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Understanding Europe's Forest Harvesting Regimes

Susanne Suvanto[1,2,3], Adriane Esquivel-Muelbert[1,2], Mart-Jan Schelhaas[4], Julen Astigarraga[5], Rasmus Astrup[6], Emil Cienciala[7,8], Jonas Fridman[9], Helena M. Henttonen[3], Georges Kunstler[10], Gerald Kändler[11], Louis A. König[4,12], Paloma Ruiz-Benito[5,13], Cornelius Senf[14], Golo Stadelmann[15], Ajdin Starcevic[4], Andrzej Talarczyk[16], Miguel A. Zavala[13], and Thomas A. M. Pugh[1,2,17]

[1]School of Geography, Earth and Environmental Sciences, University of Birmingham, Birmingham, UK, [2]University of Birmingham, Birmingham Institute of Forest Research (BIFoR), Birmingham, UK, [3]Natural Resources Institute Finland (Luke), Bioeconomy and Environment Unit, Helsinki, Finland, [4]Wageningen University and Research, Wageningen Environmental Research (WENR), Wageningen, The Netherlands, [5]Departamento de Ciencias de la Vida, Universidad de Alcalá, Grupo de Ecología y Restauración Forestal, Alcala, Spain, [6]Division of Forest and Forest Resources, NIBIO, Ås, Norway, [7]IFER—Institute of Forest Ecosystem Research Ltd., Jilove u Prahy, Czech Republic, [8]Global Change Research Institute of the Czech Academy of Sciences, Brno, Czech Republic, [9]Department of Forest Resource Management, Swedish University of Agricultural Sciences, Umeå, Sweden, [10]Université Grenoble Alpes, INRAE, LESSEM, St-Martin-d'Hères, France, [11]Department of Biometrics, Forest Research Institute Baden-Württemberg, Freiburg, Germany, [12]Wageningen University, Forest Ecology and Management Group, Wageningen, The Netherlands, [13]Departamento de Geología, Geografía y Medio Ambiente, Universidad de Alcalá, Grupo de Investigación en Teledetección Ambiental, Alcala, Spain, [14]School of Life Sciences, Technical University of Munich, Munich, Germany, [15]Swiss Federal Institute for Forest, Snow and Landscape Research (WSL), Resource Analysis, Birmensdorf, Switzerland, [16]Forest and Natural Resources Research Centre Foundation, Warsaw, Poland, [17]Department of Physical Geography and Ecosystem Science, Lund University, Lund, Sweden

Key Points:

- Harvesting of wood has a major role in shaping forest ecosystems but understanding of the spatial variation in harvest practices is limited
- Using forest inventory data, we show considerable variation in forest harvest regimes across Europe and analyse its drivers
- The results improve the quantification of human activities impacting forests and give a baseline for assessing future management changes

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

S. Suvanto,
susanne.suvanto@luke.fi

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Author Contributions:

Conceptualization: Susanne Suvanto, Adriane Esquivel-Muelbert, Mart-Jan Schelhaas, Thomas A. M. Pugh
Data curation: Susanne Suvanto, Adriane Esquivel-Muelbert, Mart-Jan Schelhaas, Julen Astigarraga, Rasmus Astrup, Emil Cienciala, Jonas Fridman, Helena M. Henttonen, Georges Kunstler, Gerald Kändler, Louis A. König, Paloma Ruiz-Benito, Cornelius Senf, Golo Stadelmann, Ajdin Starcevic, Miguel A. Zavala
Formal analysis: Susanne Suvanto

Abstract

European forests are being shaped by active human use and management, and by harvesting of wood in particular. Yet, our understanding of how forests are harvested across Europe is limited, as the real harvest regimes are not well described by currently available data. Here, we analyse recent harvests, as observed in permanent plots of forest inventories in 11 European countries, totaling to 182,649 plots and covering all major forest types. We (a) characterize harvest regimes through the frequency and intensity of harvest events spatially across Europe, and (b) build models for the probability and intensity of harvest events at the plot-level and examine the links to potential drivers of harvest, including the pre-harvest forest structure and composition, climatic, topographic and socio-economic factors, and past natural disturbances. The results revealed notable variation in harvest regimes across Europe, ranging from high-frequency and low-intensity harvests in eastern Central Europe to low-frequency and high-intensity harvests in the north, with different strategies emerging in regions with similar total harvest rates. The harvest regimes were strongly driven by country-level variation, emphasizing the role of national-level factors. Pre-harvest forest properties were important drivers for the intensity of harvest, whereas the probability of harvest was more related to socio-economic factors and natural disturbances. The presented quantification of the forest harvesting regimes provides much needed detail in our understanding of the contemporary forest management practices in Europe, providing a baseline against which to assess future changes in management and strengthening the knowledge-base for decision-making on European level.

Plain Language Summary

In Europe, forest management strongly shapes forest ecosystems and the ecosystem services they provide. Accounting for forest management is therefore crucial in any large-scale assessment of European forests, but information about management practices is limited. Here, we have quantified Europe's forest harvesting regimes with forest inventory data from 11 countries, consisting of over 180,000 sample plots from the boreal to the Mediterranean. We characterized harvest regimes spatially in terms of harvest frequency and intensity and built plot-level models for the probability and intensity of harvest events. The results show considerable variation in harvest strategies across Europe and provide insight into the different drivers behind harvesting regimes. Our results offer much needed detail in our understanding of the contemporary forest management practices in Europe and can act as a baseline against which future changes in management can be compared to.

Methodology: Susanne Suvanto, Adriane Esquivel-Muelbert, Mart-Jan Schelhaas, Thomas A. M. Pugh
Validation: Susanne Suvanto
Visualization: Susanne Suvanto
Writing – original draft: Susanne Suvanto
Writing – review & editing: Susanne Suvanto, Adriane Esquivel-Muelbert, Mart-Jan Schelhaas, Julen Astigarraga, Rasmus Astrup, Emil Cienciala, Jonas Fridman, Helena M. Henttonen, Georges Kunstler, Gerald Kändler, Louis A. König, Paloma Ruiz-Benito, Cornelius Senf, Golo Stadelmann, Ajdin Starcevic, Miguel A. Zavala, Thomas A. M. Pugh

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 & 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; Kauppi 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 & 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 regimes, that is, the frequencies and intensities applied to these forests.

It is crucial to understand harvest in order to understand European forests. Yet, 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). While the total harvest amount is important, these studies contain little detail on the harvest strategies applied, thus are not providing the full detail on how harvesting affects forest structure and functioning. 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 Breidenbach et al., 2022; Palahí et al., 2021). To move beyond the harvested amount of wood or forest area and toward 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, these studies 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 harvests across Europe (Aszalós et al., 2022; Cardellini et al., 2018; Mason et al., 2021) and to characterize harvests in modeling 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 harvest practices 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 characterizes the variation in harvesting 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 emphasized 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 by humans. Superimposed on this are the nationally and regionally varying legislations, regulations and subsidies steering the extraction of wood for human use (Bauer et al., 2004; Haeler et al., 2023; Nichiforel et al., 2018; Orazio et al., 2017), as well as different goals people have for forest management and forest use (Westin et al., 2023; Winkel et al., 2022). These affect which types of harvest strategies are applied by the forest managers. 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. Several studies have used NFI data to give detailed characterization of harvest regimes at regional and national extents (Antón-Fernández & Astrup, 2012; Kilham et al., 2019; Thompson et al., 2017), but the approach has only rarely been applied across larger spatial extents. Schelhaas et al. (2018) compared the harvest probability of individual trees in subsets of inventory data from 13 European regions, providing important insight into differences in tree-level harvest rates across Europe. An integrated and consistent analysis of NFI data across larger areas can allow going beyond the extent of individual

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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

countries or regions, while a focus on frequencies and intensities of harvest events, rather than general tree-level harvest probabilities can help in understanding how harvests are actually carried out, and thus close a major gap in understanding Europe's harvesting regimes.

Here, our goal is to improve the current understanding of contemporary harvest regimes across Europe by extracting information about harvests from re-measured plots of national forest and landscape inventories in 11 European countries, totaling 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 (a) characterize harvest regimes spatially across Europe, and (b) build models for the probability and intensity of harvest events at the plot-level and examine the links to potential drivers of harvest, including the pre-harvest forest structure and composition, climatic, topographic and socio-economic factors, and past natural disturbances.

2. Materials and Methods

2.1. Forest Inventory Data

We used a collection of data from permanent plots of national forest inventories and landscape inventories from 11 European countries (Table 1 and Table S1 in Supporting Information S1). 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 (Figure 1a). Only trees alive in the first measurement were considered. Each plot came with coordinates accurate to ca. kilometer scale. Plots with no trees in the first measurement were excluded, together with plots with a census interval of more than 15 years.

2.1.1. Data Processing and Harmonization

In Europe, each country conducts their forest inventory independently, and the sampling design and thus measurement interval differ between countries and need to be harmonized. Here, we harmonized the differing diameter-at-breast-height (DBH, measured at 1.3 m height) threshold for the minimum size of measured trees 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 Table S1 in Supporting Information S1). The sampling probability was calculated

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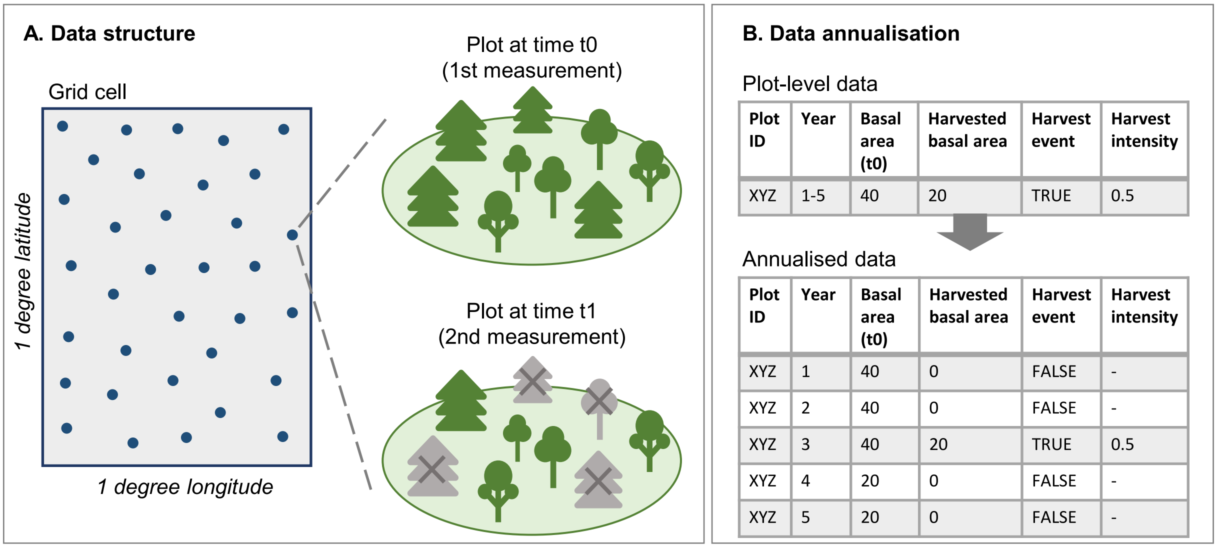

Figure 1. Visualization of the data structure (a) and the data annualization process (b). Subfigure (a) shows the data structure with tree-level information from two measurements at the same plot. The first measurement describes the pre-harvest status of the forest and the second measurement provides information about which (if any) trees were harvested between the measurements (marked with gray color and a cross). Note that the density and configuration of the plots within a cell and the exact type of the plot depend on the sampling design in each country (see Table S1 in Supporting Information S1 and references therein). Subfigure (b) provides a demonstration of the data annualization process with an example where a plot with a 5-year measurement interval is transformed into annual data points where harvest was approximated to occur in the middle and the post-harvest forest structure (basal area) was updated by removing the harvested trees.

by comparing the plot area from which a tree would be measured (which, depending on the plot design, can depend on the tree size) to the area of a hectare.

As the time interval between the two measurements varied across the data, we annualized the data by transforming the two observations from each plot into annual data points (Figure 1b). This annualized version of the data set was used for calculating the harvest frequencies for the 1° grid (Section 2.1.2) and for the model for harvest probability (Section 2.2). The annualization was done by, first, converting a single plot into data points representing each of the years between the measurements, and then assigning harvest to the middle year of the measurement interval. While harvest can occur in any of the years between the measurements, the harvest events are independent of the measurements and therefore in a large data set harvest can be approximated to occur on average in the middle (see Figures S1 and S2 in Supporting Information S1 for assessment of impacts for setting harvest to mid-interval). This approach is often used with forest inventory data (Gschwantner et al., 2024). Finally, the data points representing the post-harvest years after harvest were updated to represent changed forest structure. This update is relevant for the random forest predicting harvest probability, as it affects the forest structure variables used in the prediction (see Section 2.2.2). For example, tree basal area per hectare would be calculated from all trees in the first measurement for the annualized data points before harvest, and only from the non-harvested trees in the first measurement for data points after harvest (Figure 1b). The updated post-harvest data points were excluded 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 annualized 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. This does not affect the calculation of harvest intensity, as the post-harvest years do not contain a harvest event and therefore do not have harvest intensity specified (see illustration of the annualization process in Figure 1b). The final annualized data set contained 1,430,221 data points.

Sampling density (plots per forest area unit) varied between countries and, in some cases, within countries. We therefore calculated weights for each observation based on the forest area represented by the plot. This was either provided to us with the inventory data (Germany and Sweden), calculated following the national protocol (Finland) or calculated by dividing the forest area in the country by the number of plots included in the analysis, (see details in Table S1 in Supporting Information S1). The weights were used for the harvest variables aggregated on the 1-degree grid (Section 2.1.2, Text S1 in Supporting Information S1) and as observation weights in the random forest training and for calculating the partial dependence plots (Section 2.2).

2.1.2. Characterizing Harvesting Regimes

Harvesting regimes were characterized 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. The 1-degree grid was chosen to have a sufficient number of observations per grid cell (Figure S3 in Supporting Information S1). 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 (Figure 1a). Harvest therefore includes any event where trees are cut, including thinnings, selective harvests and clear cuts, as well as salvage loggings after natural disturbances.

We calculated the frequency of harvest events for the grid cells from the annualized data (see details of the annualization process in Section 2.1.1 and Figure 1b) 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 (Figure 1b). 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. Weights based on the represented forest area of each plot were used in all calculations. Additional detail on the calculation of the harvest variables is included in Supporting Information S1 (Text S1).

Grid cells were only included in the results when there were at least 20 inventory plots in the cell. For harvest intensity variables only grid cells with at least five harvest events were included (Figure S3 in Supporting Information S1).

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

2.2. Random Forest Models

2.2.1. Implementation

Modeling was carried out on plot-level using random forest models (RF). RF is a well-established machine learning method, that builds a large number of regression (or classification) trees from bootstrap subsets of the data and averages over them (Breiman, 2001; Hastie et al., 2009). RF has been successfully applied in forest research, often with higher predictive power compared to parametric statistical models (Hart et al., 2019; Kilham et al., 2019). RF can handle interactions between variables without pre-defining them, and non-linear responses between the predictors and the response, making it particularly useful for modeling complex phenomena such as forest harvesting.

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 annualized data set, with the binary response variable of harvest or no-harvest ($RF_{Probability}$). 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 $RF_{Intensity}$, 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 2.2.3 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 (for $RF_{Probability}$) or the mean intensity of harvest events (for $RF_{Intensity}$), 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 & Ziegler, 2017).

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

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Table 2

Descriptions of Features Used as Predictors in the Random Forest Models, Trained With the Plot-Level Data

Abbreviation	Unit	Description	Target year	Type	Source
QMeanDiameter	cm	Quadratic mean diameter of the forest pre-harvest	The 1st measurement	Forest	Forest inventory data
BasalArea	m^2 ha^{-1}	Total tree basal area of the forest pre-harvest, that is, the total cross-sectional area of trees at breast height per hectare	The 1st measurement	Forest	Forest inventory data
SizeStructure	Index 0 to 1	Gini index of tree diameters pre-harvest	The 1st measurement	Forest	Forest inventory data
SpeciesDominance	Percent	Percentage of tree basal area covered by the dominant species	The 1st measurement	Forest	Forest inventory data
SpeciesGroup	Categorical	*Eucalyptus* sp.; *Pinus pinaster*; other pines; spruces; beech and oaks; other conifers; other broadleaves	The 1st measurement	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 meters 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	2015	Human	Schiavina et al. (2022)
Access1M	Numeric, minutes	Travel time to a population center with >1M inhabitants	2015	Human	Nelson et al. (2019)
Access50k	Numeric, minutes	Travel time to a population center with >50 k inhabitants	2015	Human	Nelson et al. (2019)
PublicOwnership	Percentage	Percentage of public ownership by country	2015 (2010 for Norway)	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	Years from the 1st to the 2nd measurement per plot	Disturbance	Senf and& Seidl (2021a)
Fire	Probability	Probability of disturbance patch to originate from fire	Years from the 1st to the 2nd measurement per plot	Disturbance	Senf and& Seidl (2021a)

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2.2.2. Features Predicting Harvest

Harvest is driven by factors relating to the forest characteristics, 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, Figures S4 and S5 in Supporting Information S1).

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, which was chosen to ensure robustness across different sample plot designs). These variables were calculated using the first census at each plot, that is, pre-harvest conditions of the forest. The dominant species was defined as the species with the highest basal area in the plot and characterized by species groups modified from Verkerk et al. (2015, Table 2).

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 can also affect harvest through increased costs of harvest (Orazio et al., 2017; Spinelli et al., 2017) and through specific forest management goals, for example, protection against rockfall and avalanches (Dorren et al., 2004). The importance of topography for harvesting is shown in it being is used in the definition of "forests not available for wood supply" (FNAWS) due to the economic restrictions that high altitudes, steep slopes and challenges in accessibility pose for wood supply in mountainous regions (Alberdi et al., 2020). Here, topography is described through elevation and topographic roughness, which 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 neighbors 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.

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 centers can have either increasing or reducing effects on harvest pressures. Increasing distance from population centers 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 for example, 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 centers 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 1 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.

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 in year 2015 (2010 for Norway, where values for 2015 were not available; 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).

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 its 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 center 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).

2.2.3. Interpretation of the Random Forest 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 effect of a predictor on the response variable, marginalized over the combinations of the other input variables. To calculate a PDP for one predictor variable, predictions are calculated for each data point by changing the value of the variable of interest to cover the full range of its values in the data, while other variables are kept untouched. Then, the predictions are averaged for each value of the variable of interest (Molnar, 2018). We calculated the PDPs from a subset of 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 representing different management approaches and growing conditions: 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 & Ziegler, 2017).

2.2.4. Validation

Spatial autocorrelation in data can lead to overly optimistic cross-validation results when the assumption of independence between data points is violated (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 10×10 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 and 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 10 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 to 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

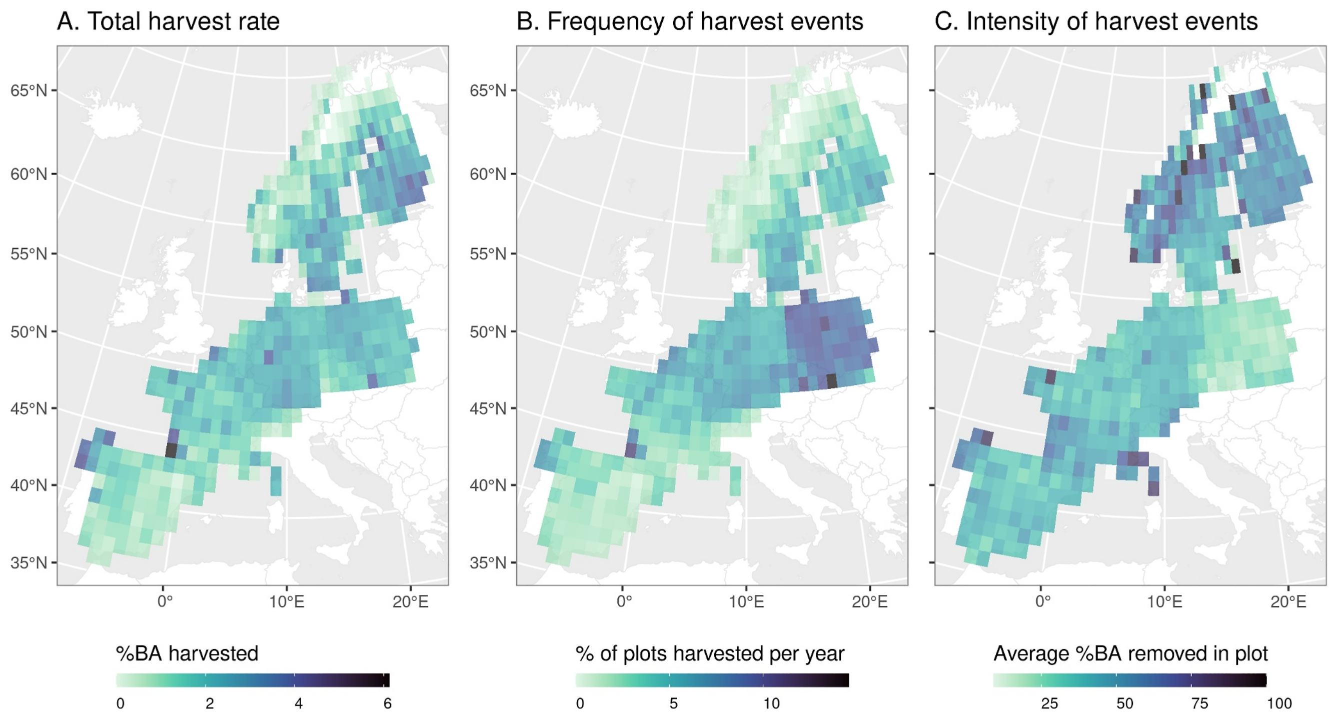

Figure 2. Harvest regimes across Europe, quantified as the total harvest rate (a, percentage of BA harvested in the grid cell per year), the frequency of harvest events (b, percentage of plots harvested per year) and intensity of harvest events (c, average percentage of tree basal area removed in a harvest event).

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 & Becker, 2021, version 1.0.1).

3. Results

3.1. Harvest Patterns Across Europe

The results showed substantial variation in harvest regimes across Europe, and the spatial patterns of total harvest rates (Figure 2a) deviated from the patterns found for the frequency and average intensity of harvest events (Figures 2b and 2c). The total harvest rate in the grid cells was positively correlated with the frequency of harvest events ($r = 0.67$, $p < 0.001$), while the correlation with intensity of harvest events was weak ($r = 0.09$, $p = 0.042$, Figure S6 in Supporting Information S1). Harvest frequencies were found to be highest in eastern Central Europe and decrease toward the north and toward the Mediterranean. High harvest frequencies were found especially in Poland and Czechia, as well as in south-western France (Figure 2b). 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 (Figure 2c). 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 ($r = -0.49$, $p < 0.001$; Figure S6 in Supporting Information S1).

We observed a continuum from high-frequency and low-intensity harvests (Poland, Czechia) toward 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% and 3% of the grid cell basal area per year (Figure 3). Conversely, the gradient of total harvest rate moves from low-frequency and low-intensity (parts of Spain) toward the few grid cells with either high-frequency and high-intensity (outliers in France and Spain) or high frequency (outliers in Poland).

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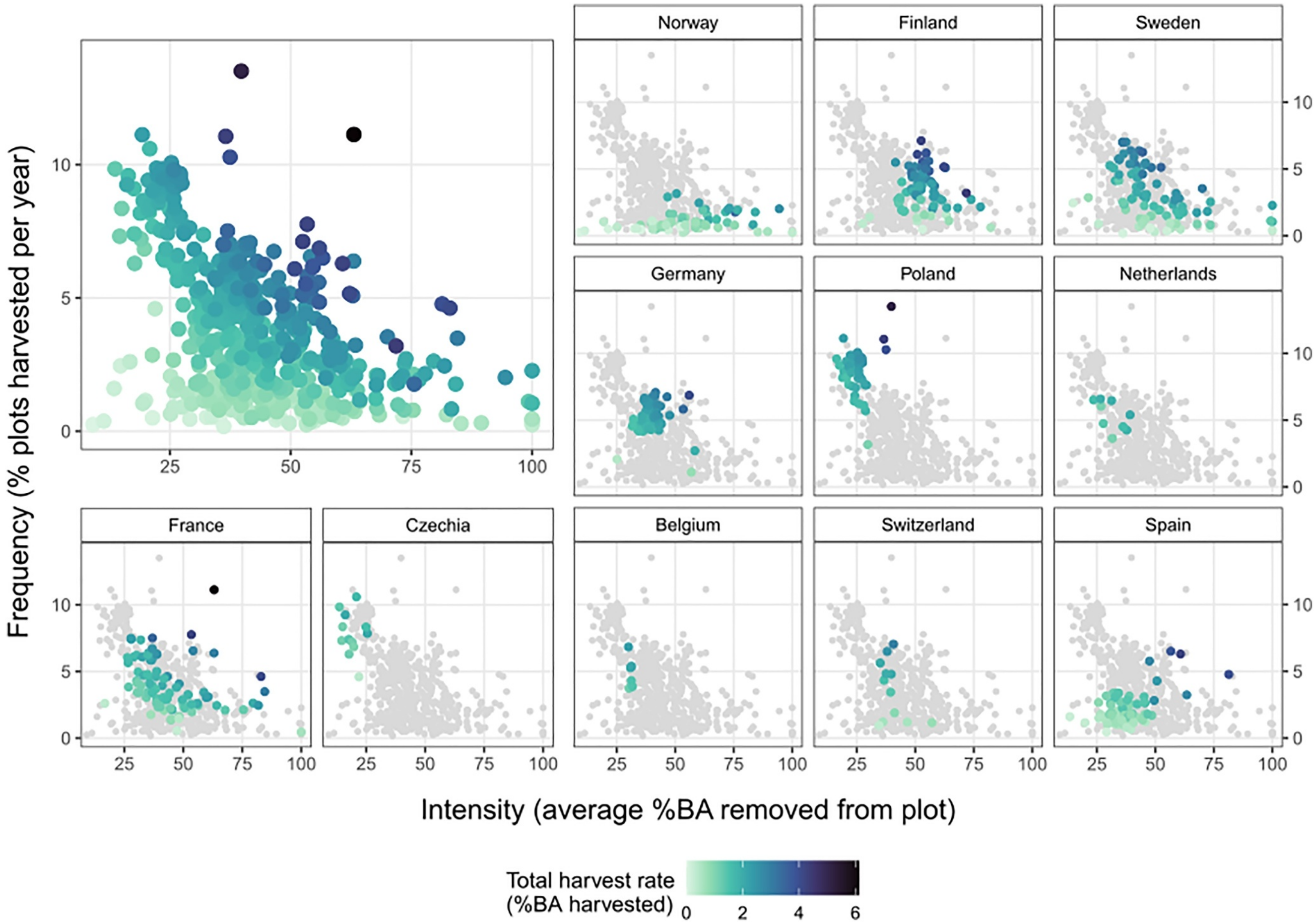

Figure 3. Frequency versus average intensity of harvest events in the grid cells for the 11 European countries together (upper-left corner) and separately per country. The color of the points represents the total harvest rate in the grid cell (% of tree basal area removed annually from the grid cell).

Very low intensity harvests (<25% of tree basal area removed) are driving the high frequency of harvests in Poland and Czechia (Figure 4). 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

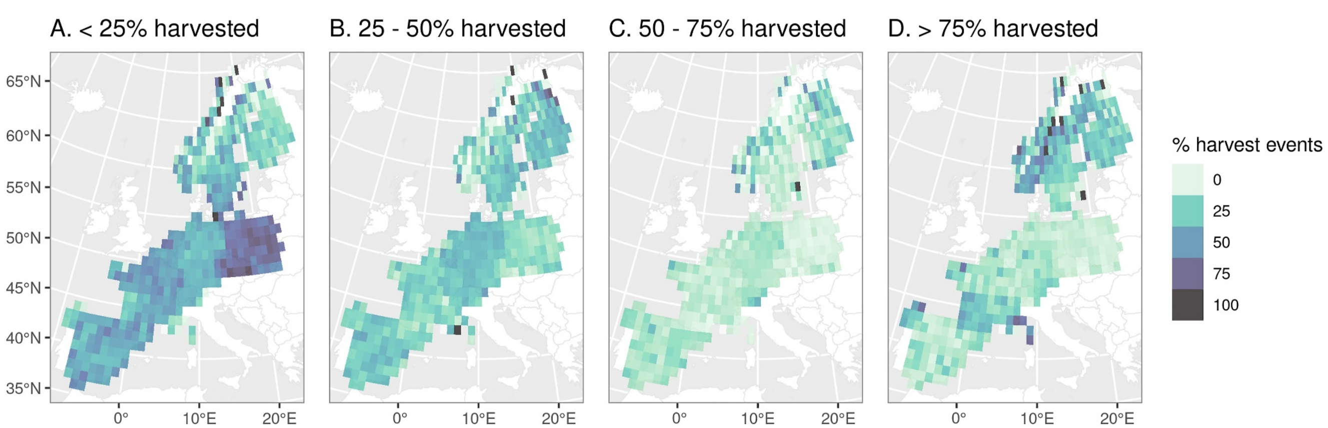

Figure 4. Percentage of harvest events within different intensity classes: harvest events removing 25% or less (a), 25%–50% (b), 50%–75% (c), and more than 75% (d) of the original basal area.

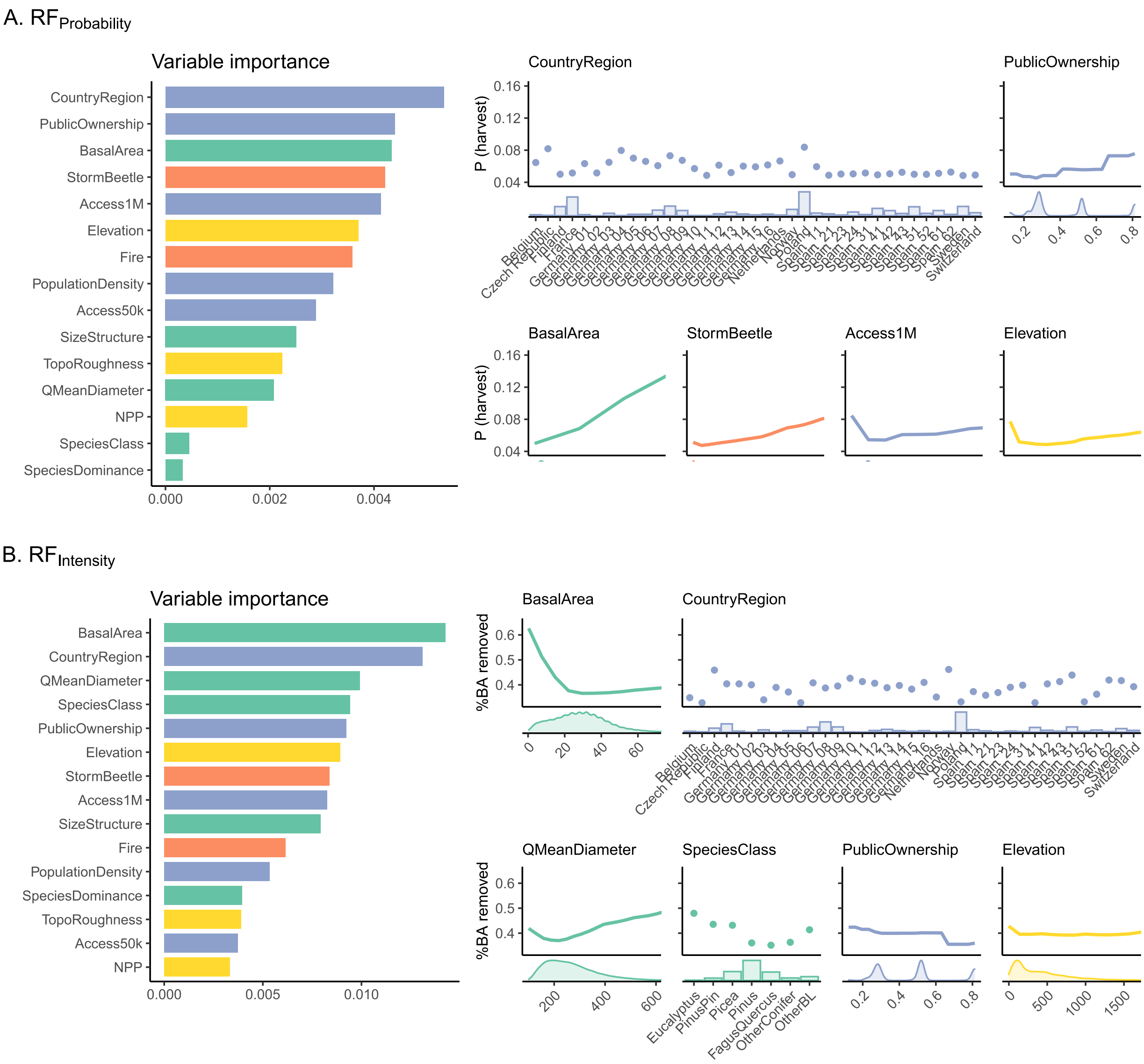

Figure 5. Variable importance plots for the probability (a, $RF_{Probability}$) and the intensity of harvest event (b, $RF_{Intensity}$), and partial dependence plots (PDP) for six variables with the highest importance scores for both models. Colors are based on the type of the variable. In PDP plots the *x*-axis is cut to the 99th percentile for the numeric predictors. The subplots beneath the PDP plots show the density distribution for the variable. Descriptions of all variables are in Table 2.

harvests (25%–50% and 50%–75%) the pattern is reversed. The share of high-intensity events from all harvests (>75% of BA harvested, Figure 4d) is the highest in northern Europe, southern France, and north-western Spain.

3.2. Random Forest 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 ($RF_{Probability}$, Figure 5a). 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 centers with more than a million people (Access1M). We observed an increasing probability of harvest ($RF_{Probability}$, Figure 5a, Figure S7 in Supporting Information S1) with the country-level share of public ownership of forests, disturbances and stand basal area. The accessibility to large population centers (Access1M) and elevation showed a similar pattern, with harvest probability first decreasing, followed by a gradual increase in harvest probability with higher values.

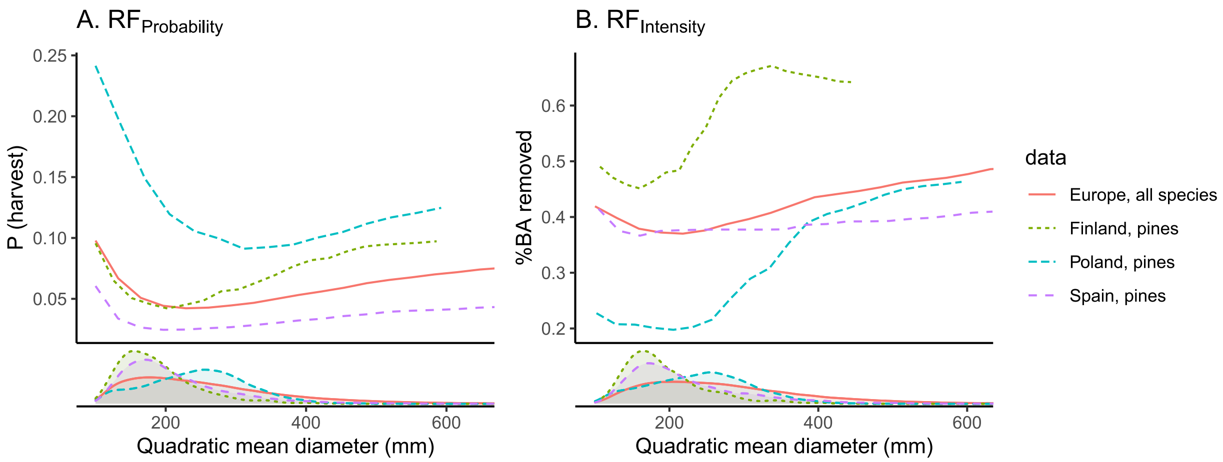

Figure 6. Partial dependence plots (PDP) showing the effects of pre-harvest QMeanDiameter on the annual probability of harvest ($RF_{Probability}$) and the intensity of harvest ($RF_{Intensity}$). Partial dependence curves are shown as calculated from the full data (solid line) and for subsets of the 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.

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 ($RF_{Intensity}$, Figure 5b). The administrative region was also important for harvest intensity, with country (or lower administrative region, where relevant) ranked second in variable importance. The intensity of harvest events decreased with increase in stand basal area (Figure 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. Results for all predictors are found in Figure S8 in Supporting Information S1.

The random forest results showed locally different responses of the harvest variables to tree size within the same species group (Figure 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 (Figure 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 0.69 (0.50 for the null model) and mean RMSE for $RF_{Intensity}$ of 0.27 (0.30 for the null model, Figure 7). In contrast, the country-wise cross-validation showed poorer performance and higher variance in the evaluation metrics, suggesting that the models did not perform well when predicting harvest in countries not included in the training data.

4. Discussion

4.1. Harvest Regimes and Drivers

Here we present the first consistent assessment of harvest regimes across 11 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 new 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; Schelhaas et al., 2018; Verkerk et al., 2015) or focused mainly on high-intensity harvests (Aszalós et al., 2022; Ceccherini et al., 2020; Senf & Seidl, 2021b).

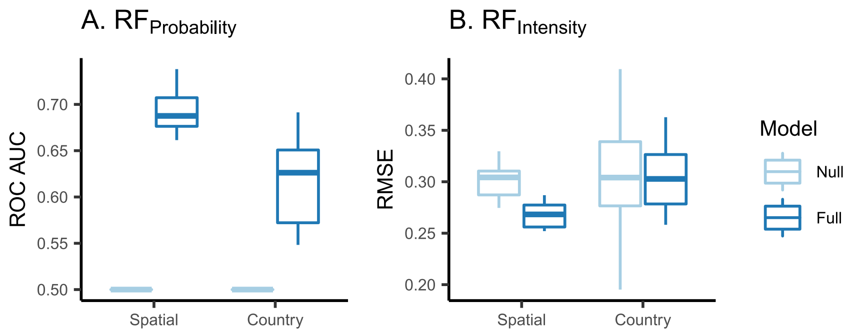

Figure 7. Cross-validation results for harvest probability (left) and the intensity of harvest (right) for the two different cross-validation set-ups: spatial blocks, and using countries as folds. Light blue boxplots show results for the null models and dark blue boxplots for the full random forest models. The upper and lower edges of the boxes correspond to the 25th and 75th percentiles and the horizontal line shows the median, while the whiskers extend to the largest value no further than 1.5 * the interquartile range.

Northern Europe was characterized by low-frequency but high-intensity harvest regimes, with decreasing harvest frequencies toward 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 & Bele, 2009; Helseth et al., 2022; 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 (Figure 4d). The lower harvest rates in Norway compared to Finland and Sweden are likely related to the highly variable topography (Figure S4 in Supporting Information S1), affecting both growing conditions and harvesting costs (Antón-Fernández & Astrup, 2012; Bergseng et al., 2013; Øyen & Nilsen, 2002), the high share of privately owned forests (Figure S4 in Supporting Information S1; FOREST EUROPE, 2020) and a smaller role of the pulp and paper industry (Järvinen et al., 2012; Moen, 1994).

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 (Figure 4a). One of the factors common for these countries is a high share of publicly owned forests (Figure S4 in Supporting Information S1, FOREST EUROPE, 2020; Pulla et al., 2013). In Poland 80% of forests are publicly owned and mostly managed by the State Forest Holdings, leading to a centralized coordination of forest management (Niedziałkowski & Chmielewski, 2023; Szramka & Adamowicz, 2020). This is in contrast to, for example, Bavaria, Germany, where the decision making of forest management is more scattered, with 54% of the forest area being owned by private owners (Statistisches Bundesamt, 2023), and where fragmentation of the forest ownership has been identified as a barrier for wood mobilization (Orazio et al., 2017). Thus, our results showing more active management (higher harvest frequency) in areas with more centralized forest management compared to areas with more fragmented ownership are in line with previous research that links ownership fragmentation to less active management (Orazio et al., 2017; Wiersum et al., 2005; Živojinović et al., 2015). Despite the similar patterns in Poland and Czechia there are also differences: for example, the management of publicly owned forests in Czechia is spread across a larger number of actors, as a considerable share of these forests are owned by the municipalities, whereas the area managed by the state forest organization is lower (44% of forest area, compared to 77% in Poland; Ministry of Agriculture of the Czech Republic, 2021; Szramka & Adamowicz, 2020). It is important to also note, that our analysis only looked at country-level public ownership, whereas ownership structure can vary substantially within countries (Pulla et al., 2013), and the implications of private versus public ownership on management are not constant (Schelhaas et al., 2018), making it challenging to cover the full complexity of the ownership-management relationship in our large-scale analysis. The observed connection between ownership structure and harvest regime may also be related to other factors, such as regulation of forest management, that can be correlated with the ownership structure (Nichiforel 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 (Figures 2 and 3). In the north, the low harvest rate was associated with low frequencies of harvest events, and it 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 (Figure 2). Similarly, south-western France stands out in the results with high frequencies and intensities of harvest. The forests in this region consist largely of maritime pine (*P. pinaster*) plantations that are actively managed in relatively short rotations (Schuck et al., 2020).

The importance of country-level drivers was emphasized 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 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 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 (Figure 5, Figures S7 and S8 in Supporting Information S1), 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 ha (Chmielewski et al., 2020), is also the most likely cause of outlier grid-cells in Poland with high harvest rates (Figure 3, see Figure S9 in Supporting Information S1 for analysis of storm year impact). 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 (Schuck et al., 2020) and storm Gudrun in southern Sweden in 2005 (Valinger et al., 2014), 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 (Figure S4 in Supporting Information S1). 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

(Figure S4 in Supporting Information S1) the harvest regimes are also characterized by lower harvest frequencies (Figure 2).

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 (Figure S10 in Supporting Information S1). In random forests, correlation between predictors can impact the variable importance scores, as the removal of a variable has a smaller impact on the prediction when another, correlated, variable is left in the model. This can have an impact in our results, even if the Pearson's correlation were in all cases below 0.7 (Figure S11 in Supporting Information S1). For NPP, the variable importance results are 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, Figure S11 in Supporting Information S1). Stand basal area also shows similar large-scale spatial patterns as NPP (Figure S4 in Supporting Information S1), potentially catching some of the variance that could otherwise be explained by NPP. Differences in the overall set-up between our work and Verkerk et al. (2015) may also contribute to explaining this difference, as the harvest variables as well as the forest productivity variables used were different.

The random forest models were able to reveal different local patterns of harvest in relation to tree size (Figure 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 (e.g., Äijälä et al., 2019). 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

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 characterizing the natural disturbance frequency during the study period). While most of the data in our study covers recent time periods, the changes in forest disturbance regimes in Europe since 2018 (Hlásny et al., 2021; Schuldt et al., 2020; Senf & 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, 2020, 2021), which have partially conflicting objectives (Lerink et al., 2023), and the need of forest management strategies 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 harmonized 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 harmonization 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 harmonization was not always feasible, for example, 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 (Table S1 in Supporting Information S1). This implies that the main results are unlikely to be affected by artifacts of sampling differences, but some effect from the sampling differences between the data sets could contribute to the observed differences between the countries.

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5. Conclusions

Our results, empirically quantifying forest harvesting regimes across Europe, revealed a range of different harvest regimes with different harvest frequencies and intensities. These results provide a fundamental basis for understanding the management of forests that shapes these ecosystems now and in the future; to understand how forest management practices should be changed in Europe under different climatic conditions, it is crucial first to have a thorough understanding of 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, emphasizing 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 also drive harvests, with both harvest probability and intensity increasing with increased storm and fire disturbances, reflecting the practice of salvage and sanitary logging that is widespread after these events. The mixture of cultural/political and biophysical drivers on the realized harvest regime reflects the complex interplay of environment, physiology, culture and policy on these socio-ecological systems.

The harvesting intensities and frequencies that we have quantified here, along with the random forest models for predicting harvest probability and intensity, provide a baseline for harvest behavior 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 (European Commission, 2020, 2021). 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.

Our analysis covered the 11 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 3, the results demonstrated the difficulties of predicting harvest in countries where no field data is available. This is a major limitation for understanding and modeling 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 11 countries studied here, and thus provide the information necessary to inform large-scale modeling 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.

Data Availability Statement

The forest inventory data supporting this research are available from the original data producers, following the individual access policies, restrictions and licensing of each data owner. Open access to data is available for France (IGN), Spain (Inventario Forestal Nacional, https://www.miteco.gob.es/es/biodiversidad/temas/inventarios-nacionales/inventario-forestal-nacional.html), Germany (Thünen-Institut, https://bwi.info) and the Netherlands (Wageningen University & Research, https://www.wur.nl/en/research-results/research-institutes/environmental-research/projects/dutch-forest-inventory.htm, Schelhaas et al., 2014). For other countries the data is not open access, but is only available with an agreement from the data owners: the National Forest Inventory of Wallonia (SPW ARNE), the Finnish National Forest Inventory (Natural Resources Institute Finland, Korhonen et al., 2021), CzechTerra (Cienciala et al., 2016), the Norwegian National Forest Inventory (Nibio, Breidenbach et al., 2020), the Polish National Forest Inventory (Talarczyk, 2014), the Swedish National Forest Inventory (Swedish University of Agricultural Sciences, Fridman et al., 2014), the Swiss National Forest Inventory (WSL, 2020). The other data sets used for predictors of the random forest models are openly accessible with access details provided in the original references of each data set: NPP (Neumann et al., 2016), topographical data (Amatulli et al., 2018), population density (Schiavina et al., 2022), accessibility to population centers (Nelson et al., 2019), public ownership of forests (FOREST EUROPE, 2020), and natural disturbances (Senf &

Seidl, 2021a). The data products generated during this work, namely the harvest grids behind Figures 2–4 and Figure S3 in Supporting Information S1, are made available with open access in Zenodo (Suvanto et al., 2025). The codes used for calculating the results in this paper are available and archived in Zenodo (Suvanto, 2025).

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