches (Schelhaas et al., 2018; Živojinović et al., 2015), the general ownership structure is also found to be correlated with the regulative environment, with countries with higher shares of public forest ownership also having more strict regulation on management of private forests (Nichiforel et al., 2018).

Harvest practises are also affected by the *cost of harvest* and *the goals of forest management*, which are represented here by variables related to population density and accessibility (but also related to topography, as mentioned above). The distance from population centres can have either increasing or reducing effects on harvest pressures. Increasing distance from population centres and lower population density is likely to imply increased transportation costs, and many protected areas are located in regions with more difficult accessibility, thus supporting a hypothesis of lower harvest pressure in regions with difficult accessibility. On the other hand, proximity of large human settlements can lead to higher pressure from other forest use types than wood production due to e.g. recreational use of forests, potentially leading to lower harvest pressure. We estimated population density using the Global Human Settlement Layer (GHSL) 2015 data (Schiavina et al., 2022) aggregated to mean density in a 10 km resolution. The distance from population centres was estimated with the global accessibility data by Nelson et al. (2019). From their data we calculated two variables describing travel time to human settlements with more than 50 000 and more than one million inhabitants. These population sizes were chosen to represent different types of human settlements that we expected to potentially have different effects on forest use.

Natural disturbances

To cover the probability of harvest occurring due to salvaging wood after *natural disturbances*, we included variables describing the fraction of natural disturbances out of all disturbances (incl. harvest) in the surrounding area. For this, we used the data set from Senf and Seidl (2021a), which identifies disturbances from Landsat satellite images from years 1986 to 2020 and attributes each disturbance polygon to it's probable cause, either storm and bark beetles, fire or background disturbance, where harvests are included in the last category. From this data we calculated separately the fractions of disturbances caused by storm and bark beetles and by fire within a hexagonal grid with 50 km sides and assigned these values to the plots in the forest inventory data located within the grid cells. The disturbance polygons were included in the grid cell in which the centre point of the polygon fell. For each inventory plot, only the disturbances within the same country and occurring in the years between the two measurements were considered.

Table 2. *Descriptions of features used as predictors in the predictive models, trained with the plot-level data.*

Abbreviation	Unit	Description	Type	Source
QMeanDiameter	cm	Quadratic mean diameter of the forest pre-harvest	Forest	Forest inventory data
BasalArea	m2 ha-1	Total tree basal area of the forest pre-harvest	Forest	Forest inventory data
SizeStructure	Index 0 to 1	Gini index of tree diameters pre-harvest	Forest	Forest inventory data
SpeciesDominance	Percent	Percentage of tree basal area covered by the dominant species	Forest	Forest inventory data
SpeciesGroup	Categorical	*Eucalyptus* sp.; *Pinus pinaster*; other pines; spruces; beech and oaks; other conifers; other broadleaves	Forest	Forest inventory data
NPP	10 g carbon m^{-2} yr^{-1}	Net primary production, average of 2000-2012	Environment	Neumann et al. 2016
Elevation	m	Elevation as metres above sea level	Environment	Amatulli et al. 2018
TopoRoughness	index	Topographic roughness index	Environment	Amatulli et al. 2018
PopulationDensity	Inhabitants km^{-2}	Population density in 10 km resolution	Human	GHSL 2015
Access1M	Numeric, minutes	Travel time to a population centre with >1M inhabitants	Human	Nelson et al. 2019
Access50k	Numeric, minutes	Travel time to a population centre with >50k inhabitants	Human	Nelson et al. 2019
PublicOwnership	Percentage	Percentage of public ownership by country	Human	Forest Europe 2020
CountryRegion	Categorical	Administrative unit	Human	Forest inventory data
StormBeetle	Probability	Probability of disturbance patch to originate from storms and bark beetles	Disturbance	Senf & Seidl 2021a
Fire	Probability	Probability of disturbance patch to originate from fire	Disturbance	Senf & Seidl 2021a

2.3.3 Interpretation of the predictive models

To understand the role of each predictor in the models, we calculated variable importance scores as the permutation importance (Strobl et al., 2007). The relationships of the predictors with the response variables were assessed with partial dependence plots (PDP). PDPs show the marginal effect of a predictor on the response variable. To calculate a PDP for one predictor variable, predictions are calculated for each data point by changing the value of the variable in interest to cover the full range of values that variable has in the data, while other variables are kept to their original values. Then, the predictions are averaged for each value of the variable in interest (Molnar, 2018). The PDPs were always calculated from a subset of data covering 50 000 data points, sampled randomly with the represented forest area as weights. The subset was used to reduce the computation time and weights were used to balance the different sampling densities in different regions, as otherwise the densely sampled regions could dominate the averaging done in the PDP calculation.

In addition to looking at the marginal effects over the whole data set, we explored how the model predictions behaved in relation to pre-harvest tree diameter (QMeanDiameter) in subsets of the study area to understand variations in the predicted harvest patterns between regions. For this, we selected plots with dominant species belonging to the “other pines” group (all pine species except *P. pinaster*) in three regions: southern Finland (below latitude 65°N), Poland and Spain. Then we calculated the PDPs for these subsets, using only data points in each subset.

The PDP plots were calculated using the R package *iml* (Molnar et al., 2018, version 0.10.1) and the variable importance was calculated during the training of the RFs with the R package *ranger* (Wright and Ziegler, 2017).

2.3.4 Validation

Spatial autocorrelation in data can lead to overly optimistic cross-validation results when the assumption of independence between data points is violated (Ploton et al., 2020; Roberts et al., 2017). Therefore, we set up cross-validation with spatial folds, where testing and training sets were always spatially separated from each other. This was done by constructing spatial blocks by overlaying a 10 x 10 cell grid on the extent of the plot data, assigning the data points to the grid cells in which they were located. Then each cell containing data points was assigned to one of the ten cross-validation folds systematically, with each fold then consisting of 3 to 4 spatial blocks in different parts of the study area. We also wanted to evaluate the ability of the models to predict to new countries with no training data and, therefore, set up a cross-validation where each of the 11 countries in the data was considered as a cross-validation fold, thus using ten countries to train the model in each iteration and testing with data from one country at a time.

Performance of the models was assessed with the area under the receiver operating characteristic curve (ROC AUC) for the $RF_{Probability}$. The ROC curve plots the true positive rate (sensitivity) and true negative rate (specificity) of the model with all potential thresholds for classifying the data points into the binary classes. The area under the curve ranges from 0 to 1, with 0.5 representing a model that cannot discriminate between harvest and no harvest any better than a random classifier and value 1 meaning a perfect discriminatory ability of the model (Hosmer et al., 2013). For the $RF_{Intensity}$, model performance was assessed with root mean squared error (RMSE).

The cross-validation of the RF models was compared with null models without any co-variates. For harvest probability ($RF_{Probability}$) the null model was set to always predict the proportion of harvest events in the full data set and for the harvest intensity ($RF_{Intensity}$), the null model always predicted the mean value of harvest intensity in the full data set.

The overall cross-validation workflow and the null models were set up with R package mlr3, (Lang et al., 2019, p. 3). Spatial cross-validation was carried out using R packages blockCV, (Valavi et al., 2019, version 2.1.4) and mlr3spatiotempcv (Schratz and Becker, 2021, version 1.0.1).

3. Results

3.1 Harvest patterns across Europe

The results showed substantial variation in harvest regimes across Europe. Harvest frequencies were found to be highest in eastern Central Europe and decrease towards the north and towards the Mediterranean. High harvest frequencies were found especially in Poland and Czechia, as well as in south-western France (Fig. 1A). Average intensities of harvest events (i.e. the fraction of tree basal area harvested in each plot) showed different spatial patterns, with more intensive harvest events in northern Europe and parts of Spain and France, and low average intensity of harvest events especially in Poland and Czechia (Fig. 1B). These differences in the spatial patterns of frequencies and intensities of harvest events were also supported by a negative correlation between the grid-cell level values of frequency and intensity of harvest events ($r = -0.48$, $p < 0.001$; Fig. S2).

We observed a continuum from high-frequency and low-intensity harvests (Poland, Czechia) towards low-frequency and high-intensity harvests (parts of Finland, Sweden, Norway and France), with the total harvest rate of the grid-cell staying on similar level, between 1 to 3% of the grid cell basal area per year (Fig. 2). Conversely, the gradient of total harvest rate moves from low-frequency and low-intensity (parts of Spain) towards the few grid cells with either high-frequency and high-intensity (outliers in France and Spain) or high frequency (outliers in Poland). The total harvest rate in the grid cells was positively correlated with the frequency of harvest events ($r = 0.68$, $p < 0.001$), while the correlation with intensity of harvest events was not significant ($r = 0.08$, $p = 0.065$, Fig. S2).

Very low intensity harvests (<25% of tree basal area removed) are driving the high frequency of harvests in Poland and Czechia (Fig. 3). While the low intensity harvests cover a considerable part of harvest events in most of Europe, in Poland and Czechia their share is clearly larger than in other countries. In mid-intensity harvests (25-50% and 50-75%) the pattern is reversed. The share of high-intensity events from all harvests (>75% of BA harvested, Fig. 3D) is the highest in northern Europe, southern France, and north-western Spain.

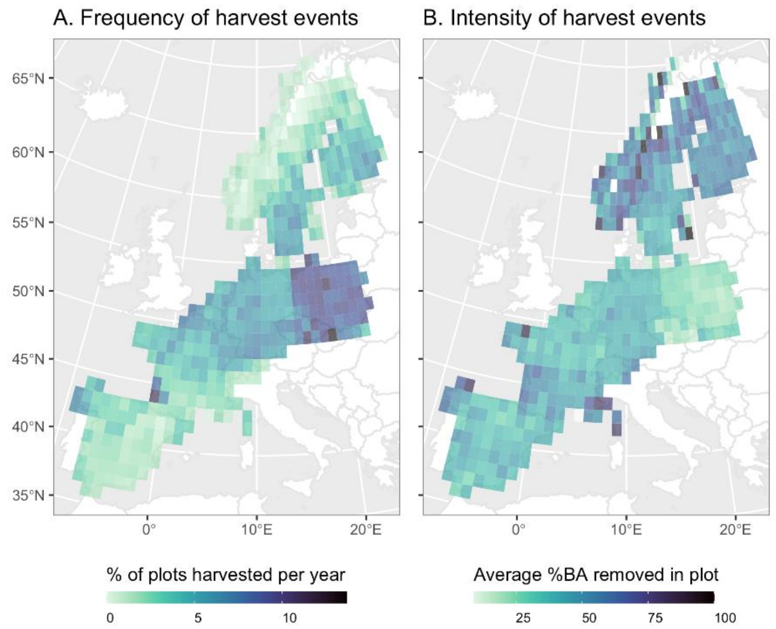

Figure 1. *Harvest regimes across Europe, as the frequency of harvest events (A, percentage of plots harvested per year) and intensity of harvest events (B, average percentage of tree basal area removed in a harvest event).*

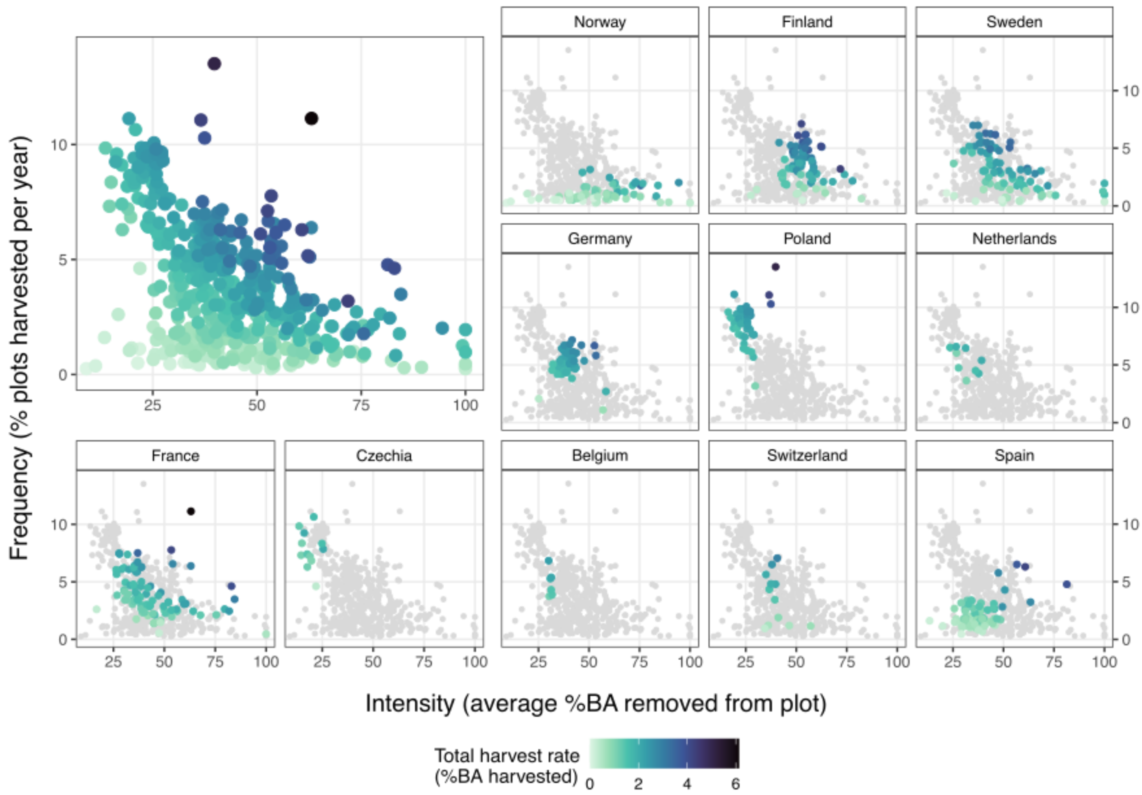

Figure 2. *Frequency versus average intensity of harvest events in the grid cells for the eleven European countries together (upper-left corner) and separately per country. The colour of the points represents the total harvest rate in the grid cell (% of tree basal area removed annually from the grid cell).*

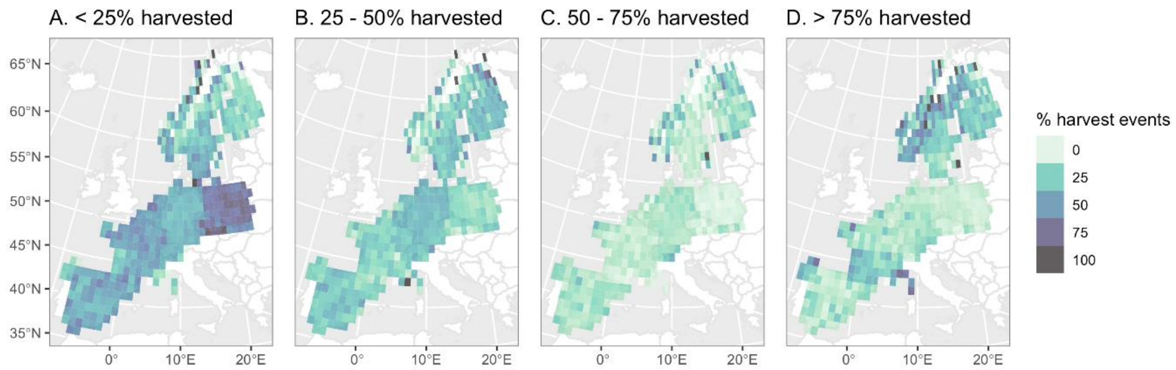

Figure 3. *Percentage of harvest events within different intensity classes: harvest events removing 25% or less (A), 25 to 50% (B), 50 to 75% (C), and more than 75% (D) of the original basal area.*

3.2 Predictive models

The probability of harvest was found to relate especially to variables concerning to the human environment and natural disturbances, as these variables gained high importance for predicting harvest probability ($RF_{Probability}$, Fig. 4). Highest importance scores were found for variables related to the administrative region (represented by variables CountryRegion and PublicOwnership). Other variables with high importance scores were natural disturbances (StormBeetle, but also Fire), stand basal area and travel time to population centres with more than a million people (Access1M).

The intensity of harvest events was more driven by forest structure and composition, with basal area, quadratic mean diameter and dominant species group all ranking within the four most important variables ($RF_{Intensity}$, Fig. 4). The administrative region was also important for harvest intensity, with country (or lower administrative region, where relevant) ranked second in variable importance.

We observed an increasing probability of harvest ($RF_{Probability}$, Fig. 5A) with the country-level share of public ownership of forests, frequency storm/bark beetle disturbances (and fire, Fig. S9) and stand basal area. The accessibility to large population centres (Access1M) and elevation showed a similar pattern, with harvest probability first decreasing, followed by a gradual increase in harvest probability after that.

The intensity of harvest events decreased with increase in stand basal area (Fig 5B). Higher intensities were observed for small and large quadratic mean diameters with lowest harvest intensities found with values of approx. 20 cm. Higher harvest intensities occur in forests dominated by Eucalypt species, *Pinus pinaster*, or spruce species. The marginal (averaged) responses of harvest intensity to elevation were rather modest, with increased intensities in low elevations. Country-level share of public ownership showed a non-linearly decreasing trend for the harvest intensity. PDP plots for all predictors can be found in Fig. S10.

The random forest results showed locally different responses of the harvest variables to tree size within the same species group (Fig. 6). For example, in Poland the harvest probability was clearly higher in small-diameter forests compared to the other regions. In Finland the harvest probability started to increase again in stands with quadratic mean diameter of approximately 20 cm, implying regeneration cuttings starting with this tree size, whereas in Poland this increase only started with plots having tree diameters around 30 cm. The intensity of harvest was higher in plots with larger tree size in most data combinations, but the pattern was more pronounced for Finland and Poland than in Spain or the full data set (Fig. 6).

The spatial blocks cross-validation showed substantially better performance of the random forests compared to the null models, with mean ROC AUC for $RF_{Probability}$ of 0.70 (0.50 for the null model) and mean RMSE for $RF_{Intensity}$ of 0.27 (0.31 for the null model, Fig. 7). In contrast, the country-wise cross-validation showed poor performance and high variance in the evaluation metrics, suggesting that the models performed poorly when predicting harvest in countries not included in the training data.

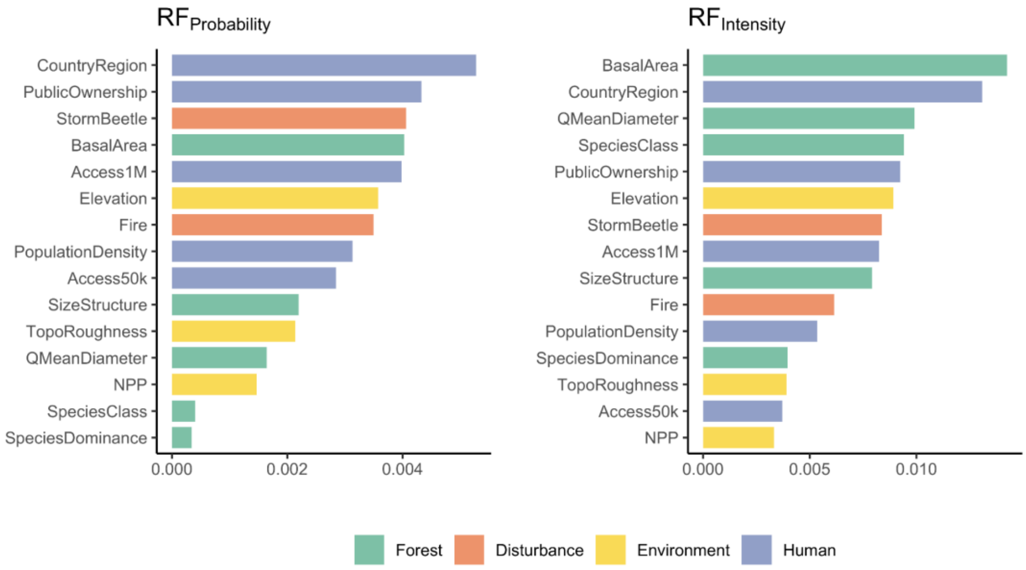

Figure 4. *Variable importance plots for the probability* ($RF_{Probability}$) *and the intensity of harvest event* ($RF_{Intensity}$)*. Bars are coloured based on the type of the variable. Descriptions of all variables are in Table 2.*

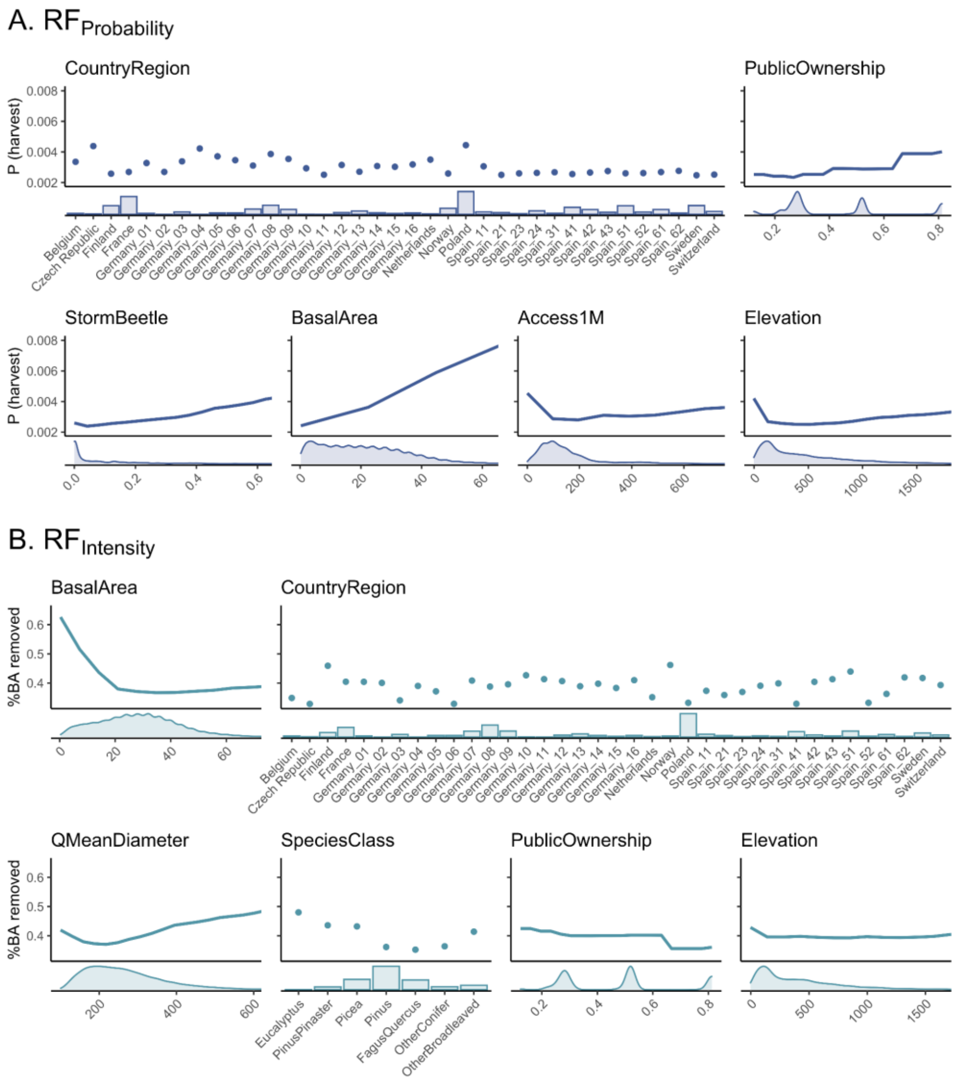

Figure 5. *Partial dependence plots for the six predictor features with highest variable importance values in $RF_{Probability}$, showing the marginal effect of these variables on annual harvest probability (A) and $RF_{Intensity}$, showing the marginal effect on intensity of harvest (B). The x-axis is cut to the 99th percentile for the numeric predictors. The subplots beneath the x-axis show the density distribution for each variable. Variables are plotted from left to right according to their importance value ranking.*

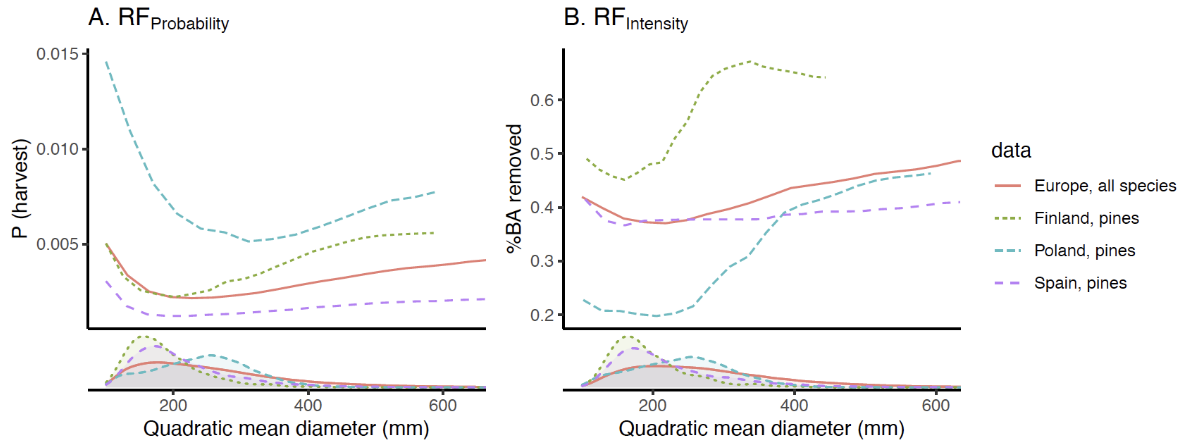

Figure 6. *Partial dependence plots (PDP) showing the effects of pre-harvest QMeanDiameter on the annual probability of harvest (*$RF_{Probability}$*) and the intensity of harvest (*$RF_{Intensity}$*). Partial dependence curves are shown as calculated from the full data (solid line) and for subsets of the data (dashed lines, pines in southern Finland, Poland and Spain) to demonstrate how the RFs predictions differ locally. The smaller subplots show the density distribution of the variable. The x-axis is cut to the 99th percentile of the data.*

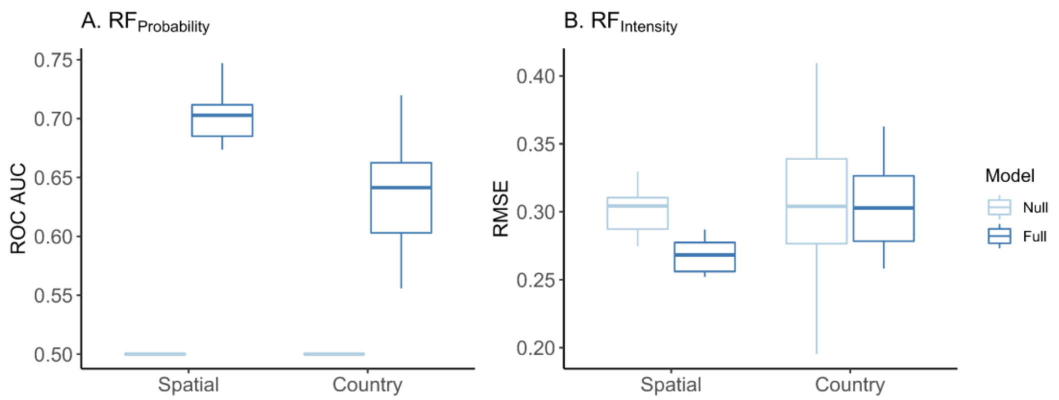

Figure 7. *Cross-validation results for harvest probability (left) and the intensity of harvest (right) for the two different cross-validation set-ups:spatial blocks, and using countries as folds. Light blue boxplots show results for the null models and dark blue boxplots for the full random forest models.*

4. Discussion

4.1 Harvest regimes and drivers

Here we present the first consistent assessment of harvest regimes across eleven European countries, based on field observations from forest inventory data sets. The results revealed variation in harvest strategies between regions with similar total harvest rates, from high-frequency and low-intensity harvests in eastern Central Europe to low-frequency and high-intensity harvests in the Nordic countries. These patterns give important insight about forest management in Europe compared to previous studies, which have either worked on aggregated harvest information at larger scales (Levers et al., 2014; Verkerk et al., 2015; Schelhaas et al., 2018) or focused on high-intensity harvests. Low intensity harvests have been excluded either by study design, e.g. Aszalós et al. (2022) who excluded lower intensity thinnings, or because of chosen methodology, e.g. when harvests or losses in canopy cover in general are quantified through satellite data where low intensity harvests are not easily distinguished (Ceccherini et al., 2020; Senf and Seidl, 2021b).

Northern Europe was characterised by low-frequency but high-intensity harvest regimes, with decreasing harvest frequencies towards the northern parts of the region. Since the mid-20th century, forest management in this region has been dominated by even-aged forestry with the stand rotation ending in a clear cut. The shift to even-aged management was initiated largely by state-driven forest policies to secure the supply of wood for the forest industry, leading to half-a-century of increasing forest productivity and wood production (Aasetre and Bele, 2009; Kauppi et al., 2022; Korhonen et al., 2021; Lundmark et al., 2017). Other management approaches outside of the even-aged rotation forestry are only applied in small areas (Aszalós et al., 2022) and are unlikely to affect the patterns of a large-scale assessment such as ours. The even-aged rotation management approach is observed in our results as low frequencies but high intensities of harvest events, and a large share of intensive harvests compared to other studied countries (Fig. 3D). The lower harvest rates in Norway compared to Finland and Sweden are likely related to the highly variable topography, affecting both growing conditions and harvesting costs, and the high share of privately owned forests (FOREST EUROPE, 2020).

In Poland and Czechia, the results showed a distinctive pattern of high-frequency and low-intensity harvesting regimes, where the low average intensity of harvests was driven by an exceptionally large share of the low-intensity harvests (Fig. 3A). One of the factors common for these countries in comparison to other countries in the study is the high share of public ownership of forests (FOREST EUROPE, 2020; Pulla et al., 2013). Therefore, the decision making on forest management strategies is more centralised compared to countries with a higher share of private forests. We speculate that this leads to a more uniform implementation of the management plans and guidelines, compared to regions with higher percentages of private forest ownership. This might be especially true in comparison to regions with high shares of small-scale private forest owners. There, the actual management can be expected to deviate more from the guidelines, as fragmentation of forest ownership, increasing detachment and decreasing economic dependency from forests within small-scale private owners has been linked to less active management of forests (Orazio et al., 2017; Wiersum et al., 2005; Živojinović et al., 2015). It is good to note however, that our analysis only looked at country-level share of public ownership, whereas ownership structure can also vary substantially within countries (Pulla et al., 2013), and the implications of private versus public ownership on management can vary across regions (Schelhaas et al., 2018).

Regions with low total harvest rates were found in the northernmost parts of the Nordic countries, and in southern and eastern parts of Spain (Figs 1 and 2). In the north, the low harvest rate was associated with low frequencies of harvest events and relates to slow growth of trees in the cold climate, high percentage of protected areas and increased costs from long transport distances and complex topography. In Spain, regions with low total harvest rates had both low harvest frequency and intensity, and the inactive harvest regimes can be explained by low productivity due to the dry climatic conditions (Neumann et al., 2016; Ruiz-Benito et al., 2014). After the 1970s an increased abandonment of forest management has occurred, especially in the Mediterranean forests, where the economic profitability of timber harvesting is low (Vadell et al., 2022; Vilà-Cabrera et al., 2023). On the other hand, many forests in northern Spain along the Atlantic coast are intensively managed for wood or biomass in short-rotation cycles (Unrau et al., 2018; Vadell et al., 2022). This geographic difference in harvest intensity in Spain can be observed in our results (Fig. 2). Similarly, in south-western France the Landes forest stands out in the results with high frequencies and intensities of harvest. The forests in this region consist mainly of maritime pine (*P. pinaster*) plantations that are actively managed in relatively short rotations.

The importance of country-level drivers was emphasised throughout our results. This large between-country variation was also reported by Levers et al. (2014) and it can relate to differences in the ownership structure, legislation, regulations and subsidies for forestry (Bauer et al., 2004; Haeler et al., 2023; Nichiforel et al., 2018). Harvest practices can also be expected to vary based on the national (or state) level variation in the guidelines for forest management (Cardellini et al., 2018), values of the forest owners (Westin et al., 2023) and the valuation of different ecosystem services provided by the forests (Winkel et al., 2022). On the other hand, countries also differ in other aspects not directly related to the socio-political environment, with, for example climatic conditions and topography varying notably from country to country. While this can also contribute to the observed country-effect in our results, clear contrasts in harvest strategies were also found in regions with similar climatic conditions. In the random forest results also the variable describing the administrative region (in most cases country) gained high variable importance scores even when variables describing topography and productivity were also included, suggesting that these are not sufficient in explaining the variation in harvest regimes between countries.

Natural disturbances are important drivers of harvest. In the random forest results high frequencies of storm and fire disturbances led to increased probability and intensity of harvest events (Figs 5, S9, S10), as natural disturbances lead to unplanned salvage loggings. A heavy storm event in 2017 in Poland, causing damage in forests in an area of approximately 80,000 hectares (Chmielewski et al., 2020), is also the most likely cause of outlier grid-cells in Poland with high harvest rates (Fig. 2, see Fig. S4 for details). The impact of natural disturbances on harvest was demonstrated also by Verkerk et al. (2015), who showed that largest annual deviations in wood production compared to long-term mean were related to major natural disturbances, such as several high-intensity storms in late 1990s. In the time window of the data used in our analysis (Table 1), major storm events were, for example, the 2017 storm in Poland and the 2007 storm Kyrill in Germany. Some other major storm events, such as storm

Klaus in Southern France in 2009 and storm Gudrun in southern Sweden in 2005, occurred before the time windows of data covered here (first measurements in France in 2010 and in Sweden in 2008). Salvage logging from these storms are not expected to have a major effect on the results, although we note that insect outbreaks triggered by the storm events could cause salvaging even when the actual storm event is not within the studied time window.

Pre-harvest stand basal area was an important driver of both frequency and intensity of harvest events. Higher basal area led to higher probability of harvest, but lower intensity of harvests. Basal area varies locally due to factors such as forest age, species and site type, but it also has large-scale spatial patterns across Europe, with regions with lower basal area found especially in northern Europe and in parts of Spain. Both of these patterns are likely to affect the relationship between basal area and the harvest variables in our results. The higher probability of harvest events with high basal area is logical from both perspectives. For example in a forest managed with an even-aged rotation system, harvest would not be expected in a low-basal-area phase of the stand rotation (see e.g. the Finnish forest management recommendations, Äijälä et al., 2019). At the same time, regions where basal area on average is lower, such as northern parts of Europe (Fig. S6) the harvest regimes are also characterised by lower harvest frequencies (Fig. 1).

Net primary productivity (NPP) was not ranked high in the variable importance results. This is seemingly in contrast with earlier results from Verkerk et al. (2015), who showed that productivity was an important factor driving spatial patterns of wood production in Europe. However, also in our results the total harvest rate was positively correlated with the NPP (Fig. S3). The variable importance results are also likely affected by other variables correlated with NPP, such as population density ($r = 0.52$),and fire and storm/bark beetle disturbances ($r = -0.43$ and 0.60, respectively, Fig. S8). Stand basal area also shows similar large-scale spatial patterns as NPP (Fig. S6), potentially catching some of the variance that could otherwise be explained by NPP.

The random forest models were able to reveal different local patterns of harvest in relation to tree size (Fig. 6). For all explored regions the response to the quadratic mean diameter shows a somewhat similar overall pattern – a U-shaped response with high harvest probabilities with low and high diameters, and a higher intensity of harvest with larger diameters. This is logical, considering for example thinnings performed at early phases of stand rotation when trees are smaller, and more intensive regeneration cuttings later with larger diameters. Yet, there are clear differences between the regions, such as the markedly higher harvest probability in low diameter stands in Poland. This demonstrates the ability of the models to identify regional differences in harvest regimes.

4.2 Limitations and future steps

Forest management and harvesting of wood cannot be expected to be static, but change dynamically with the changing political (Kronenberg et al., 2021; Munteanu et al., 2016), economic (Adams et al., 1991; Infante-Amate et al., 2022; Sjølie et al., 2019) and natural environment (Hlásny et al., 2021; Verkerk et al., 2015). The presented results provide a snapshot of management regimes in the time-window covered by the data, although we aim to control for these drivers in our study (e.g. using predictors characterising the natural disturbance frequency during the study period). While most of the data in our study covers very recent time periods, the changes in forest disturbance regimes in Europe since 2018 (Hlásny et al., 2021; Schuldt et al., 2020; Senf and Seidl, 2021c) have since affected harvests in some regions because of logging reactions to the natural disturbances (Toth et al., 2020). In the future, changes to the observed harvest frequencies and intensities can be expected already from change in forest age-class distribution, but harvesting will also be affected by the implementation of EU bioeconomy, forest and biodiversity strategies (European Commission, 2018, 2021, 2022), which have partially conflicting objectives (Lerink et al. 2023). Forest management strategies also need to adjust to better adapt to the changing climate (Bolte et al. 2009).

The different sampling designs in each country can have an influence on the results, even though we harmonised the diameter thresholds and accounted for the different plot designs and intervals. For example, the data sets from different countries cover different time periods and have different time intervals between the two measurements. The differences in sample plot size and type can affect the detection of harvest events, even despite our harmonisation efforts, as different sample plot designs would have different probabilities for none of the harvested trees being located within the plot, even if harvest occurred in the forest. In addition, full harmonisation was not always feasible, e.g. for Switzerland where the minimum DBH threshold (12 cm) was above the 10 cm threshold we applied to the data sets. We assumed that the benefit of additional information gained from including more trees in the other countries outweighed the disadvantage of introducing bias for one country rising from a slightly higher threshold. In any case, major patterns observed in our results do not seem to follow differences in sampling designs (see Table S1 for details). This implies that the main results are unlikely to be affected by artefacts of sampling differences, but some effect from the sampling differences between the data sets could contribute to the observed differences between the countries.

Our analysis covered the eleven European countries from which re-measured inventory plot data was available. Whilst it is reasonable to assume that harvest event regimes within other European countries fall within the continuum identified in Figure 2, the results demonstrated the difficulties of predicting harvest in countries where no field data is available. This is a major limitation for understanding and modelling harvest regimes at continental scales. While data availability and access has improved in recent years (Ruiz-Benito et al., 2020), relying on the availability of remeasured data from field plots restricts the spatial extent that can be covered. To extend the analysis beyond the eleven countries studied here, and thus provide the information necessary to inform large-scale modelling studies, will require either new arrangements to extend access to NFI data in the many additional countries where it exists or combining information from several different sources. Such sources may include remotely sensed information about high-intensity harvests, national-level statistics and information about legislation regulating forest use, socio-economic factors and the role of the forest sector in the country, management guidelines and plans, as well as expert knowledge from each country.

5. Conclusions

In this work, we empirically quantified forest harvest regimes across Europe, with data from forest inventories from eleven countries. The results revealed a range of different harvest approaches with different harvest frequencies and intensities, improving our knowledge of how forests in Europe are currently harvested. These results are crucial for understanding how human management of forests shapes these ecosystems now and in the future. To understand how forest management practices should be changed in Europe when the climatic conditions will be different, it is crucial to have a thorough understanding how the management is currently carried out.

Our results also provided insight into the drivers of harvest regimes in Europe. Country was an important driver for both the probability and intensity of harvest events, emphasising the national-level variation in harvest practices. Otherwise the role of different drivers varied between harvest probability and intensity, with variables related to forest characteristics being more important for the intensity of harvest events. Natural disturbances drive harvests, with both harvest probability and intensity increasing with increased storm and fire disturbances.

The harvesting intensities and frequencies that we have quantified here, along with the random forest models for predicting harvest probability, provide a baseline for harvest behaviour at a time when practices are likely to undergo substantial change to accommodate the impacts of climate change and a growing focus on preserving and enhancing biodiversity on (European Commission, 2021, 2020). Coupling this information with continental-scale demographic forest models (Lindeskog et al., 2021) has the potential to provide consistent large-scale assessments of recent forest productivity, harvest and carbon cycling, providing a significant step forward over the rule-based approaches that might otherwise be used. Similarly, they can provide an evidence-based counterfactual for simulations of the effect of future changes in forest harvest policy.

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References

Aasetre, J., Bele, B., 2009. History of forestry in a central Norwegian boreal forest landscape: Examples from Nordli, Nord-Tr∅ndelag. Nor. Geogr. Tidsskr. - Nor. J. Geogr. 63, 233–245. https://doi.org/10.1080/00291950903368342

Adams, D.M., Binkley, C.S., Cardellichio, P.A., 1991. Is the Level of National Forest Timber Harvest Sensitive to Price? Land Econ. 67, 74–84.

Äijälä, O., Koistinen, A., Sved, J., Vanhatalo, K., Väisänen, P., 2019. Metsänhoidon suositukset, Tapion julkaisuja.

Amatulli, G., Domisch, S., Tuanmu, M.-N., Parmentier, B., Ranipeta, A., Malczyk, J., Jetz, W., 2018. A suite of global, cross-scale topographic variables for environmental and biodiversity modeling. Sci. Data 5, 180040. https://doi.org/10.1038/sdata.2018.40

Antón-Fernández, C., Astrup, R., 2012. Empirical harvest models and their use in regional business-as-usual scenarios of timber supply and carbon stock development. Scand. J. For. Res. 27, 379–392. https://doi.org/10.1080/02827581.2011.644576

Aszalós, R., Thom, D., Aakala, T., Angelstam, P., Brūmelis, G., Gálhidy, L., Gratzer, G., Hlásny, T., Katzensteiner, K., Kovács, B., Knoke, T., Larrieu, L., Motta, R., Müller, J., Ódor, P., Roženbergar, D., Paillet, Y., Pitar, D., Standovár, T., Svoboda, M., Szwagrzyk, J., Toscani, P., Keeton, W.S., 2022. Natural disturbance regimes as a guide for sustainable forest management in Europe. Ecol. Appl., e2596. https://doi.org/10.1002/eap.2596

Bauer, J., Kniivilä, M., Schmithüsen, F., 2004. Forest legislation in Europe: How 23 countries approach the obligation to reforest, public access and use of non-wood forest products (No. 37), Geneva Timber and Forest Discussion Paper.

Beach, R.H., Pattanayak, S.K., Yang, J.-C., Murray, B.C., Abt, R.C., 2005. Econometric studies of non-industrial private forest management: a review and synthesis. For. Policy Econ. 7, 261–281. https://doi.org/10.1016/S1389-9341(03)00065-0

Bolte, A., Ammer, C., Löf, M., Madsen, P., Nabuurs, G.J., Schall, P., Spathelf, P. and Rock, J., 2009. Adaptive forest management in central Europe: climate change impacts, strategies and integrative concept. Scandinavian Journal of Forest Research, 24(6), pp.473-482.

Breidenbach, J., Ellison, D., Petersson, H., Korhonen, K.T., Henttonen, H.M., Wallerman, J., Fridman, J., Gobakken, T., Astrup, R., Næsset, E., 2022. Harvested area did not increase abruptly—how advancements in satellite-based mapping led to erroneous conclusions. Ann. For. Sci. 79, 2. https://doi.org/10.1186/s13595-022-01120-4

Cardellini, G., Valada, T., Cornillier, C., Vial, E., Dragoi, M., Goudiaby, V., Mues, V., Lasserre, B., Gruchala, A., Rørstad, P.K., Neumann, M., Svoboda, M., Sirgmets, R., Näsärö, O.-P., Mohren, F., Achten, W.M.J., Vranken, L., Muys, B., 2018. EFO-LCI: A New Life Cycle Inventory Database of Forestry Operations in Europe. Environ. Manage. 61, 1031–1047. https://doi.org/10.1007/s00267-018-1024-7

Ceccherini, G., Duveiller, G., Grassi, G., Lemoine, G., Avitabile, V., Pilli, R., Cescatti, A., 2020. Abrupt increase in harvested forest area over Europe after 2015. Nature 583, 72–77.

https://doi.org/10.1038/s41586-020-2438-y

Chmielewski, T., Szer, J., Bobra, P., 2020. Derecho wind storm in Poland on 11–12 August 2017: results of the post-disaster investigation. Environmental Hazards 19, 508–528.

Daigneault, A., Baker, J.S., Guo, J., Lauri, P., Favero, A., Forsell, N., Johnston, C., Ohrel, S.B., Sohngen, B., 2022. How the future of the global forest sink depends on timber demand, forest management, and carbon policies. Glob. Environ. Change 76, 102582. https://doi.org/10.1016/j.gloenvcha.2022.102582

Dalmonech, D., Marano, G., Amthor, J.S., Cescatti, A., Lindner, M., Trotta, C., Collalti, A., 2022. Feasibility of enhancing carbon sequestration and stock capacity in temperate and boreal European forests via changes to management regimes. Agric. For. Meteorol. 327, 109203. https://doi.org/10.1016/j.agrformet.2022.109203

Dorren, L.K.A., Berger, F., Imeson, A.C., Maier, B., Rey, F., 2004. Integrity, stability and management of protection forests in the European Alps. For. Ecol. Manag. 195, 165–176. https://doi.org/10.1016/j.foreco.2004.02.057

Duncker, P., Barreiro, S., Hengeveld, G., Lind, T., Mason, W., Ambrozy, S., Spiecker, H., 2012. Classification of Forest Management Approaches: A New Conceptual Framework and Its Applicability to European Forestry. Ecol. Soc. 17. https://doi.org/10.5751/ES-05262-170451

European Commission, 2018. A sustainable bioeconomy for Europe: strengthening the connection between economy, society and the environment. Updated Bioeconomy Strategy.

European Commission, 2021. New EU Forest Strategy for 2030, Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. Brussels.

European Commission, 2020. EU Biodiversity Strategy for 2030, Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. Brussels.

FAO, 2020. Global Forest Resources Assessment 2020: Main report. FAO, Rome, Italy. https://doi.org/10.4060/ca9825en

FOREST EUROPE, 2020. State of Europe’s Forests 2020, Ministerial Conference on the Protection of Forests in Europe - FOREST EUROPE, Liaison Unit Bratislava.

Gregor, K., Knoke, T., Krause, A., Reyer, C.P.O., Lindeskog, M., Papastefanou, P., Smith, B., Lansø, A.-S., Rammig, A., 2022. Trade-Offs for Climate-Smart Forestry in Europe Under Uncertain Future Climate. Earths Future 10, e2022EF002796. https://doi.org/10.1029/2022EF002796

Haeler, E., Bolte, A., Buchacher, R., Hänninen, H., Jandl, R., Juutinen, A., Kuhlmey, K., Kurttila, M., Lidestav, G., Mäkipää, R., Rosenkranz, L., Triplat, M., Vilhar, U., Westin, K., Schueler, S., 2023. Forest subsidy distribution in five European countries. For. Policy Econ. 146, 102882. https://doi.org/10.1016/j.forpol.2022.102882

Härkönen, S., Neumann, M., Mues, V., Berninger, F., Bronisz, K., Cardellini, G., Chirici, G., Hasenauer, H., Koehl, M., Lang, M., Merganicova, K., Mohren, F., Moiseyev, A., Moreno, A., Mura, M., Muys, B., Olschofsky, K., Del Perugia, B., Rørstad, P.K., Solberg, B., Thivolle-Cazat, A., Trotsiuk, V., Mäkelä, A., 2019. A climate-sensitive forest model for assessing impacts of forest management in Europe. Environ. Model. Softw. 115, 128–143. https://doi.org/10.1016/j.envsoft.2019.02.009

Hastie, T., Tibshirani, R., Friedman, J., 2009. The elements of statistical learning, 2nd ed, Springer Series in Statistics. Springer-Verlag New York.

Hlásny, T., Zimová, S., Merganičová, K., Štěpánek, P., Modlinger, R., Turčáni, M., 2021. Devastating outbreak of bark beetles in the Czech Republic: Drivers, impacts, and management implications. For. Ecol. Manag. 490, 119075. https://doi.org/10.1016/j.foreco.2021.119075

Hosmer, D.W., Lemeshow, S., Strudivant, R.X., 2013. Applied Logistic Regression, 3rd ed. John Wiley & Sons, New York.

Infante-Amate, J., Iriarte-Goñi, I., Urrego-Mesa, A., Gingrich, S., 2022. From woodfuel to industrial wood: A socio-metabolic reading of the forest transition in Spain (1860–2010). Ecol. Econ. 201, 107548. https://doi.org/10.1016/j.ecolecon.2022.107548

Kauppi, P.E., Stål, G., Arnesson-Ceder, L., Hallberg Sramek, I., Hoen, H.F., Svensson, A., Wernick, I.K., Högberg, P., Lundmark, T., Nordin, A., 2022. Managing existing forests can mitigate climate change. For. Ecol. Manag. 513, 120186. https://doi.org/10.1016/j.foreco.2022.120186

Kilham, P., Hartebrodt, C., Kändler, G., 2019. Generating Tree-Level Harvest Predictions from Forest Inventories with Random Forests. Forests 10, 20. https://doi.org/10.3390/f10010020

Korhonen, K.T., Ahola, A., Heikkinen, J., Henttonen, H.M., Hotanen, J.-P., Ihalainen, A., Melin, M., Pitkänen, J., Räty, M., Sirviö, M., Strandström, M., 2021. Forests of Finland 2014–2018 and their development 1921–2018. Silva Fenn. 55.

Kronenberg, J., Łaszkiewicz, E., Sziło, J., 2021. Voting with one's chainsaw: What happens when people are given the opportunity to freely remove urban trees? Landsc. Urban Plan. 209, 104041. https://doi.org/10.1016/j.landurbplan.2021.104041

Lang, M., Binder, M., Richter, J., Schratz, P., Pfisterer, F., Coors, S., Au, Q., Casalicchio, G., Kotthoff, L., Bischl, B., 2019. mlr3: A modern object-oriented machine learning framework in R. J. Open Source Softw. 4, 1903. https://doi.org/10.21105/joss.01903

Lerink, B.J., Schelhaas, M.J., Schreiber, R., Aurenhammer, P., Kies, U., Vuillermoz, M., Ruch, P., Pupin, C., Kitching, A., Kerr, G. and Sing, L., 2023. How much wood can we expect from European forests in the near future?. Forestry: An International Journal of Forest Research, p.cpad009.

Lesiv, M., Schepaschenko, D., Buchhorn, M., See, L., Dürauer, M., Georgieva, I., Jung, M., Hofhansl, F., Schulze, K., Bilous, A., Blyshchyk, V., Mukhortova, L., Brenes, C.L.M., Krivobokov, L., Ntie, S., Tsogt, K., Pietsch, S.A., Tikhonova, E., Kim, M., Di Fulvio, F., Su, Y.-F., Zadorozhniuk, R., Sirbu, F.S., Panging, K., Bilous, S., Kovalevskii, S.B., Kraxner, F., Rabia, A.H., Vasylyshyn, R., Ahmed, R., Diachuk, P., Kovalevskyi, S.S., Bungnamei, K., Bordoloi, K., Churilov, A., Vasylyshyn, O., Sahariah, D., Tertyshnyi, A.P., Saikia, A., Malek, Ž., Singha, K., Feshchenko, R., Prestele, R., Akhtar, I. ul H., Sharma, K., Domashovets, G., Spawn-Lee, S.A., Blyshchyk, O., Slyva, O., Ilkiv, M., Melnyk, O., Sliusarchuk, V., Karpuk, A., Terentiev, A., Bilous, V., Blyshchyk, K., Bilous, M., Bogovyk, N., Blyshchyk, I., Bartalev, S., Yatskov, M., Smets, B., Visconti, P., Mccallum, I., Obersteiner, M., Fritz, S., 2022. Global forest management data for 2015 at a 100 m resolution. Sci. Data 9, 199. https://doi.org/10.1038/s41597-022-01332-3

Levers, C., Verkerk, P.J., Müller, D., Verburg, P.H., Butsic, V., Leitão, P.J., Lindner, M., Kuemmerle, T., 2014. Drivers of forest harvesting intensity patterns in Europe. For. Ecol. Manag. 315, 160–172. https://doi.org/10.1016/j.foreco.2013.12.030

Lundmark, H., Josefsson, T., Östlund, L., 2017. The introduction of modern forest management and clear-cutting in Sweden: Ridö State Forest 1832–2014. Eur. J. For. Res. 136, 269–285. https://doi.org/10.1007/s10342-017-1027-6

Manrique-Alba, À., Beguería, S., Camarero, J.J., 2022. Long-term effects of forest management on post-drought growth resilience: An analytical framework. Sci. Total

Environ. 810, 152374. https://doi.org/10.1016/j.scitotenv.2021.152374

Mason, W.L., Diaci, J., Carvalho, J., Valkonen, S., 2021. Continuous cover forestry in Europe: usage and the knowledge gaps and challenges to wider adoption. For. Int. J. For. Res. cpab038. https://doi.org/10.1093/forestry/cpab038

Molnar, C., 2018. Interpretable Machine Learning (Second Edition). Leanpub.

Molnar, C., Casalicchio, G., Bischl, B., 2018. iml: An R package for Interpretable Machine Learning. J. Open Source Softw. 3, 786. https://doi.org/10.21105/joss.00786

Munteanu, C., Nita, M.D., Abrudan, I.V., Radeloff, V.C., 2016. Historical forest management in Romania is imposing strong legacies on contemporary forests and their management. For. Ecol. Manag. 361, 179–193. https://doi.org/10.1016/j.foreco.2015.11.023

Nabuurs, G.J., Päivinen, R., Schanz, H., 2001. Sustainable management regimes for Europe's forests — a projection with EFISCEN until 2050. For. Policy Econ. 3, 155–173. https://doi.org/10.1016/S1389-9341(01)00058-2

Nabuurs, G.-J., Verweij, P., Van Eupen, M., Pérez-Soba, M., Pülzl, H., Hendriks, K., 2019. Next-generation information to support a sustainable course for European forests. Nat. Sustain. 2, 815–818. https://doi.org/10.1038/s41893-019-0374-3

Nelson, A., Weiss, D.J., van Etten, J., Cattaneo, A., McMenomy, T.S., Koo, J., 2019. A suite of global accessibility indicators. Sci. Data 6, 266. https://doi.org/10.1038/s41597-019-0265-5

Neumann, M., Moreno, A., Thurnher, C., Mues, V., Härkönen, S., Mura, M., Bouriaud, O., Lang, M., Cardellini, G., Thivolle-Cazat, A., Bronisz, K., Merganic, J., Alberdi, I., Astrup, R., Mohren, F., Zhao, M., Hasenauer, H., 2016. Creating a Regional MODIS Satellite-Driven Net Primary Production Dataset for European Forests. Remote Sens. 8, 554. https://doi.org/10.3390/rs8070554

Nichiforel, L., Keary, K., Deuffic, P., Weiss, G., Thorsen, B.J., Winkel, G., Avdibegović, M., Dobšinská, Z., Feliciano, D., Gatto, P., Gorriz Mifsud, E., Hoogstra-Klein, M., Hrib, M., Hujala, T., Jager, L., Jarský, V., Jodłowski, K., Lawrence, A., Lukmine, D., Pezdevšek Malovrh, Š., Nedeljković, J., Nonić, D., Krajter Ostoić, S., Pukall, K., Rondeux, J., Samara, T., Sarvašová, Z., Scriban, R.E., Šilingienė, R., Sinko, M., Stojanovska, M., Stojanovski, V., Stoyanov, N., Teder, M., Vennesland, B., Vilkriste, L., Wilhelmsson, E., Wilkes-Allemann, J., Bouriaud, L., 2018. How private are Europe's private forests? A comparative property rights analysis. Land Use Policy 76, 535–552. https://doi.org/10.1016/j.landusepol.2018.02.034

Orazio, C., Kies, U., Edwards, D., 2017. Handbook for wood mobilisation in Europe, European Forest Institute.

Palahí, M., Valbuena, R., Senf, C., Acil, N., Pugh, T.A.M., Sadler, J., Seidl, R., Potapov, P., Gardiner, B., Hetemäki, L., Chirici, G., Francini, S., Hlásny, T., Lerink, B.J.W., Olsson, H., González Olabarria, J.R., Ascoli, D., Asikainen, A., Bauhus, J., Berndes, G., Donis, J., Fridman, J., Hanewinkel, M., Jactel, H., Lindner, M., Marchetti, M., Marušák, R., Sheil, D., Tomé, M., Trasobares, A., Verkerk, P.J., Korhonen, M., Nabuurs, G.-J., 2021. Concerns about reported harvests in European forests. Nature 592, E15–E17. https://doi.org/10.1038/s41586-021-03292-x

Ploton, P., Mortier, F., Réjou-Méchain, M., Barbier, N., Picard, N., Rossi, V., Dormann, C., Cornu, G., Viennois, G., Bayol, N., Lyapustin, A., Gourlet-Fleury, S., Pélissier, R., 2020. Spatial validation reveals poor predictive performance of large-scale ecological mapping models. Nat. Commun. 11, 4540. https://doi.org/10.1038/s41467-020-18321-y

Pozzolo, A.D., Caelen, O., Johnson, R.A., Bontempi, G., 2015. Calibrating Probability with Undersampling for Unbalanced Classification, in: 2015 IEEE Symposium Series on Computational Intelligence. Presented at the 2015 IEEE Symposium Series on Computational Intelligence (SSCI), IEEE, Cape Town, South Africa, pp. 159–166. https://doi.org/10.1109/SSCI.2015.33

Pukkala, T., Laiho, O., Lähde, E., 2016. Continuous cover management reduces wind damage. For. Ecol. Manag. 372, 120–127. https://doi.org/10.1016/j.foreco.2016.04.014

Pulla, P., Schuck, A., Verkerk, P.J., Lasserre, B., Marchetti, M., Green, T., 2013. Mapping the distribution of forest ownership in Europe | European Forest Institute (No. 88), Technical Report. European Forest Institute.

R Core Team, 2021. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

Roberts, D.R., Bahn, V., Ciuti, S., Boyce, M.S., Elith, J., Guillera-Arroita, G., Hauenstein, S., Lahoz-Monfort, J.J., Schröder, B., Thuiller, W., Warton, D.I., Wintle, B.A., Hartig, F., Dormann, C.F., 2017. Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. Ecography 40, 913–929. https://doi.org/10.1111/ecog.02881

Ruiz-Benito, P., Madrigal-González, J., Ratcliffe, S., Coomes, D.A., Kändler, G., Lehtonen, A., Wirth, C., Zavala, M.A., 2014. Stand Structure and Recent Climate Change Constrain Stand Basal Area Change in European Forests: A Comparison Across Boreal, Temperate, and Mediterranean Biomes. Ecosystems 17, 1439–1454. https://doi.org/10.1007/s10021-014-9806-0

Ruiz-Benito, P., Vacchiano, G., Lines, E.R., Reyer, C.P.O., Ratcliffe, S., Morin, X., Hartig, F., Mäkelä, A., Yousefpour, R., Chaves, J.E., Palacios-Orueta, A., Benito-Garzón, M., Morales-Molino, C., Camarero, J.J., Jump, A.S., Kattge, J., Lehtonen, A., Ibrom, A., Owen, H.J.F., Zavala, M.A., 2020. Available and missing data to model impact of climate change on European forests. Ecol. Model. 416, 108870. https://doi.org/10.1016/j.ecolmodel.2019.108870

Savilaakso, S., Johansson, A., Häkkilä, M., Uusitalo, A., Sandgren, T., Mönkkönen, M., Puttonen, P., 2021. What are the effects of even-aged and uneven-aged forest management on boreal forest biodiversity in Fennoscandia and European Russia? A systematic review. Environ. Evid. 10, 1. https://doi.org/10.1186/s13750-020-00215-7

Schelhaas, M.-J., Fridman, J., Hengeveld, G.M., Henttonen, H.M., Lehtonen, A., Kies, U., Krajnc, N., Lerink, B., Dhubháin, Á.N., Polley, H., Pugh, T.A.M., Redmond, J.J., Rohner, B., Temperli, C., Vayreda, J., Nabuurs, G.-J., 2018. Actual European forest management by region, tree species and owner based on 714,000 re-measured trees in national forest inventories. PLOS ONE 13, e0207151. https://doi.org/10.1371/journal.pone.0207151

Schiavina, M., Freire, S., MacManus, K., 2022. GHS-POP R2022A - GHS population grid multitemporal (1975-2030).European Commission, Joint Research Centre (JRC).

Schratz, P., Becker, M., 2021. mlr3spatiotempcv: Spatiotemporal Resampling Methods for “mlr3”. R package version 0.4.1.

Schuldt, B., Buras, A., Arend, M., Vitasse, Y., Beierkuhnlein, C., Damm, A., Gharun, M., Grams, T.E.E., Hauck, M., 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., Kahmen, A., 2020. A first assessment of the impact of the extreme 2018 summer drought on Central European forests. Basic Appl. Ecol. 45, 86–103.

https://doi.org/10.1016/j.baae.2020.04.003

Schulze, K., Malek, Ž., Verburg, P.H., 2019. Towards better mapping of forest management patterns: A global allocation approach. For. Ecol. Manag. 432, 776–785. https://doi.org/10.1016/j.foreco.2018.10.001

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

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

Senf, C., Seidl, R., 2021c. Persistent impacts of the 2018 drought on forest disturbance regimes in Europe. Biogeosciences 18, 5223–5230. https://doi.org/10.5194/bg-18-5223-2021

Sjølie, H.K., Wangen, K.R., Lindstad, B.H., Solberg, B., 2019. The importance of timber prices and other factors for harvest increase among non-industrial private forest owners. Can. J. For. Res. 49, 543–552. https://doi.org/10.1139/cjfr-2018-0292

Soimakallio, S., Böttcher, H., Niemi, J., Mosley, F., Turunen, S., Hennenberg, K.J., Reise, J., Fehrenbach, H., 2022. Closing an open balance: The impact of increased tree harvest on forest carbon. GCB Bioenergy 14, 989–1000. https://doi.org/10.1111/gcbb.12981

Spinelli, R., Visser, R., Riond, C., Magagnotti, N., 2017. A Survey of Logging Contract Rates in the Southern European Alps. Small-Scale For. 16, 179–193. https://doi.org/10.1007/s11842-016-9350-1

Strobl, C., Boulesteix, A.-L., Zeileis, A., Hothorn, T., 2007. Bias in random forest variable importance measures: Illustrations, sources and a solution. BMC Bioinformatics 8, 25. https://doi.org/10.1186/1471-2105-8-25

Thompson, J.R., Canham, C.D., Morreale, L., Kittredge, D.B., Butler, B., 2017. Social and biophysical variation in regional timber harvest regimes. Ecol. Appl. 27, 942–955. https://doi.org/10.1002/eap.1497

Toth, D., Maitah, M., Maitah, K., Jarolínová, V., 2020. The Impacts of Calamity Logging on the Development of Spruce Wood Prices in Czech Forestry. Forests 11, 283. https://doi.org/10.3390/f11030283

Triviño, M., Morán-Ordoñez, A., Eyvindson, K., Blattert, C., Burgas, D., Repo, A., Pohjanmies, T., Brotons, L., Snäll, T., Mönkkönen, M., 2023. Future supply of boreal forest ecosystem services is driven by management rather than by climate change. Glob. Change Biol. n/a. https://doi.org/10.1111/gcb.16566

Unrau, A., Becker, G., Spinelli, R., Lazdina, D., Magagnotti, N., Nicolescu, V.-N., Buckley, P., Bartlett, D., Kofman, P.D., 2018. Coppice forests in Europe, COST Action FP1301 EuroCoppice. Freiburg i. Br., Germany, Albert Ludvig University of Freiburg.

Vadell, E., Pemán, J., Verkerk, P.J., Erdozain, M., de-Miguel, S., 2022. Forest management practices in Spain: Understanding past trends to better face future challenges. For. Ecol. Manag. 524, 120526. https://doi.org/10.1016/j.foreco.2022.120526

Valavi, R., Elith, J., Lahoz-Monfort, J.J., Guillera-Arroita, G., 2019. blockCV: An r package for generating spatially or environmentally separated folds for k-fold cross-validation of species distribution models. Methods Ecol. Evol. 10, 225–232. https://doi.org/10.1111/2041-210X.13107

Vauhkonen, J., Berger, A., Gschwantner, T., Schadauer, K., Lejeune, P., Perin, J., Pitchugin, M., Adolt, R., Zeman, M., Johannsen, V.K., Kepfer-Rojas, S., Sims, A., Bastick, C., Morneau, F., Colin, A., Bender, S., Kovácsevics, P., Solti, G., Kolozs, L., Nagy, D., Nagy, K., Twomey, M., Redmond, J., Gasparini, P., Notarangelo, M., Rizzo, M., Makovskis, K., Lazdins, A., Lupikis, A., Kulbokas, G., Antón-Fernández, C., Rego, F.C., Nunes, L., Marin, G., Calota, C., Pantić, D., Borota, D., Roessiger, J., Bosela, M., Šebeň, V., Skudnik, M., Adame, P., Alberdi, I., Cañellas, I., Lind, T., Trubins, R., Thürig, E., Stadelmann, G., Ditchburn, B., Ross, D., Gilbert, J., Halsall, L., Lier, M., Packalen, T., 2019. Harmonised projections of future forest resources in Europe. Ann. For. Sci. 76, 1–12. https://doi.org/10.1007/s13595-019-0863-6

Verkerk, P.J., Levers, C., Kuemmerle, T., Lindner, M., Valbuena, R., Verburg, P.H., Zudin, S., 2015. Mapping wood production in European forests. For. Ecol. Manag. 357, 228–238. https://doi.org/10.1016/j.foreco.2015.08.007

Vilà-Cabrera, A., Astigarraga, J., Jump, A.S., Zavala, M.A., Seijo, F., Sperlich, D., Ruiz-Benito, P., 2023. Anthropogenic land-use legacies underpin climate change-related risks to forest ecosystems. Trends Plant Sci. 0. https://doi.org/10.1016/j.tplants.2023.04.014

Wallentin, C., Nilsson, U., 2014. Storm and snow damage in a Norway spruce thinning experiment in southern Sweden. For. Int. J. For. Res. 87, 229–238. https://doi.org/10.1093/forestry/cpt046

Westin, K., Bolte, A., Haeler, E., Haltia, E., Jandl, R., Juutinen, A., Kuhlmey, K., Lidestav, G., Mäkipää, R., Rosenkranz, L., Triplat, M., Skudnik, M., Vilhar, U., Schueler, S., 2023. Forest values and application of different management activities among small-scale forest owners in five EU countries. For. Policy Econ. 146, 102881. https://doi.org/10.1016/j.forpol.2022.102881

Wiersum, K.F., Elands, B.H.M., Hoogstra, M.A., 2005. Small-scale forest ownership across Europe: Characteristics and future potential. Small-Scale For. Econ. Manag. Policy 4, 1–19. https://doi.org/10.1007/s11842-005-0001-1

Winkel, G., Lovrić, M., Muys, B., Katila, P., Lundhede, T., Pecurul, M., Pettenella, D., Pipart, N., Plieninger, T., Prokofieva, I., Parra, C., Pülzl, H., Roitsch, D., Roux, J.-L., Thorsen, B.J., Tyrväinen, L., Torralba, M., Vacik, H., Weiss, G., Wunder, S., 2022. Governing Europe's forests for multiple ecosystem services: Opportunities, challenges, and policy options. For. Policy Econ. 145, 102849. https://doi.org/10.1016/j.forpol.2022.102849

Wright, M.N., Ziegler, A., 2017. ranger: A Fast Implementation of Random Forests for High Dimensional Data in C++ and R. J. Stat. Softw. 77, 1–17. https://doi.org/10.18637/jss.v077.i01

Živojinović, I., Weiss, G., Lidestav, G., Feliciano, D., Hujala, T., Dobšinská, Z., Lawrence, A., 2015. Forest Land Ownership Change in Europe. COST Action FP1201 FACESMAP Country Reports, Joint Volume, EFICEEC-EFISEE Research Report. University of Natural Resources and Life Sciences, Vienna (BOKU), Vienna, Austria.

Supplementary material

1. Details about the forest inventory data and processing

Forest area used in the calculation of represented forest area was taken from FOREST EUROPE (2020) for the Czechia, France, the Netherlands, Norway, Poland, Spain and Switzerland, from the National Forest Accounting Plan of Belgium (2018) for the Walloon Region in Belgium, from county level statistics (Statistics Sweden 2019) for Sweden to account for different sampling densities across the country. For Finland the represented forest areas were calculated following Tomppo et al. (2011), and for Germany these values were provided with the forest inventory data.

Table S1. Details on the sampling designs and data processing of each data set.

Country	Plot type	Plot design details *(a harmonised threshold of 10 cm min dbh was set to harmonise the different sample plots)*	Data processing details and notes	Source/more information
Belgium (Wallonia)	Concentric circles	Radius 4.5 m for dbh >= 6.37 cm (circ. >= 20 and < 70 cm) Radius 9 m for dbh >= 22.28 cm (circ. >= 70 and < 120 cm) Radius 18 m for dbh >= 38.2 (circ. >120 cm)		http://iprfw.spw.wallonie.be/ Ratcliffe et al. 2016, appendix S1 Tomppo et al. 2010
Czech Republic (CzechTerra)	Concentric circles	Radius 3 m for dbh >= 7 cm Radius 12.62 m for dbh >= 12 cm		https://www.czechterra.cz/
Finland	Angle count with max radius (1st measurement from NFI11) Concentric circles (2nd measurement from NFI12)	NFI11: Basal area factor 2 (Southern Finland) and 1.5 (Northern Finland) Maximum radius of 12.52 (Southern Finland) and 12.45 in Northern Finland) NFI12: radius 9 m for dbh >= 9.5 cm. radius 5.64 m for dbh 4.5-9.4 cm Relascope plot for dbh < 4.5 cm (basal area factor 1.5) While the sample plot design changed between the measurements, tree status in NFI12 was recorded for all trees included in NFI11 even if they were not included in the new sample plot, and we were thus able to use all trees in the NFI11 sample plots in our analysis.	The subset of plots included here contains permanent plots located in forest area (following the FAO definition) Here we are only including the forest stand in which the plot centre is located.This is to control the effects of changing plot radius (due to angle count sampling), which would otherwise lead to different sampling probability for stands with different tree sizes.	VMI11 maastotyöohje 2009 Koko Suomi, http://urn.fi/URN:NBN:fi-fe201603038534 VMI12 maastontyön ohje 2017, https://opendata.luke.fi/dataset/aec03411-9249-4cb6-8860-00d56f97d042/resource/e1b9d675-7bce-43d3-a654-c59cde7e7d73/download/2018-ohje.pdf Korhonen et al. 2021

France	Concentric circles	Radius 6 m for dbh >= 7.5 Radius 9 m for dbh >= 22.5 cm Radius 15 m for dbh > 37.5 cm		IGN – Inventaire forestier national français, Données brutes, Campagnes annuelles 2005 et suivantes, https://inventaire-forestier.ign.fr/dataIFN/, site consulté le 16/01/2023. Documentation des données brutes de l'inventaire forestier mises en ligne sur DataIFN. Version 2.1, date 16/01/2023 (is included in the files when data is downloaded from https://inventaire-forestier.ign.fr/dataifn/) Tomppo et al. 2010
Germany	Angle count	Basal area factor 4		https://www.thuenen.de/en/thuenen-topics/forests/the-german-national-forest-inventory Ratcliffe et al. 2016, appendix S1
Netherlands	Variable radius	Radius fit to have min. 20 trees (dbh >= 5 cm) included. If dbh on average <5cm, plot radius = 5 m Radius min 5 m, max 20 m.		Veldinstructie NBI7 https://www.wur.nl/en/research-results/research-institutes/environmental-research/projects/dutch-forest-inventory.htm
Norway (permanent plots)	Fixed area	Radius 8.92 m for dbh >= 5 cm		Breidenbach et al. 2020 Landsskogtakseringens feltinstruks 2018 https://www.nibio.no/en/subjects/forest/national-forest-inventory
Poland	Fixed radius	Stand age 1-60 years, plot area 200m2 (r=7.98m) stand age > 60 years, plot area 400m2 (r=11.28m) regeneration phase, plot size 500 m2 (radius 12.62 m) note that different radii can be used in the same plot if plot area covers stands with different ages	The subset of plots included here contains only plots that were not divided to different age classes in the forest measurement. This is to handle the effects of changing plot size.	Talarczyk 2014 https://www.bdl.lasy.gov.pl/portal/wisl-en

Spain	Concentric circles	Radius 5 m for dbh >= 7.5cm Radius 10 m for dbh >= 12.5 cm Radius 15 m for dbh >= 22.5 cm Radius 25 m for dbh >= 42.5 cm	The Canary Islands were excluded, as they were not covered by several of the data sets used for predictors in the random forests.	https://www.miteco.gob.es/es/biodiversidad/temas/inventarios-nacionales/inventario-forestal-nacional/default.aspx Ratcliffe et al. 2016, appendix S1 Tomppo et al. 2010
Sweden (permanent plots)	Concentric circles	Radius 3.5 m for dbh >= 4 cm Radius 10 m for dbh >= 10 cm	The subset of plots included here contains permanent plots located in forest areas (following the FAO definition) that have been measured in three last censuses.	Fridman et al. 2014 https://www.slu.se/en/Collaborative-Centres-and-Projects/the-swedish-national-forest-inventory/
Switzerland	Concentric circles	Radius 7.98 m for dbh >= 12 cm Radius 12.62 for dbh >= 36 cm	Min DBH in the data (12 cm) is higher than the 10 cm threshold used here across the other data sets	https://www.lfi.ch/index-en.php

References

Breidenbach, J., Granhus, A., Hylen, G., Astrup, R. (2020). A century of National Forest Inventory in Norway – informing past, present, and future decisions. Forest Ecosystems 7, 46.

Fridman J., Holm S., Nilsson M., Nilsson P., Ringvall A.H., Ståhl G. (2014). Adapting National Forest Inventories to changing requirements – the case of the Swedish National Forest Inventory at the turn of the 20th century. Silva Fennica vol. 48 no. 3 article id 1095. 29 p.

Korhonen K. T., Ahola A., Heikkinen J., Henttonen H. M., Hotanen J.-P., Ihalainen A., Melin M., Pitkänen J., Räty M., Sirviö M., Strandström M. (2021). Forests of Finland 2014–2018 and their development 1921–2018. Silva Fennica vol. 55 no. 5 article id 10662. https://doi.org/10.14214/sf.10662

National Forest Accounting Plan of Belgium (2018). https://www.cnc-nkc.be/sites/default/files/report/file/national_forest_accounting_plan_-_belgium.pdf

Ratcliffe, S., Liebergesell, M., Ruiz-Benito, P., Madrigal González, J., Muñoz Castañeda, J.M., Kändler, G., Lehtonen, A., Dahlgren, J., Kattge, J., Peñuelas, J., Zavala, M.A., Wirth, C., 2016. Modes of functional biodiversity control on tree productivity across the European continent. Glob. Ecol. Biogeogr. 25, 251–262. https://doi.org/10.1111/geb.12406

Statistics Sweden (2019). Land use in Sweden, 7th edition.

Talarczyk, A. (2014). National Forest Inventory in Poland. Baltic Forestry 20(2): 333-340.

Tomppo, E., Gschwantner, T., Lawrence, M., McRoberts, E. (eds) 2010. National Forest Inventories - Pathways for Common Reporting. Springer.

Tomppo, E., Heikkinen, J., Henttonen, H.M., Ihalainen, A., Katila, M., Mäkelä, H., Tuomainen, T., Vainikainen, N. (2011). Designing and conducting a forest inventory - case: 9th National Forest Inventory of Finland. Managing Forest Ecosystems 21, Springer. 270 p.

2. Details on the calculation of the harvest variables

Frequency of harvest events was calculated for each grid cell and defined as:

$$Frequency = \frac{N_{harvest}}{N} * 100 \qquad [1]$$

where

$N_{harvest}$ is the number of annualised data points with harvest in the grid cell, and

N is the total number of annualised data points in the grid cell.

Note that while this variable is calculated from the annualized data, it is aggregated across all the years, i.e. resulting in one value per grid cell (not separate values for each year).

Intensity of a harvest event was calculated for each harvested plot and was defined as:

$$Intensity = \frac{BA_{harvest}}{BA} * 100 \qquad [2]$$

where

BA is the total tree basal area (m2/ha) in the plot (extended to a hectare) in the first measurement,

$BA_{harvest}$ is the tree basal area (m2/ha) in the first measurement for those trees that were harvested between the two measurements.

The *intensity* is calculated on plot level, and for grid cell level aggregation we calculated an arithmetic mean of all the plots located in the grid cell, and the percentage of harvest events falling into different intensity classes within the grid cell (< 25%, 25-50%, 50-75%, >75% of BA harvested).

Note that on plot level this variable gives one intensity value for each harvested plot. When aggregated to the grid cell level (as described in the paragraph above), it is aggregated over all the harvested plots, i.e. separate values for different years are not provided.

Total harvest rate was calculated for each grid cell and was defined as:

$$HarvestRate = \frac{\sum_{i=1}^{n}(BA_{harvest,i} \div census.interval_i)}{\sum_{i=1}^{n} BA_i} \qquad [3]$$

where

n is the number of plots in a grid cell,

$BA_{harvest,\,i}$ is the tree basal area (m2/ha) of the harvested trees in plot i,

$census.interval_i$ is the time between the two measurements (years) in plot i, and

BA_i is the total tree basal area of plot i in the first measurement.

Note that this variable is calculated by aggregating the harvest information from all the plots within the grid cell, and gives one value per cell (i.e., not separate values for different years).

3. Additional figures: harvest regimes in Europe

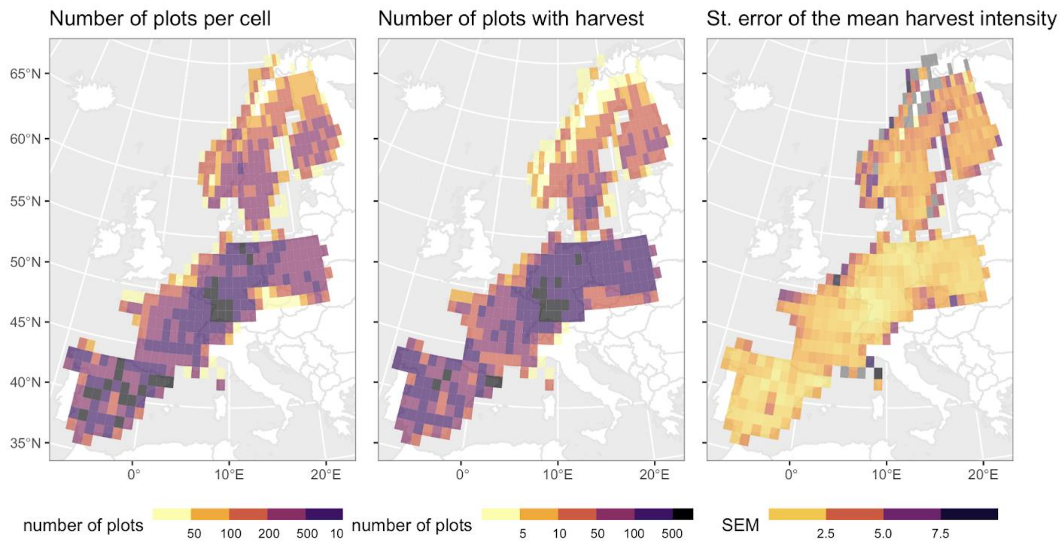

Figure S1. Number of plots per grid cell (left) and number of plots with harvest per grid cell (middle) and the standard error of the mean (SEM, right) for the mean harvest intensity. Note the different color scales in the maps.

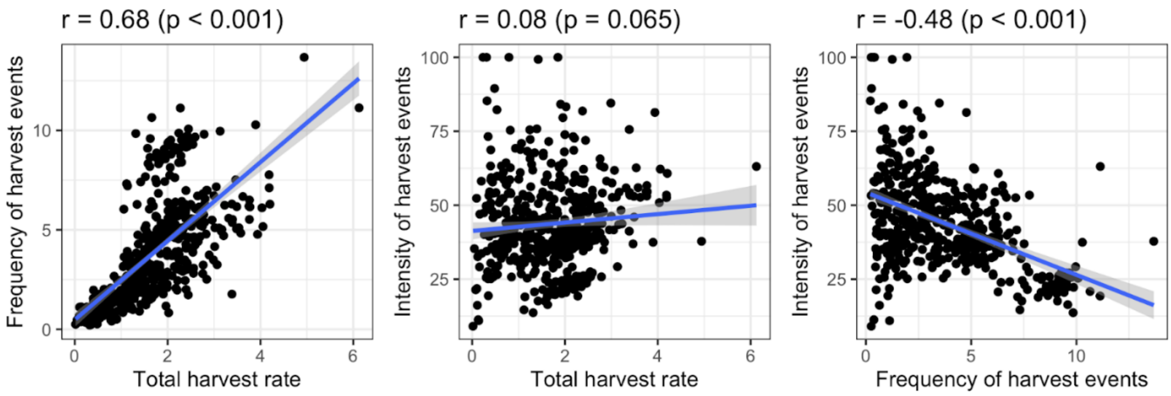

Figure S2. Scatter plots and Pearson's correlation coefficients (r) between overall harvest intensity, the frequency of harvest events and the intensity of harvest events. The blue lines show linear regression lines fitted to the data. The shaded areas show the 95% confidence intervals for the regression slope. All units are percentages.

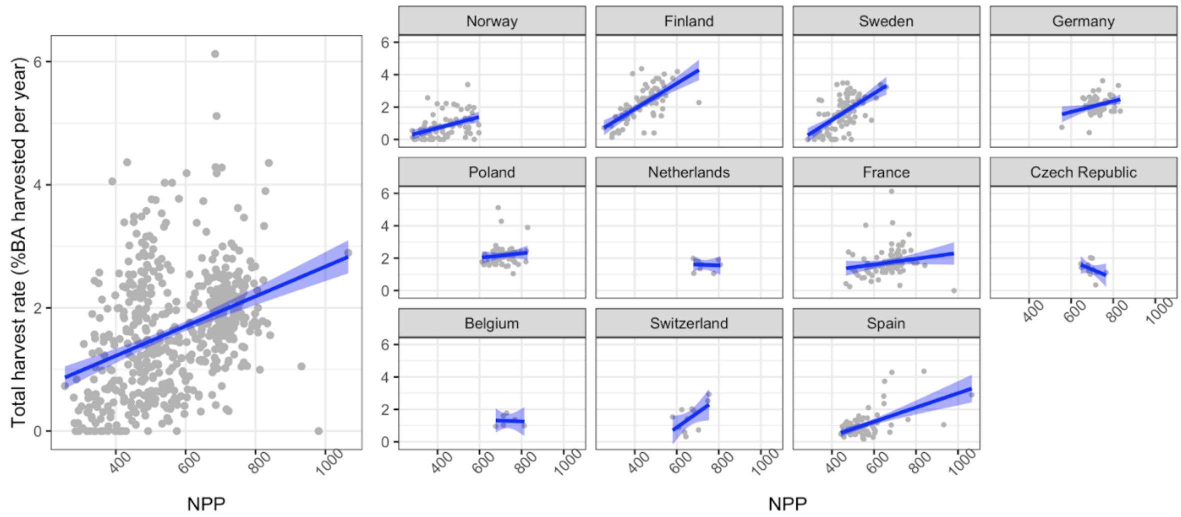

Figure S3. Total harvest rate vs NPP from the Neumann et al. (2016) data. The shaded areas show the 95% confidence intervals for the regression slope.

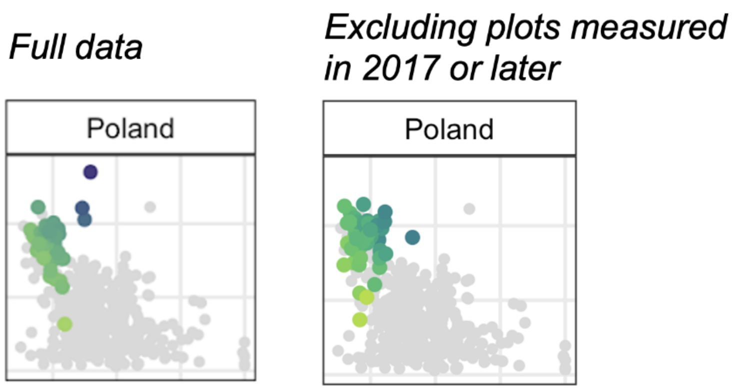

Figure S4. The harvest intensity-frequency space for grid cells in Poland (see Figure 2 for the full original figure) in the full data (left) and when excluding observations from 2017 or later. Excluding the 2017 and later years (i.e., years where the second measurement occurred after the large windstorm in 2017) leads to the high-frequency/mid-intensity outliers disappearing and most grid cells moving slightly towards lower harvest intensities.

4. Class balancing tests for $RF_{Probability}$

As the classes were strongly unbalanced, with a lower number of harvest cases compared to non-harvested data points, different resampling methods to balance the classes were tested and evaluated with cross-validation to find the approach leading to best performance of the model. For balancing the classes, we tested undersampling the majority class (no-harvest) and oversampling the minority class (harvest) by conducting a grid search for different under/oversampling ratios. The tested sampling ratios ranged from values corresponding to the original ratio of the classes in the data (under/oversampling ratio of 1) to values resulting in close-to-equal shares of the two classes (undersampling ratio 0.05, oversampling ratio 20). Balancing was tested with 10-fold cross-validation by always training the model on a balanced training set and testing with a non-balanced test set.

Best cross-validation results were achieved when undersampling the no-harvest class to have approximately equal size as the harvest class. Therefore, we balanced the data by undersampling of the no-harvest class with a ratio 0.05 for training the harvest probability random forest model ($RF_{probability}$).

The class balancing tests were conducted using R packages mlr3 (Lang et al. 2019) and mlr3pipelines (Binder et al. 2019).

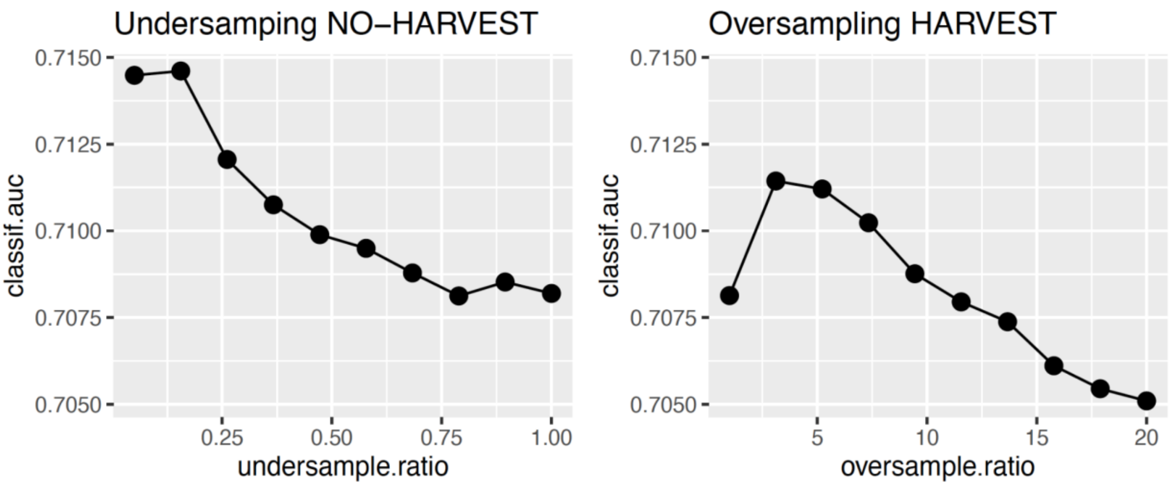

Figure S5. Results for tests with different undersampling and oversampling ratios to balance the ratio between harvested and non-harvested data points.

5. Additional figures: predictive models

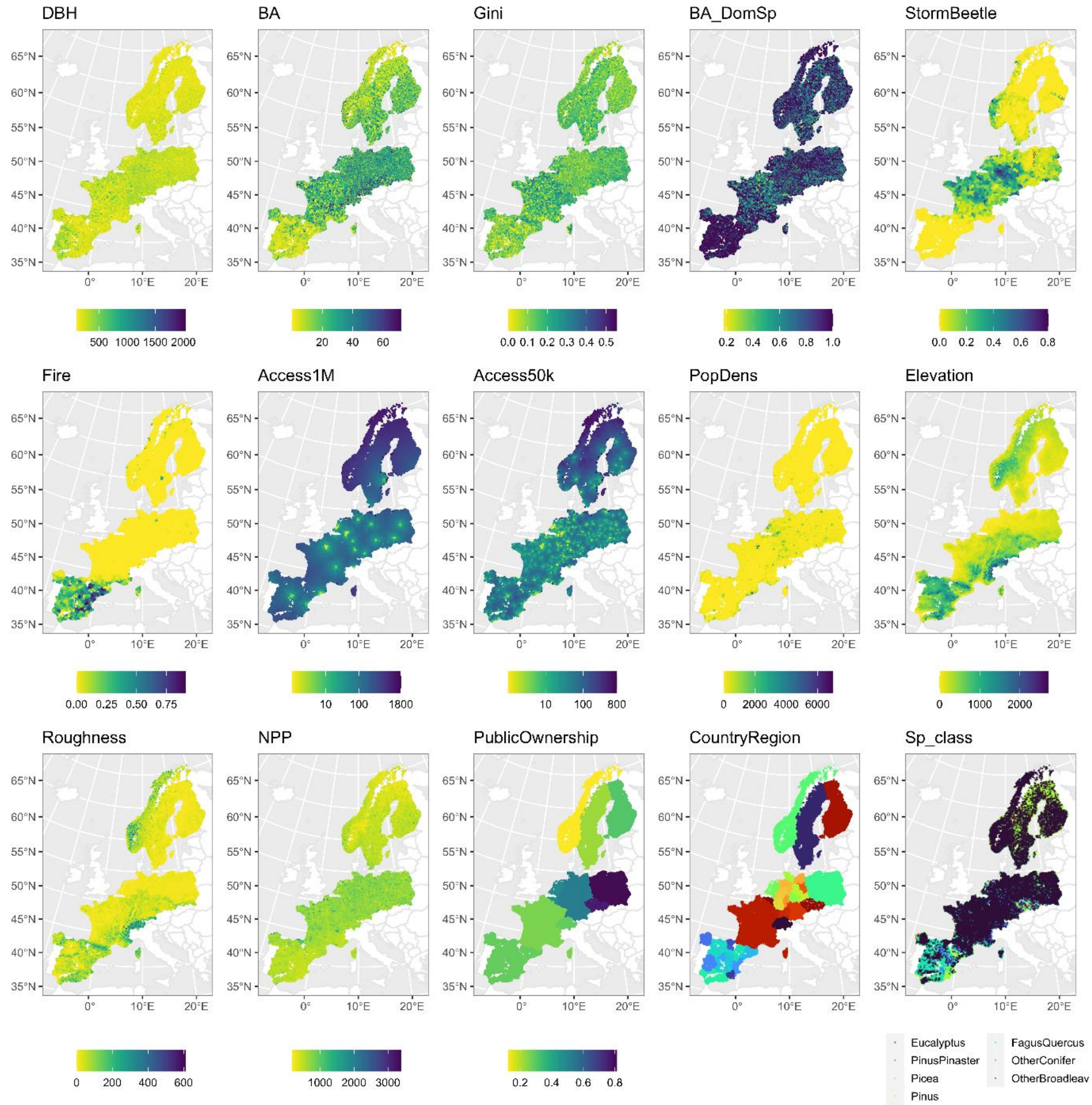

Figure S6. Spatial variation in predictor variables used in the random forest models. The maps present the values of the variables for each forest inventory plot, find description of each variable in Table 2 (main text). Note that the color scales for the Access1M and Access50k variables have been log-transformed to better visualise their differences. Please see Fig. S6 for a more detailed presentation of the species classes (Sp_class).

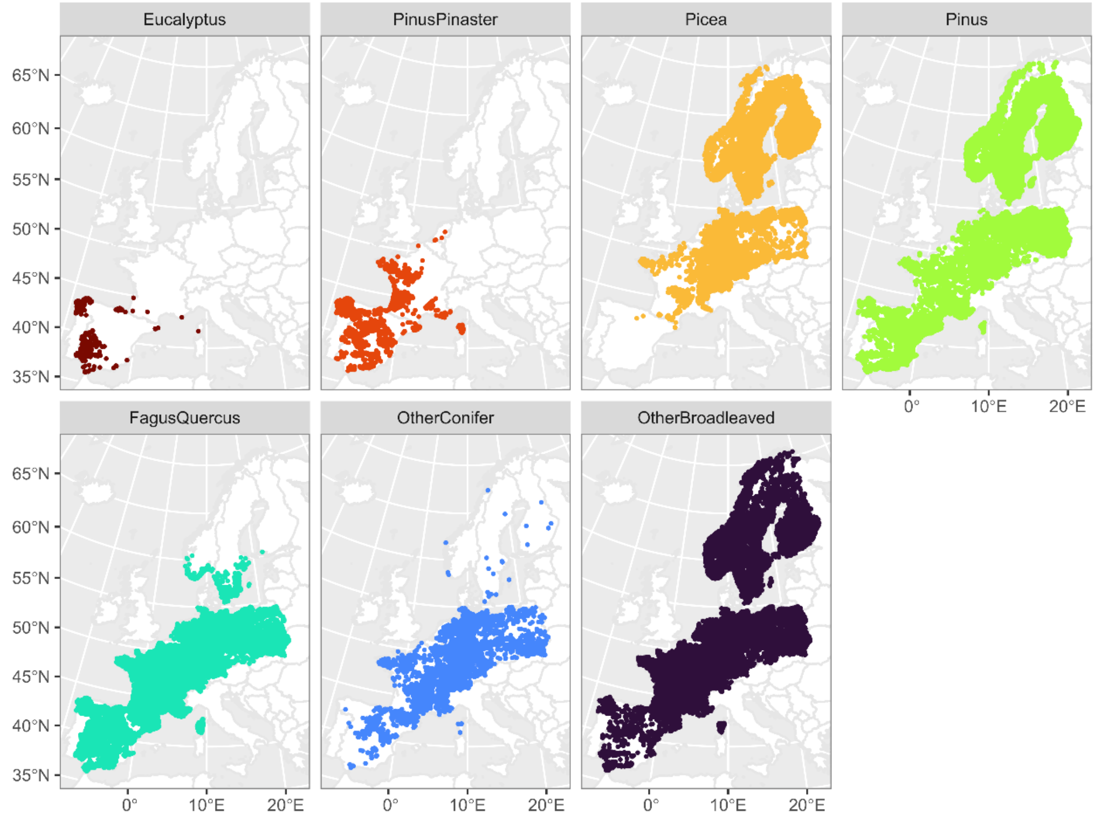

Figure S7. Locations of plots with dominant species from each species class (Sp_class) category.

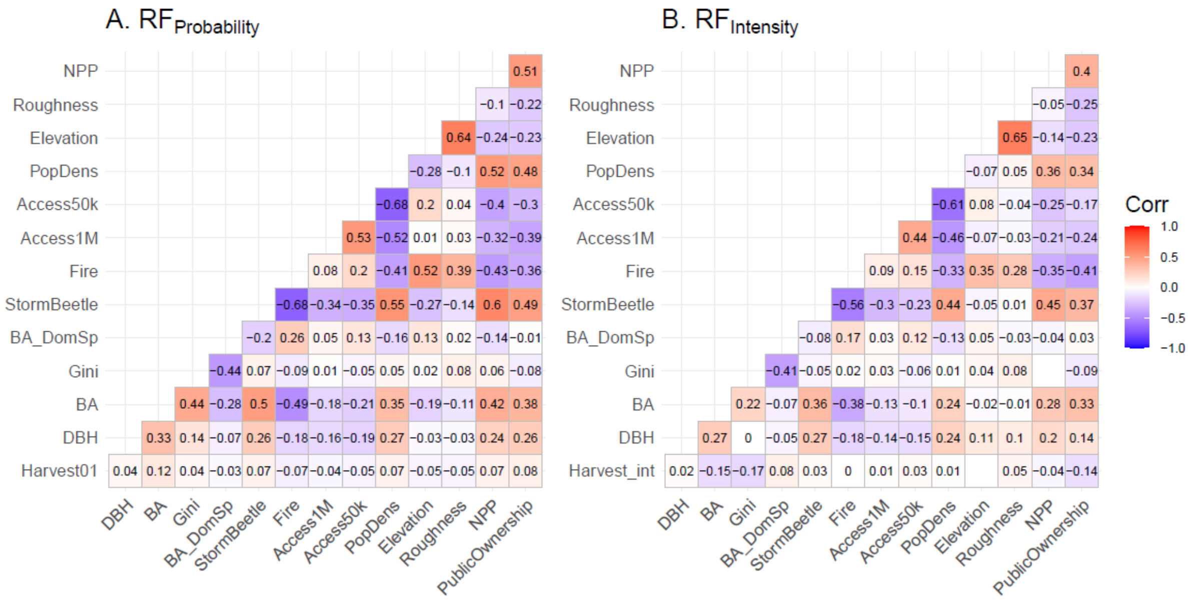

Figure S8. Correlation matrix for predictor features in RFProbaility (A) and RFIntensity (B). The correlations are different because the used input data sets differ in the two random forest models (see details in the methods description of the main text).

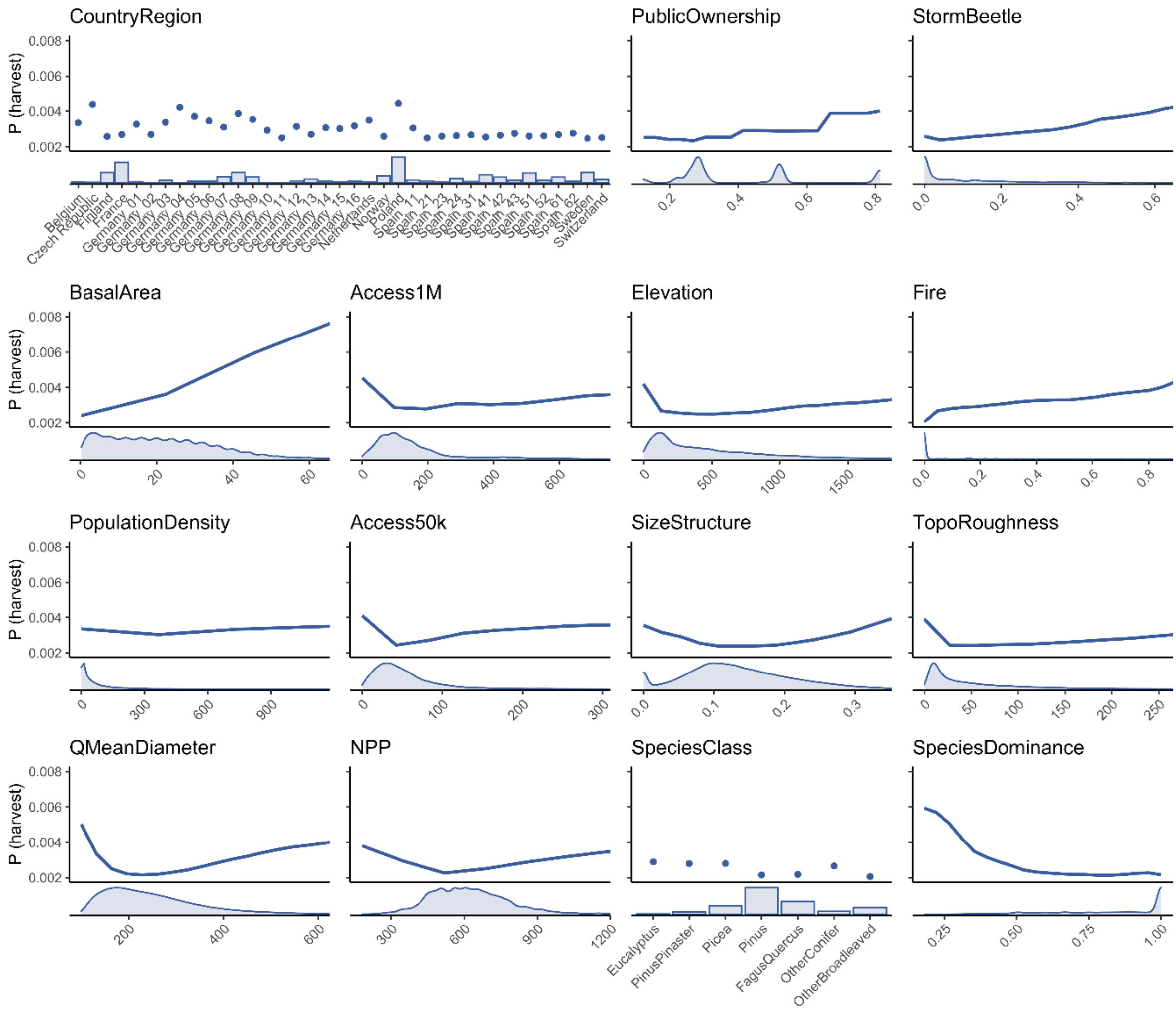

Figure S9. PDP plots for all predictor features in $RF_{Probability}$.

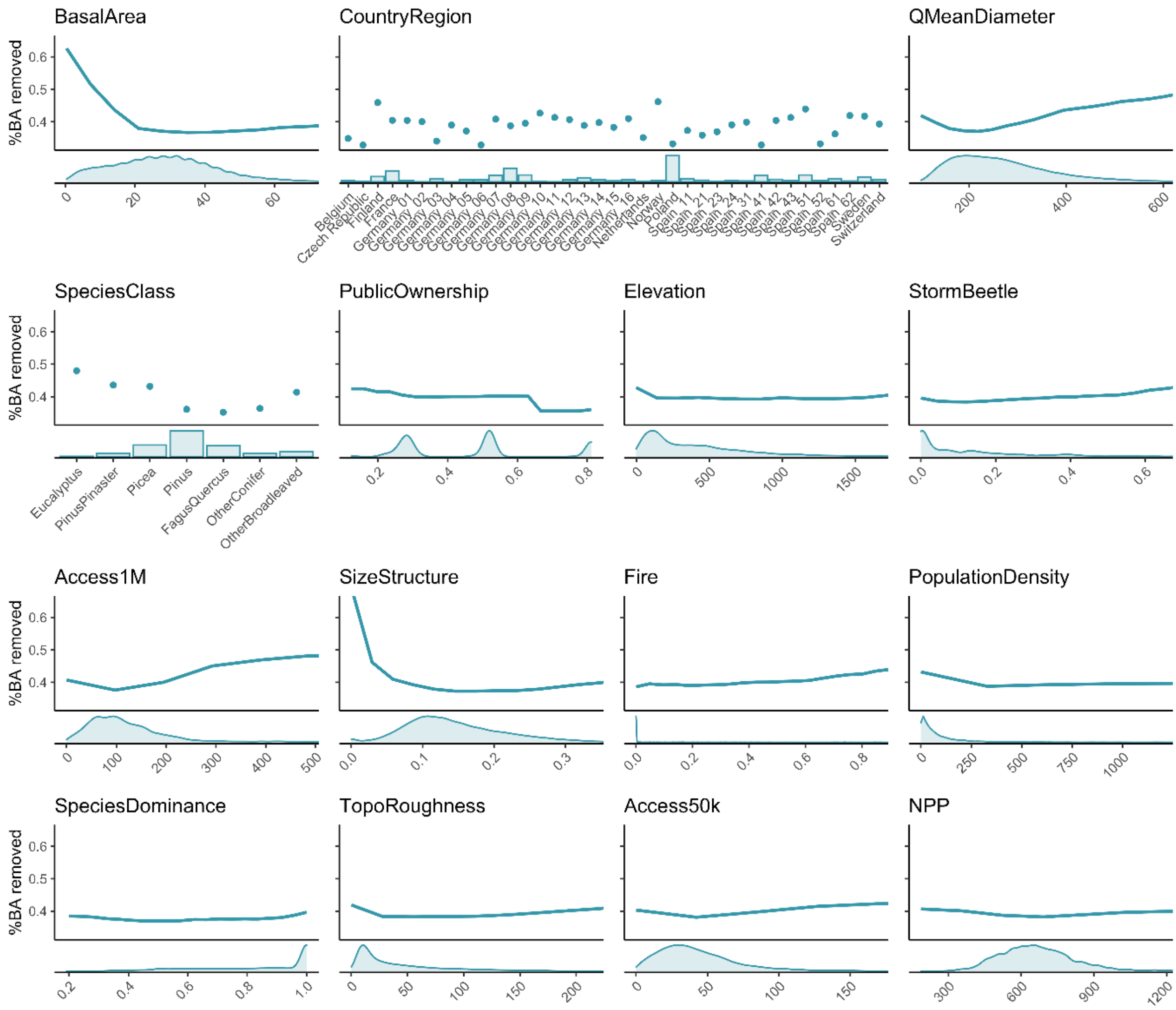

Figure S10. PDP plots for all predictor features in $RF_{Intensity}$.