



Consistent and Harmonized Forest Statistics for Forest-use Intensity Analyses Across Europe (2000–2023)

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30 Abstract.

Forests play a crucial role in Europe as carbon sinks, biodiversity reservoirs, and sources of renewable raw materials. Reliable Europe-wide statistics on forest biomass stocks, forest area, and harvest at national and subnational scales are essential for monitoring biomass dynamics and supporting sustainable forest management. However, the availability of such data remains incomplete, and differences in definitions, methodologies, and reporting standards introduce substantial uncertainties that hinder robust interpretation. Here, we present EuFor, an open-access database of key forest indicators for 38 European countries, derived from National Forest Inventories (NFIs), census statistics, and datasets from international organizations. It is openly available at <https://doi.org/10.5281/zenodo.20815146>. EuFor consists of two subsets: (i) EuFor-reported, a compilation of primary statistical data for 1990–2023, and (ii) EuFor-harmonized, a stock-flow consistent annual time series of forest area, roundwood volumes of growing stock and harvest for 2000–2023 across 21 national and 193 subnational units. EuFor shows near-perfect agreement with an authoritative reference dataset at the European aggregate level. At the country level, however, discrepancies vary substantially. Agreement is highest for forest area (mean relative deviation: 3.2%; mean Pearson correlation: $r = 0.743$), followed by growing stock (7.4%; $r = 0.872$), and harvest (14.5%; $r = 0.654$). We further derived four indicators of forest-use intensity. Data uncertainties propagated into these estimates, leaving the direction of change ambiguous in 20% of assessments. Moreover, the indicators often revealed contrasting spatial patterns and trends, highlighting both substantial uncertainty in trend interpretation and the multidimensional nature of forest-use intensity. By providing open-access, harmonized forest statistics together with an explicit assessment of uncertainty, EuFor offers a valuable resource for future analyses of forest biomass dynamics, carbon balances, forest-use intensity, and sustainable forest management across Europe.

1 Introduction

Forests play a crucial role in global carbon cycles, acting either as carbon sinks or sources depending on management, disturbance regimes, and natural ecosystem dynamics (Pan et al., 2024). Europe’s forests store a substantial share of the continent’s biomass carbon, but they are increasingly exposed to anthropogenic and environmental pressures (Migliavacca et al., 2025). These pressures have contributed to a weakening of the European forest carbon sink in recent decades and, in some regions, to a temporary shift from sink to a source (Ritter et al., 2026). Understanding how societal use of forest resources interacts with forest ecosystem dynamics is therefore essential for the sustainable management of European forests (Erb et al., 2022; Migliavacca et al., 2025), particularly as natural disturbances intensify with climate change (Grünig et al., 2026; Seidl et al., 2017). This issue is becoming increasingly important as the EU transition towards a bio-based economy is expected to increase demand of biomass for materials and energy (Schipfer et al., 2017), despite evidence that current biomass extraction already exceeds planetary boundaries (Roux et al., 2025). At the same time, human appropriation of terrestrial ecosystems is already extensive, with most productive land globally under some form of management, leaving limited scope to expand biomass production without severe biodiversity and carbon trade-offs (Ellis et al., 2019; Erb et al., 2024; Meyfroidt et al.,



2022). As a result, additional biomass demand will largely need to be met through land use change or through intensive use of already managed ecosystems, including forests. This makes the analysis of forest-use intensity increasingly important.

65 Forest-use intensity can be measured using indicators that relate harvest to different ecological baselines, such as forest area, biomass stocks, or forest biomass growth, commonly expressed as increment. Because land-use intensity is a multidimensional concept, different indicators capture different dimensions of forest use and have different ecological implications (Erb et al., 2013). Area-based indicators describe production pressure per unit of land and provide a broad measure of raw material supply (e.g., Barredo et al., 2025). Increment-based indicators express harvest relative to annual forest growth and are widely used to
 70 assess sustainable harvest intensity and the balance between forest carbon gains and losses. This perspective is also reflected in the gain-loss method used in LULUCF (Land Use, Land-Use Change, and Forestry) accounting (e.g., Levers et al., 2014). Stock-based indicators relate harvest to standing biomass and provide insight into biomass turnover rates, indicating how rapidly carbon stored in forest biomass is cycled through harvest (e.g., Erb et al., 2016; Pugh et al., 2019). However, the baselines used in these three intensity indicators are themselves shaped by past and present forest management. A
 75 complementary perspective is provided by the Human Appropriation of Net Primary Production framework (Haberl et al., 2007, 2014), which relates harvest to potential net primary productivity (NPP_{pot}), the hypothetical biomass production of potential natural vegetation under current climatic conditions in the absence of direct human influence. Such approaches are used in assessments of planetary boundaries (Stenzel et al., 2025) or in analyses of the biophysical role of society in Earth system processes (Matej et al., 2025; Semenchuk et al., 2022).

80 Calculating and interpreting forest use indicators requires consistent data on forest area, harvest, growing stock, and increment. Ideally, these data should be available as temporally resolved, internally consistent time series with sufficient spatial resolution. At the European level, however, current analyses of forest use intensity and biomass stock dynamics typically face a trade-off between spatial and temporal resolution, providing either high spatial but low temporal resolution (e.g., Levers et al., 2014; Verkerk et al., 2019) or high temporal but low spatial resolution (e.g., Joint Research Centre, 2021; Korosuo et al., 2023).

While remote sensing has proven highly useful for monitoring forest disturbances with adequate spatial and temporal resolution (e.g., the European Forest Disturbance Atlas (EFDA); Viana-Soto and Senf, 2025) comparisons with national forest inventory
 90 data indicate that such products capture large-scale disturbance events well but are less sensitive to lower-intensity harvesting activities such as thinning (Runge et al., 2025b). Although a new generation of high-resolution remote sensing products is rapidly emerging (e.g., Welsink et al., 2025; van der Woude et al., 2026), these datasets currently cover only approximately the last decade, limiting their applicability for long-term assessments of forest-use dynamics. Furthermore, differences in the definitions of forest disturbances and harvesting complicate direct comparisons between remotely sensed products and ground-



95 based statistics. Consequently, ground-based data remain indispensable for quantifying harvest volumes and assessing forest-
 use intensity over long time periods (e.g., Erb et al., 2016; Winkler et al., 2023).

Ground-based forest data collection has a long tradition in Europe and has been institutionalized in many countries through
 National Forest Inventories (NFIs) (Gschwantner et al., 2022; Tomppo et al., 2010). NFIs are typically based on systematic
 100 grid sampling designs, but plot-level data are rarely fully publicly accessible and are usually released only in aggregated form
 at subnational or national scales. Despite their high value for national forestry and their central role in compiling forest-related
 greenhouse gas inventories reported under the United Nations Framework Convention on Climate Change (UNFCCC)
 (Eggleston et al., 2006), differences in national definitions and reporting practices have limited the use of NFIs for pan-
 European analyses (Gschwantner et al., 2019, 2022). Ongoing harmonization efforts (e.g., Gschwantner et al., 2019, 2022;
 105 Pilli et al., 2024) have already contributed to a recent dataset of harmonized forest statistics by the Joint Research Centre (JRC)
 presented by Avitabile et al. (2024), hereafter referred to as the “JRC” dataset. This dataset provides harmonized subnational
 statistics for European countries on forest area, biomass stock, and increment at various time points, reflecting differences in
 national NFI reporting periods, and includes modelled values for 2020.

110 Such harmonized subnational datasets, together with recent studies such as Gschwantner et al. (2024) and Pilli et al. (2024),
 represent an important step forward. However, they still lack an adequate (i.e. annual) temporal resolution and internally
 consistent harvest information needed to analyse forest use dynamics across Europe, particularly at the subnational level and
 from multiple perspectives using different forest-use intensity indicators. At the same time, NFIs often do not report harvest
 data, making economic and census statistics important complementary data sources. Not all European countries conduct NFIs,
 115 which further limits the scope of NFI-based assessments. At the national level, datasets such as the State of Europe’s Forests
 (SoEF) report (FOREST EUROPE, 2020), the Global Forest Resources Assessment report (FRA) (FAO, 2025), and the forest
 product tables from the FAOSTAT database (FAO, 2024), provide authoritative data and use relatively consistent definitions
 across countries. However, previous studies have shown substantial discrepancies between NFIs and international reporting
 systems, for example, in estimates of harvest levels in Italy (Pilli et al., 2025).

120 To address these challenges, we have developed the EuFor database, which compiles available subnational and national data
 from NFIs, national census statistics, and international datasets, including SoEF, FRA and FAOSTAT, for key forest indicators.
 The database consists of two subsets. The first subset (“EuFor-reported”) compiles primary statistical data from these sources
 for the period 1990–2023, including forest area, harvest, and growing stock, as well as increment and species-level information
 125 where available. These data, together with additional information from other datasets and the literature, were used to harmonize
 definitions and reconcile discrepancies across sources. The resulting harmonized subset (“EuFor-harmonized”) provides a
 stock–flow-consistent annual time series of forest biomass dynamics in Europe for 2000–2023, including forest area, growing
 stock, and harvest expressed as roundwood volumes. The database is openly available through a Zenodo repository



(<https://doi.org/10.5281/zenodo.20815146>) and includes both subsets as variable-specific CSV files together with a consolidated Excel workbook for convenient browsing. The repository further provides a vector dataset corresponding to the EuFor-harmonized regions and an overview table of all collected National Forest Inventories (NFIs). Detailed information on the database structure, file contents, attributes, and spatial and temporal coverage is provided in the Methods section. The database is intended to support analyses of forest biomass dynamics, carbon balances, forest-use intensity, and sustainable forest management across Europe. It also enables systematic assessments of data uncertainty by comparing estimates derived from different sources.

In this paper, we use EuFor to address two objectives. First, we evaluate the agreement between EuFor and SoEF, a widely used reference dataset, to identify data inconsistencies and quantify the uncertainty associated with using alternative data sources. Second, we assess spatial patterns and temporal trends in forest-use intensity across Europe using the four indicators introduced above, while examining how these data uncertainties influence the interpretation of observed patterns and trends.

2 Methods

We created the EuFor database following the workflow shown in Figure 1. The workflow consists of two components: the construction of EuFor-reported and the construction of EuFor-harmonized. EuFor-reported was developed through data collection and initial database construction. EuFor-harmonized was then produced through a series of harmonization steps and the creation of continuous, annual time-series for each indicator. In the final section of the Methods chapter, we describe the procedures used to evaluate agreement between data sources and to assess forest-use intensity.

All calculations and mapping were carried out in Python (Python Software Foundation, 2025), using pandas (McKinney, 2010), GeoPandas (Jordahl et al., 2020), NumPy (Harris et al., 2020), GDAL (Rouault et al., 2026), rasterstats (Perry, 2026), and Matplotlib (Hunter, 2007).

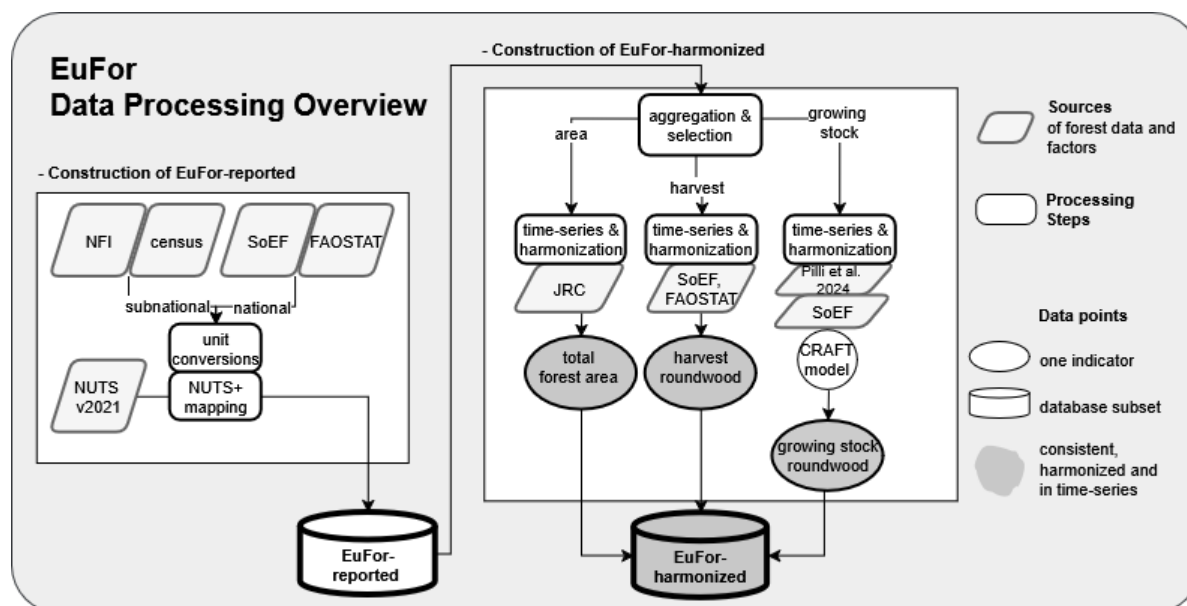


Figure 1: Overview of the processing steps used to construct EuFor-reported and EuFor-harmonized. Input sources are shown in light grey and include NFI and census data, NUTS region classifications (European Union, 2022), the JRC dataset (Avitabile et al., 2024), SoEF (FOREST EUROPE, 2020), FAOSTAT (FAO, 2024) and Pilli et al. (2024). Harmonized growing stock time series were constructed using the CRAFT model of Le Noë et al. (2020).

2.1 Creation of EuFor-reported

2.1.1 Data Collection

The primary aim of EuFor-reported was to compile a subnational dataset with European coverage for the period 1990–2023, integrating species-group-specific information on forest area, growing stock, increment, and harvest. The dataset compiles all available information as reported and therefore includes variables with both well-documented definitions and definitions that are only implicitly described or not fully specified by the data source. Data collection started from the Forest Information System for Europe data catalogue (FISE, 2023), which provides curated forest statistics and references to NFI and forest statistics portals. For some countries, we obtained data directly from FISE. For most countries, however, we collected NFI and census data directly from national web portals in order to obtain more complete information and close any data gaps.

We prioritised EU27 countries with large forest areas. For smaller countries, or countries with comparatively small forest areas such as the BENELUX countries, we did not collect subnational NFI data, even where such data were available. In these cases, national territories are comparable in size to subnational regions in larger countries, and the additional compilation effort was considered disproportionate to the expected analytical benefit. We also collected subnational data for the non-EU member countries United Kingdom and Norway.



Overall, EuFor-reported includes subnational data for 19 countries, representing 89% of the EU27 forest area. The dataset contains 355 subnational units for forest area, 254 for harvest, 285 for growing stock, and 213 for increment. For some countries, these data are available at two different administrative levels, for example, at both NUTS2 and NUTS3. In addition, one country (Bulgaria) was included only at the national level based on NFI and census data. National-level data for a further 18 countries were obtained from the SoEF report (FOREST EUROPE, 2020), resulting in coverage of 38 European countries in total. Small or data-limited regions were excluded because of insufficient data availability. These included microstates and territories such as Andorra, Liechtenstein, Malta, Monaco, San Marino, Vatican City, Kosovo, the Warsaw metropolitan area, and the Kaliningrad Oblast. A comprehensive overview of the collected data is provided in Figure 2. A detailed summary of the NFI and census data sources used is provided in the Supplementary Data (SD), which consists of a Microsoft Excel Table.

The accessibility and format of NFI data varied considerably across countries. Some NFI web portals provided user-friendly interfaces and machine-readable formats such as XLSX or CSV files. However, in many cases, NFI data were only available as tables in PDF documents in the respective national languages, which required translation and manual data entry. In contrast, census data were generally more accessible, both in terms of machine readability and language availability. Wherever possible, we collected information on forest area definitions, such as total forest area versus managed forests; harvest categories, including industrial roundwood, fellings, and fuelwood; and tree species information. In contrast, growing stock and increment data, which were obtained primarily from NFIs, were often not accompanied by explicitly documented or readily accessible variable definitions, such as tree compartment inclusion or whether net or gross increment was reported.

Data were first compiled in Excel spreadsheets (Microsoft Corporation, 2024) and then transferred to an SQLite database (Hipp, 2025) using a Python script (Python Software Foundation, 2025). During this process, we performed minor data cleaning steps, such as removing extra spaces and decimal points. The database was visually inspected using SQLiteStudio (SalSoft, 2025). We entered data for all years referenced by the respective NFI or census statistic, taking into account that harvest and increment values are often calculated from differences between two NFI inventory periods.

To ensure consistency across sources, we converted all indicators to common units: 1,000 ha for forest area, 1,000 m³ for growing stock, and 1,000 m³/yr for harvest and increment. For some countries, additional calculations were required. In Poland, harvest and increment were reported as intensity values, for example in m³/ha/yr, and were converted to absolute values by multiplying them by forest area. The same procedure was applied to increment data for Estonia. Wood fuel harvest data for Spain were converted from tonnes to m³ using wood density factors from IPCC (2003).

2.1.2 Consistent Regional Mapping

We matched each data entry to the 2021 NUTS regional classification (European Union, 2022) using the reported region names. This enabled spatial aggregation and mapping in subsequent processing steps. However, for some countries, the



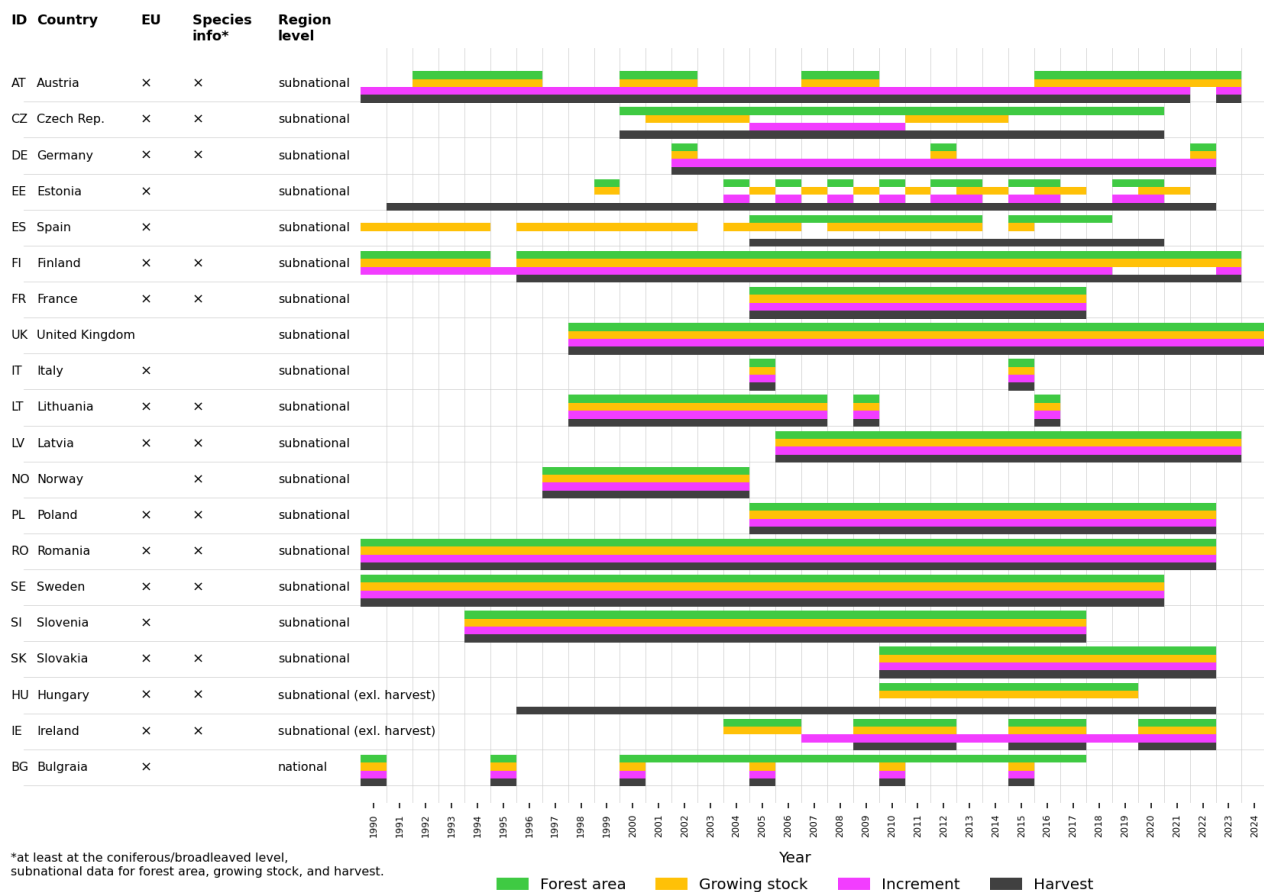
205 statistical regions used in the source data did not align directly with standard NUTS levels. To accommodate these cases, we
 expanded the NUTS classification by introducing intermediate regional levels. For example, Sweden's four harvest regions
 were assigned to level 1.5, between NUTS1, which contains three regions, and NUTS2, with eight regions. We refer to this
 expanded NUTS classification, which includes the intermediate levels of 0.5, 1.5, 2.5, and 3.5 as NUTS+. Further details,
 including an example for Sweden, are provided in the SI Section S1.1.

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Vector data for mapping EuFor in GIS applications were obtained from Eurostat for NUTS version 2021 in EPSG:3035
 (Eurostat, 2021). For Romania, Sweden, and the United Kingdom, vector layers at intermediate NUTS+ levels were derived
 by merging smaller NUTS regions to match the country-specific statistical regions used in the source data. Additional country-
 specific vector layers at intermediate NUTS+ levels were obtained from the Slovenian Forest Service (2023) for Slovenia and
 215 from Hijmans (2015) for Norway. The resulting Europe-wide vector dataset (“EuFor-regions”) is provided as part of the data
 records (see “Data Availability” section).

2.1.3 Overview of EuFor-reported

The EuFor-reported database subset contains the originally reported values, converted to common units but not harmonized
 across national definitions. It therefore reflects the official statistics provided by the respective countries. Figure 2 provides an
 220 overview of the spatial, temporal, and indicator coverage of the collected NFI and census data included in EuFor-reported. A
 complete overview, including additional SoEF data, is provided in Figure S2. Table S1 provides an overview of the variables,
 or data columns, contained in the EuFor-reported dataset. For the period 1990–2023, EuFor-reported contains 45,253 entries
 for forest area, 29,839 for growing stock, 30,382 for harvest, and 21,566 for increment. These entries correspond to 386 regions
 for forest area, 314 for growing stock, 288 for harvest, and 230 for increment, covering subnational regions from NUTS+ level
 225 3.5 to national-level regions across Europe. Entries may be available at multiple NUTS+ levels within the same country (e.g.,
 at both NUTS2 and NUTS3), and may also be reported for multiple categories, particularly for forest area and harvest. Where
 available, tree species information was collected and is provided as shown in Figure 2. A detailed overview of available species
 information for each country and variable is provided in Table S2.



230 **Figure 2: Overview of forest indicators (forest area, growing stock, increment, harvest) included in EuFor-reported by year for countries where NFI and census data were collected. For countries not listed, data were obtained from SoEF (FOREST EUROPE, 2020) at the national level. A complete overview including SoEF data is provided in the Figure S2. Detailed species information availability is provided in Table S2.**

2.2 Creation of EuFor-harmonized

235 The first step in creating EuFor-harmonized was to apply a consistent set of definitions for forest area, harvest and growing stock across all countries (see Table 1). The processing workflow included classifying forest area and harvest categories, aggregating and selecting data to derive consistent totals, applying correction and expansion factors for harmonization, and creating annual time series to close temporal data gaps. These steps are illustrated in Figure 1 and described in detail below.

240 To ensure transparency and traceability, we included processing flags in the database column “flag_calc”. These flags indicate whether values originate directly from EuFor-reported data or were generated through processing steps such as interpolation, aggregation or harmonization. Further details are provided in Tables S3-S6. The variables, columns and attributes in EuFor-harmonized are summarized in Table S7.



245 We excluded increment information from the harmonization process because its coverage in EuFor-reported was relatively
 low, accounting for only around 17% of all records and being available for only 21 of the 38 included countries. In addition,
 it was often unclear whether reported values referred to gross or net annual increment. However, an estimate of net annual
 increment (NAI) can be calculated from EuFor-harmonized as the change in growing stock plus harvest. A distinction between
 coniferous and non-coniferous species-group could also not be retained, because this information was not consistently available
 250 across countries and because the reference database used for area harmonization, i.e., the JRC dataset, did not provide this
 distinction.

Table 1 Overview of EuFor-harmonized forest indicators, including their definitions and the methods used for harmonization and gap filling.

Indicator	Unit	Definition	Harmonization	Time-series creation
Total forest area	1000 ha	“Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use.” (FAO, 2020a)	With JRC total forest area	linear interpolation & constant-value extrapolation
Harvest “EuFor-estimate”	1000 m3 /yr	Removed roundwood under bark volumes	Bark factors, residue factors	linear interpolation & extrapolation based on average of 3 nearest neighbors
Harvest “SoEF-normalized”	1000 m3 /yr	Removed roundwood under bark volumes	-	Use of FAOSTAT trends & extrapolation based on average of 3 nearest neighbors
Harvest “EuFor-harmonized”	1000 m3 /yr	Removed roundwood under bark volumes	Average of EuFor-estimate and SoEF_normalized	Already in time-series
Growing stock	1000 m3	Roundwood under bark volumes of standing living trees at total forest area	Use of correction factors from (Pilli et al., 2024)	CRAFT model (Le Noë et al., 2020)



and expansion to total
forest area with SoEF
and JRC.

255 **2.2.1 Classification of Forest Area and Harvest Categories**

Although NFIs generally report on similar forest indicators, their definitions can differ substantially across countries. To illustrate, we identified 40 different terms describing forest area (e.g., “high forest”, “forest stands”, “timberland”, “total forest”), as well as 34 terms or definitions for harvest categories (e.g., “roundwood removal”, “gross felled volume”, “actual harvest”, “final and intermediate felling”). To address this variation, we developed hierarchical classifications for forest area and harvest (Figure 3) and reclassified all relevant data entries accordingly.

The upper levels of the forest area classification (wooded land, total forest, other wooded land) follow the land-use categories defined by the FRA (FAO, 2025). The distinction between used and unused forest broadly corresponds to the categories forest available for wood supply (FAWS) and forest not available for wood supply (FNAWS), which are commonly used in forest sciences and international forest reporting (Alberdi et al., 2020). However, we avoided the FAWS and FNAWS terminology because it primarily refers to stem wood extraction and does not adequately capture other forms of forest use. Although this distinction may have limited practical implications in the European context, since our analysis does not quantify activities such as litter raking or livestock grazing, the terms used forest and unused forest are conceptually broader and more closely aligned with land-system science terminology. We also distinguished between stocked and unstocked used forest area, because some countries report temporarily unstocked areas separately, for example, recent clear-cuts or areas newly designated for afforestation.

For harvest categories, we adopted a hierarchy consistent with classifications commonly used in international forest statistics, including FAOSTAT or SOEF. Some classifications could not be derived directly from NFI or census information. In these cases, we assumed that the reported values referred to used forest and to roundwood over bark. Information on whether bark was included or excluded was more often missing from NFI data, whereas census statistics usually specified whether volumes were reported over or under bark.

(a) Hierarchical categories used for **forest area** classification

wooded land			
total forest			other wooded land
used forest		unused forest	
stocked forest	unstocked forest		

(b) Hierarchical categories used for **forest harvest** classification.

fellings			
roundwood removals over bark			residues
roundwood removals under bark		bark	
industrial roundwood	wood fuel		

280 **Figure 3** Nested, hierarchical categories for (a) forest area and (b) forest harvest used to classify NFI and census data. Forest-area categories follow the definitions used in the Food and Agriculture Organization Global Forest Resources Assessment (FAO, 2025),



while harvest categories follow classifications used in FAOSTAT (FAO, 2024) and SoEF (FOREST EUROPE, 2020) reporting. Target categories used in the harmonization process are highlighted in grey.

2.2.2 Data Aggregation and Selection for Consistency

285 To ensure consistency between the variables forest area, growing stock, and harvest, we performed a series of aggregation, data selection, and cleaning steps.

First, we calculated totals for coniferous and non-coniferous species groups from tree-species entries where such totals were not already available (flag_calc: “species”, Table S3). We then aggregated these species-group totals to obtain overall totals where these were missing (flag_calc: “tree_stock”, Table S3). For forest area, this aggregation also included entries classified as “other”, “unknown”, or “unstocked”. Aggregation across species groups was not directly possible for Spain because of temporal inconsistencies in subnational harvest reporting. For example, one region might report coniferous harvest data for 2000, while another reported non-coniferous harvest data for 2001. We therefore first interpolated harvest data in Spain to generate complete annual time series before calculating totals. For all other countries, interpolation was performed in a later step, as described in the section “Harmonization and Completion of Annual Time Series: Harvest”.

295 For forest area, we aimed to reproduce the “total forest” category as closely as possible (see Figure 3a), thereby minimizing discrepancies with the total forest values in the JRC dataset. However, further aggregation of forest-area categories was not required, because either “total forest” values were already available or only a single forest area category was reported. The final forest area categories used for subsequent harmonization are summarized in Table 2.

300 For harvest, the category “roundwood removals” served as the starting point for the subsequent harmonization steps. Where this category was not already present in EuFor-reported, we calculated roundwood removals by summing industrial roundwood and wood fuel entries, while distinguishing between under or over bark values (flag_calc: “Removals (industrial roundwood (under/over bark), wood fuel (under/over bark))”, Table S3). For Lithuania and Norway, only industrial roundwood harvest entries were available at the subnational level. We therefore added subnational wood fuel harvest estimates derived from national SoEF data by distributing national wood fuel volumes proportionally across subnational regions according to their shares of industrial roundwood removals (flag_calc: “wood_fuel_of_indr_rdwd”, Table S3).

310 For growing stock data, no aggregation was necessary because subcategories were not reported. Differences in national growing stock definitions (e.g., inclusion of bark, logs, or other wood compartments) were addressed during the harmonization process described below.



Finally, spatial aggregates were calculated using the consistent NUTS+ regions and added to the EuFor-reported database (flag_calc: “regions”, Table S3).

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These aggregation steps produced multiple alternative entries for several countries and indicators. To obtain consistent inputs for the harmonization process, we therefore selected one “data stream” per country and indicator. A data stream was defined as all available entries for a given combination of NUTS+ level, forest class, harvest class, and source at the overall species-group total. Data-stream selection was guided by two prioritized criteria: (i) selecting the subnational NUTS+ level data that are available for all three indicators, and (ii) where both census and NFI data were available, prioritizing the data stream with the more complete time series at the subnational level. This process resulted in 214 spatially consistent regions for all three indicators, of which 21 were national-level regions and 193 were subnational regions. A summary of the selected data streams is provided in Table 2.

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325 **Table 2 Overview of selected data streams from aggregated EuFor-reported entries used for the subsequent harmonization procedures.**

Country ID	ISO	NUTS+ level	forest area class	harvest class	area source	harvest source	stock source
AT		2.0	total forest	roundwood removals (over bark)	NFI	NFI	NFI
BG		0.0	stocked forest	roundwood removals (over bark)	census	census	census
CZ		3.0	stocked forest	roundwood removals (over bark)	census	census	NFI
DE		1.0	total forest	roundwood removals (under bark)	NFI	NFI	NFI
EE		3.0	total forest	fellings	NFI	census	NFI
ES		2.0	total forest	roundwood removals (over bark)	NFI	census	NFI
FI		3.0	used forest	roundwood removals (over bark)	NFI	census	NFI
FR		2.0	stocked forest	roundwood removals (over bark)	NFI	NFI	NFI
HU		0.0	wooded land	fellings	NFI	census	NFI
IE		0.0	stocked forest	roundwood removals (over bark)	NFI	NFI	NFI
IT		2.0	stocked forest	roundwood removals (over bark)	NFI	NFI	NFI
LT		3.0	stocked forest	roundwood removals (over bark)	NFI	NFI	NFI
LV		3.0	stocked forest	roundwood removals (over bark)	census	census	census
NO		0.5	stocked forest	roundwood removals (under bark)	NFI	census	NFI
PL		2.0	total forest	roundwood removals (over bark)	NFI	NFI	NFI
RO		1.5	stocked forest	roundwood removals (over bark)	census	census	NFI
SE		1.5	used forest	Fellings	NFI	census	NFI
SI		3.5	total forest	roundwood removals (over bark)	NFI	NFI	NFI
SK		3.0	stocked forest	roundwood removals (over bark)	census	census	census
UK		0.5	stocked forest	roundwood removals (over bark)	census	census	census



AL, BA, BE, BY, CH, CY, DK, GR, HR, LU, MD, ME, MK, NL, PT, RS, TR, UA	0.0	total forest	roundwood removals (under bark)	SoEF	SoEF	SoEF
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2.2.3 Harmonization and Completion of Annual Time Series: Forest area

To harmonize selected forest area data streams (see Table 2), we used forest area data from the JRC dataset and SoEF. Both sources apply the FAO definition of “total forest”, which we also adopted for EuFor-harmonized (see Table 1). The main advantage of the JRC dataset is that it provides harmonized subnational data reported directly by NFI institutions. However, it does not provide a continuous time series. Instead, it includes individual NFI data points for various years between 1997 and 2015, as well as modelled data for 2020. We used SoEF data where the JRC dataset did not provide country level information, which applied to all non-EU countries except Norway.

The harmonization process was based on calculating deviation factors between the selected EuFor-reported data streams and the corresponding JRC or SoEF values for matched regions and years. These factors account for differences between national NFI forest area classes, such as used forest area, and the target category of total forest area, as well as for remaining discrepancies between sources, which are likely attributable to definitional differences and reporting errors but cannot be further resolved here. However, the process required addressing both temporal mismatches, arising from different reporting years, and spatial mismatches, arising from differences in regional classifications and NUTS levels.

To address temporal mismatches, we first used linear interpolation and extrapolation (by keeping the last available value constant) to complete the time series (flag_calc = 'inter' or 'extra', Table S4) for the selected data streams from EuFor-reported. To establish a spatial match, we intersected EuFor NUTS+ and JRC NUTS regions and incorporated SoEF country-level data at NUTS0 for the residual countries (see Table S8). This resulted in 177 matched regions, corresponding to 83% of the 214 EuFor-harmonized regions, for which forest area deviation factors could be calculated for matched years. We then applied these deviation factors to the entire time series (flag_calc: “harm()”, Table S4). This assumes that deviations primarily reflect definitional differences that affect all regions and time points within a country consistently. The forest area harmonization factors are provided in Table S8 and mapped in Figure S3.

2.2.4 Harmonization and Completion of Annual Time Series: Harvest

The harmonization and construction of an annual time series for the selected harvest data streams from aggregated EuFor-reported entries (see Table 2) relied mainly on national-level SoEF harvest data, complemented with additional information



from FAOSTAT (data source overview shown in Table 3) where needed. SoEF data were integrated for two main reasons. First, they increased the temporal resolution of harvest estimates, since many NFI harvest values are reported as annual averages over or between inventory reporting periods. For example, a harvest level may remain constant from 2000 to 2004 if it represents the average between NFI1 and NFI2. Second, SoEF provided an empirical basis for completing the annual harvest time series.

Table 3 Description of data sources for forest harvest harmonization.

Source	Spatial unit	Temporal characteristics	Included biomass compartments
EuFor-reported	sub-/national	periodic	roundwood under bark up to fellings
SoEF (FOREST EUROPE, 2020)	national	annually 1988-2017	roundwood under bark
FAOSTAT (FAO, 2024)	national	annually 1961-2023	roundwood under bark

As a first step, we converted the selected harvest data streams to roundwood removals under bark to ensure categorical consistency with SoEF harvest data. Where data streams reported roundwood over bark, bark factors were applied to convert values to roundwood under bark. These bark factors were derived from Table 2.3.2 of the FAO (2020b) report “Forest product conversion factors” and are provided in Table S9. For countries not included in this table, we applied the median bark factor of 0.89. For data streams reported as felling volumes, residue factors were calculated using national data sources for Hungary and Sweden, and SoEF data for Estonia, where national data were not available. The factors and sources are provided in Table S10.

Applying these factors enabled the estimation of roundwood removals under bark for all countries. We then completed the roundwood under bark time series for each NUTS+ region using linear interpolation between available data points. Values before the first and after the last data point were extrapolated using the average of the three nearest years (flag_calc: “inter”, “extra”; Table S5). This produced an annual harvest time series derived primarily from EuFor-reported data, which we refer to as “EuFor-estimate” harvest.

To harmonize the EuFor-harvest-estimate with SoEF roundwood under bark harvest data, we first constructed a complete annual SoEF time series. Missing years, as well as the extension of the series from 2017 to 2023, were filled using relative trends from country-level harvest data reported in FAOSTAT. Where SoEF data started after 1990, the series was extended backwards to 1990 by assigning constant values equal to the average of the three years closest to the first available data point.

The resulting complete time series, including information on the origin of each data point is provided in Table S11.



To derive subnational harvest estimates consistent with national SoEF totals, we calculated each EuFor NUTS+ region's share of national harvest from the EuFor-estimate time series. These shares were then applied to the extended national SoEF harvest totals. We refer to this estimate as "SoEF-normalized" harvest.

385

In the final step, we calculated the annual average between the EuFor-estimate and the SoEF-normalized harvest for each NUTS+ region. This final estimate is referred to as "EuFor-harmonized" harvest (flag_calc: "harm(SoEF)", Table S5). All three estimates (EuFor-estimate, SoEF-normalized, and EuFor-harmonized harvest) are included in the final data records at the level of roundwood removals under bark.

390 2.2.5 Harmonization and Completion of Annual Time Series: Growing Stock

Developing a complete annual time series for the selected growing stock data streams (see Table 2) required three main steps: (1) converting growing stock volumes to roundwood under bark, (2) constructing a continuous annual time series, and (3) estimating growing stock for the total forest area in a consistent manner.

395 We first converted growing stock volumes from NFI and census data to roundwood under bark using the growing stock volume correction factors provided by Pilli et al. (2024) (flag_calc: "PilliCorr()", see Table S6). For non-EU countries included in EuFor but not covered by Pilli et al. (2024), we approximated correction factors using averages for European macro-regions (see Table S12). Since SoEF growing stock values are reported as roundwood over bark, we converted them to roundwood under bark using the same bark factors as those applied in the harvest harmonization (Table S9).

400

In the next step, we completed the growing stock time series using the CRAFT model of Le Noë et al. (2020); further details are provided in the SI Section S1.6.2. The CRAFT model was developed to reconcile forest area, harvest and biomass stock dynamics for larger spatial units, such as countries or regions. It is based on the empirically observed relationship between annual increment and biomass stock, requiring at least two data points over the modelling period, and accounts for changes in growth conditions over time.

405

As input to the CRAFT model, we calculated growing stock densities (m^3/ha) using the original forest area and growing stock values from EuFor-reported. This ensured that densities were derived directly from the original NFI, census, or SoEF data and were not affected by changes in forest area introduced during the area harmonization step. We also reduced periodic NFI values that had been entered in EuFor-reported for all years within a reporting period (i.e., the same value over e.g. 4 years) to a single data point representing the central year, or the central year plus one. This allowed natural annual growth to be modelled and avoided creating artificial steps in the time series (flag_calc: "CRAFT(sourceyear)", Table S6). Region-specific CRAFT model runs were initiated in the first year for which growing stock information was available, or no later than 2000 where no earlier data existed, as shown in Figure 2 (flag_calc: "CRAFT(modelled)", Table S6). Finally, we calculated absolute growing

410



415 stock totals by multiplying the modelled growing stock density values by the same forest area values used to derive stock densities in the previous step.

Many countries provided growing stock estimates for their entire forest area. However, some countries reported growing stock only for specific forest categories at the subnational level, resulting in incomplete coverage of the total forest area. Therefore, 420 for Austria, France, Germany, Italy, Latvia, Norway, Slovakia, Slovenia, Sweden, and the United Kingdom, we estimated growing stock volumes for the forest areas not covered by the reported data. These areas typically corresponded to unmanaged or unused forests.

To estimate growing stock in non-reported forest areas, we used the ratio between growing stock in FNAWS and FAWS 425 reported in the SoEF database. We used relative shares rather than absolute values to avoid propagating potential errors arising from definitional differences between datasets. Annual country-specific ratios were derived by interpolating between reporting years and extrapolating missing years by holding the closest available value constant. The resulting annual ratios (Table S13) were applied to growing stock entries from the selected EuFor-reported data streams to estimate national growing stock for non-reported areas.

430 We then allocated these national growing stock estimates for non-reported areas to subnational regions. For most countries, this allocation was based on the shares of subnational to national FNAWS areas derived from the JRC dataset. For Slovenia, we used a fuzzy match between the JRC and EuFor regions because the boundaries did not align exactly (see Figure S4). For Italy, Latvia and Sweden, we calculated shares of unused to used forest directly from the NFI data collected in EuFor-reported. 435 The resulting FNAWS shares for all relevant countries are provided in Table S14. These calculations are flagged with “GS_unused_subshare([allocation_source], [reference year])” (Table S6).

EuFor-harmonized therefore provides consistent annual estimates of growing stock expressed as roundwood under bark volumes for total forest area across 214 NUTS+ regions. Over bark volumes can be calculated using the bark factors provided 440 in Table S9.

2.3 Assessment of Forest Dynamics and Forest-Use Intensity

2.3.1 Calculation of Status, Change and Temporal Patterns of Forest Area, Growing Stock and Harvest

Forest area, growing stock and harvest from EuFor-harmonized were mapped by linking the data with the corresponding vector geometries from the compiled “EuFor-regions” dataset. Mapping was carried out in Python using Matplotlib (Hunter, 2007) 445 and GeoPandas (Jordahl et al., 2020). Forest area was expressed as a share of total regional area (%), with regional areas derived directly from the vector geometries using GeoPandas. Growing stock and harvest, both expressed as roundwood under



bark, were mapped as area-specific values (m^3/ha and $\text{m}^3/\text{ha yr}^{-1}$, respectively), using forest area from the EuFor-harmonized dataset.

450 Relative changes in forest area and growing stock were calculated between 2000 and 2023. For harvest, we compared period averages, using the mean for 2000–2005 and the mean for 2018–2023, to reduce the influence of extreme annual values.

Temporal patterns were derived from annual time series for 2000–2023 for each region and indicator. For each time series, we fitted a linear trend and expressed the slope relative to the mean value. Regions were classified as increasing or decreasing
 455 when the trend exceeded $\pm 0.2\%$ per year and showed a consistent direction, defined as $R^2 \geq 0.3$. Trends within $\pm 0.2\%$ per year were classified as stable, while stronger but inconsistent trends, defined as $R^2 < 0.3$, were classified as fluctuating.

2.3.2 Calculation of Status, Change and Temporal Patterns of Forest Use Intensities

We calculated forest-use intensity as the ratio of harvest to four different baselines: (i) forest area, (ii) growing stock, (iii) NAI, and (iv) NPPpot. Forest area, growing stock, NAI and harvest were derived directly from EuFor-harmonized while forest
 460 NPPpot per region had to be derived from external spatial data.

We used annually resolved gridded NPPpot for above- and below-ground biomass [gC/yr] from Roux et al. (2023) for the period up to 2018. These data were originally derived from the LPJmL dynamic global vegetation model (Schaphoff et al., 2018). For 2019 to 2020, NPPpot values were held constant at 2018 levels. We downscaled the data from 0.5° resolution to
 465 30 arcsec (approx. 1 km), following the approach of Weidinger et al. (2025). This enabled us to apply an annual forest mask based on the ESA CCI Land Cover (ESA and Defourny, 2019) for the years 2000–2020, which we aggregated from 300 m to 30 arcsec resolution to match the downscaled NPPpot grid. Annual forest cover fractions were derived by combining land-cover classes 50, 60, 70, 80, and 90. We then calculated annual regional NPPpot per area values from the masked NPPpot map within each EuFor region and applied these values to EuFor-harmonized forest areas to obtain total forest NPPpot per region.
 470 For 2021–2023, NPPpot values per region were held constant at 2020 levels. An overview of the variables and data sources used is provided in Table 4.

Forest-use intensities were calculated at the roundwood under bark level, except for harvest per NPPpot, where we did not convert or expand roundwood volumes to biomass. This avoided introducing additional uncertainties associated with biomass
 475 conversion factors while still allowing relative changes in use intensity to be interpreted consistently over time. We calculated and mapped the status, change, and temporal patterns of forest-use intensity using the same approach as for forest area, growing stock, and harvest. However, for forest-use intensity, we used five-year-averages for status and change calculations to reduce the influence of interannual variability in harvest data.



480 **Table 4 Variables used to calculate forest-use intensity and data source uncertainty envelopes**

Variable	Source 1	Source 2
harvest [roundwood under bark m ³ /yr]	EuFor-harmonized	SoEF
total forest area [m ²]	EuFor-harmonized	SoEF
growing stock [roundwood under bark m ³]	EuFor-harmonized	SoEF
net annual increment (NAI) [roundwood under bark m ³ /yr]	Calculated from EuFor-harmonized: annual stock difference + harvest	SoEF
Net Primary Productivity (NPP _{pot}) [gC/yr]	LPJmL (Schaphoff et al., 2018) run from Roux et al. (2023), downscaled with Weidinger et al. (2025), masked with ESA and Defourny (2019).	

2.3.3 Synthesis of Change Agreement between Forest-use Intensities

To assess agreement in temporal changes across the four forest-use intensity indicators derived from EuFor-harmonized, we applied a simplified version of the change classification used in the indicator-specific analyses. Instead of deriving change classes from linear trends over the full annual time series, we compared average indicator values between two periods: p0
 485 (2000–2005) and p1 (2018–2023). This reduced methodological complexity and facilitated the comparison of change directions across multiple indicators. For each indicator, forest-use intensity was classified as (i) increasing or (ii) decreasing if the relative change exceeded $\pm 10\%$, and as (iii) little to no change if changes remained within this threshold. Consequently, the fluctuating class used in the indicator-specific analyses was no longer applicable, while the stable class was replaced by a broader category of little-to-no-change.

490 To synthesize information across the four intensity indicators, we counted the number of indicators showing an increase, decrease, or little to no change in forest-use intensity. This produced combinations in the form of “increase count / decrease count / little-to-no-change count”. For example, a combination of 2/1/1 indicates that two indicators increased, one decreased, and one showed little to no change, whereas 0/0/4 indicates little to no change across all four indicators. In total, 15 such
 495 combinations are possible.

These combinations were then grouped into eight agreement classes (Figure S5) based on the consistency of directional signals across indicators. High agreement was assigned when three or four indicators showed the same direction of change (e.g. 3/0/1 or 4/0/0 for increases, and 0/3/1 or 0/4/0 for decreases). Low to medium agreement was assigned when one or two indicators
 500 showed the same directional change while the remaining indicators showed little to no change (e.g. 1/0/3, 2/0/2, 0/1/3, or 0/2/2). Disagreement classes captured combinations containing both increases and decreases. These were further distinguished



as increase-dominated (e.g. 2/1/1 or 3/1/0), decrease-dominated (e.g. 1/2/1 or 1/3/0), or balanced disagreement (2/2/0 or 1/1/2). Combinations of 0/0/4 were classified as little to no-change agreement.

505 To visualize potential scale effects, the agreement and disagreement classes were mapped at both the subnational (where available) and national scales.

2.4 Data Agreement and Robustness of Forest-Use Intensity Estimates

Data uncertainty and the robustness of forest-use intensity estimates derived were examined in two steps: First, we evaluated the level of agreement between EuFor-harmonized estimates and SoEF data. Second, we investigated how remaining
 510 differences between both datasets propagate into uncertainty in the four forest-use intensity indicators. As SoEF data are only available at the national level, these analyses were conducted at that scale. Those analyses were restricted to the 20 European countries for which NFI and/or census data were available (see Table 2).

2.4.1 Calculation of Data Source Agreements between EuFor and SoEF

We assessed agreement between EuFor-harmonized and SoEF by comparing forest area, growing stock, and harvest data. This
 515 comparison was used to identify remaining discrepancies after aligning EuFor entries with SoEF definitions. For forest area and growing stock, we used EuFor-harmonized estimates. For harvest, we used the “EuFor-estimate” values (see Table 1), because the EuFor-harmonized harvest is partly based on SoEF and would therefore reduce observable differences between the two datasets. To compare EuFor-harmonized growing stock volumes with SoEF estimates, we converted growing stock to roundwood over bark using the bark factors provided in Table S9.

520 For each country, annual EuFor time series for 2000–2023 were compared with available SoEF data. SoEF data are typically reported at five-year intervals for forest area and growing stock for 2000–2020, and as annual time series for harvest removals for 2000–2017. Directional agreement was quantified using the Pearson correlation coefficient, while level agreement was expressed as the mean relative differences between matched EuFor and SoEF values. These metrics describe agreement
 525 between the datasets, but they should not be interpreted as measures of statistical uncertainty.

Countries were classified into data agreement classes using a tercile-based approach based on the distribution of agreement metrics across all available countries. For each indicator, countries were ranked according to two metrics: (i) the deviation of the mean relative difference from unity, representing level agreement, and (ii) the Pearson correlation coefficient, representing
 530 temporal agreement. Countries were then divided into three equally sized groups: bottom, mid, and top terciles. These terciles therefore represent each country’s relative agreement performance compared with other countries, rather than absolute agreement thresholds. Missing correlation values for harvest in France, resulting from the lack of multi-year harvest data, were assigned to the bottom tercile. The two tercile rankings were then combined into five ordered agreement classes: High,



Medium-high, Medium, Medium-low, and Low. The highest agreement was assigned to countries in the top tercile for both
 level and temporal agreement, while the lowest agreement was assigned to countries in the bottom tercile for both metrics.
 Intermediate classes represent combinations of adjacent terciles.

To assess consistency in data agreement across variables and countries, the five agreement classes were aggregated into three
 broader categories: High, Medium, and Low. “High” and “Medium-high” were combined into “High”, while “Low” and
 “Medium-low” were combined into “Low”. Based on this simplified scheme, each country was assigned a three-part agreement
 pattern across forest area, growing stock, and harvest. These patterns were further summarised using a composite score ranging
 from 0 to 6, where High = 2, Medium = 1, and Low = 0. For example, a country with high agreement for all three variables
 would receive the maximum score of 6. This score provides a simple summary measure for comparing overall agreement
 across indicators and countries.

2.4.2 Calculation of Uncertainty Envelopes of Forest-Use Intensity

To assess how differences between datasets propagate into forest-use intensity estimates, we generated uncertainty envelopes
 using all possible combinations of harvest, forest area, growing stock, NAI, and NPPpot estimates from EuFor-harmonized,
 SoEF, and external NPPpot data (see Table 4). For area-, stock-, and NAI-based use intensities, four combinations were
 calculated: EuFor/EuFor, EuFor/SoEF, SoEF/EuFor, and SoEF/SoEF. For NPPpot-based use intensity, two combinations were
 calculated: EuFor/NPPpot and SoEF/NPPpot. For each country and year, we identified the minimum and maximum values
 across all combinations. These values define a cross-source uncertainty envelope that represents a plausible range of forest-
 use intensity estimates under data-source differences.

Because the used SoEF data did not consistently cover all required variables outside the period 2000–2015, the analysis was
 restricted to changes between $t_0 = 2000$ and $t_1 = 2015$. This enabled consistent comparisons across indicators and countries.
 Temporal dynamics under data-source uncertainty were assessed using a classification analogous to the one applied in the
 synthesis of forest-use intensity change agreement across indicators (Section 2.3.3 Synthesis of Change Agreement between
 Forest-use Intensities): Changes in the lower and upper envelope bounds between t_0 and t_1 were classified independently as
 increasing, decreasing, or little to no change using the same $\pm 10\%$ threshold. Contradictory envelope behaviour was assessed
 separately from this classification. A contradiction was identified when the lower and upper envelope bounds changed in
 opposite directions between t_0 and t_1 for a given country and indicator. For example, this occurred when the minimum estimate
 at t_1 indicated a decrease while the maximum estimate indicated an increase, or vice versa. Contradictions were also recorded
 when one or both bounds were classified as showing little to no change. Contradictory envelopes therefore indicate cases in
 which alternative data-source combinations show different directions of forest-use intensity change.



We also tested a stricter definition of contradiction. Under this definition, trends were classified as contradictory whenever the width of the uncertainty envelope at t_0 , defined as the difference between t_0 -min and t_0 -max, exceeded the change in forest-use intensity between t_0 and t_1 based on the envelope average. Under this criterion, opposite trends could be obtained from alternative envelope combinations (e.g. t_0 -min to t_1 -max versus t_0 -max to t_1 -min), even when both envelope bounds indicated the same directional change. However, we did not adopt this stricter definition as the main analytical perspective because the relatively short assessment period of 15 years limits the likelihood that changes exceed uncertainty bounds. In addition, this stricter approach overemphasizes level differences between data sources even when both envelope bounds indicate the same direction of change.

3. Results and Discussion

In this section, we present and discuss the main results of the EuFor database. We begin by using the harmonized database to describe recent changes in key European forest indicators and evaluate its agreement with SoEF, an independent international forest statistics dataset. We then demonstrate its application for analysing forest-use intensity across Europe, including how data uncertainties influence the resulting patterns and their interpretation. Finally, the section concludes with an overview of the EuFor database, followed by a discussion of uncertainties, best practices, priorities for future development, and potential applications in research and policy.

3.1 Spatial and Temporal Patterns of Forest Area, Growing Stock, and Harvest in Europe

Figure 4 presents the spatial distribution and temporal dynamics of forest area, growing stock, and harvest across European regions, based on EuFor-harmonized. The first row (a–c) shows the status in 2023 in relative terms. The second row (d–f) shows relative changes in absolute values over the study period 2000–2023. The third row (g–i) summarizes temporal dynamics based on a trend classification.

The highest shares of forest area are found in Northern Europe, while the lowest shares occur in north-western Atlantic coastal regions. Beyond these broad patterns, forest area shares are spatially heterogeneous across Europe. Forest area declines are rare and limited to a few regions, such as South Savo in Finland and the Islas Baleares in Spain. In contrast, increases are mainly observed in Western and Southern Europe, whereas forest area in central and northern Europe remained largely stable over the study period. Overall, total forest area across the 38 European countries increased from approximately 214 million hectares to 226 million hectares, corresponding to an increase of about 5.6%.

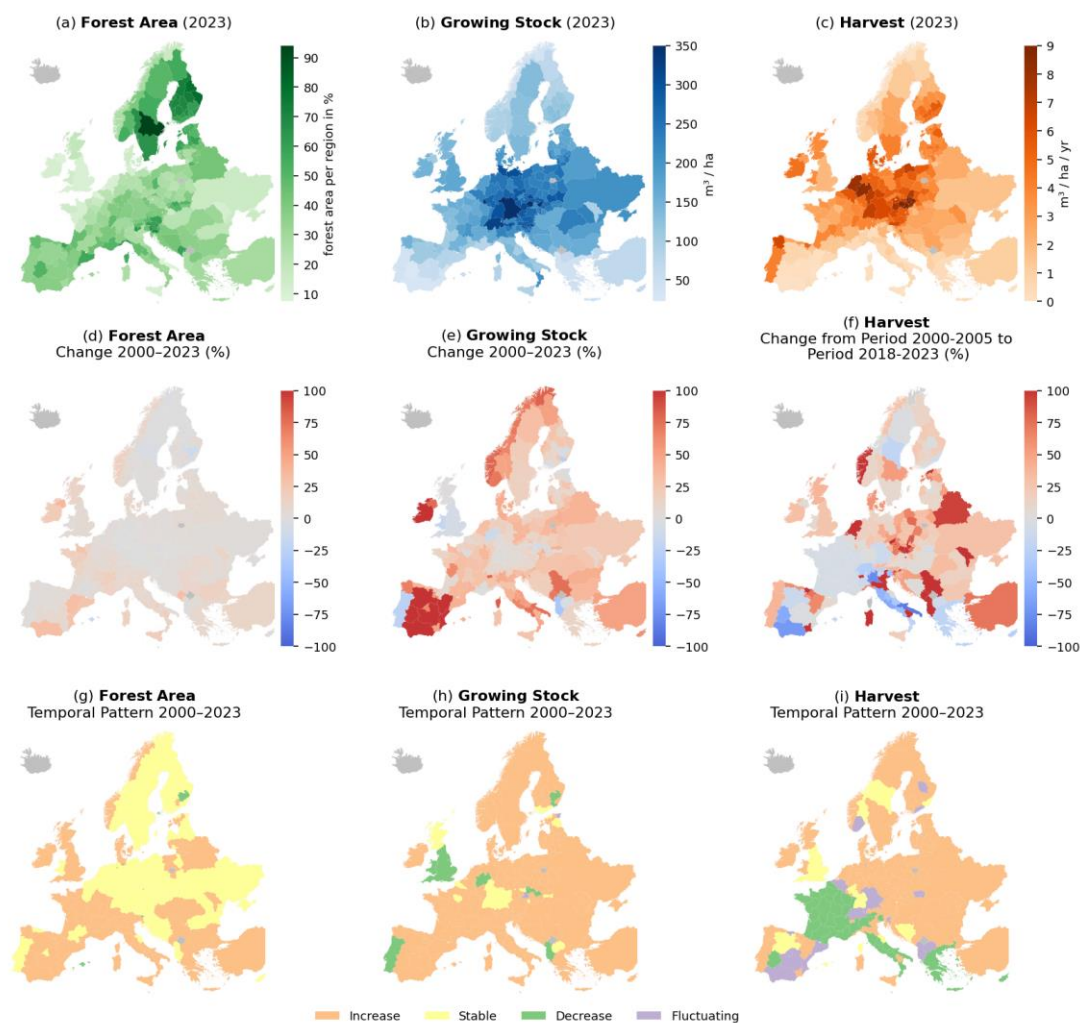


Figure 4 Spatial patterns of total forest area per regional area, growing stock (roundwood under bark) per total forest area, and harvest (roundwood under bark) per total forest area based on the EuFor-harmonized dataset of 214 regions across 38 European countries. The first row shows values for 2023; the second row shows relative changes between 2000 and 2023 (for harvest: mean 2000–2005 vs. 2018–2023); the third row shows overall temporal patterns (2000–2023). Regions were classified as increasing or decreasing when values showed a clear directional trend over time, stable when little overall change was observed, and fluctuating when interannual variability was present but no consistent direction was apparent. Missing data are shown in dark grey.

Growing stock density shows a different spatial pattern from that of forest area share. The highest densities occur in central Europe, while medium densities are found across other temperate regions. Lower densities are observed in the northern and southern parts of Europe. Growing stock density increased substantially over the study period, with much stronger relative growth than forest area. Increases were particularly pronounced in countries with initially low stock densities, such as Spain, Ireland, Norway, as well as Serbia and Montenegro. While most regions experienced increasing growing stock densities, some remained relatively stable (e.g., Scotland, southern Germany, and North Macedonia) and some decreased (e.g. England,



Portugal, South Savo in Finland, two regions in Czech Republic, and Albania). Only two regions exhibited fluctuating trends, namely the South Moravian Region in Czech Republic and northeastern Estonia. Overall, growing stock increased from approximately 25.9 billion m³ to 32.5 billion m³ (roundwood under bark), corresponding to an increase of about 26%. However, the annual increase of growing stock, which is the main factor for driving living biomass carbon sink in forests, declined markedly over the same period, decreasing from 311 million m³/yr in 2001 to 183 million m³/yr in 2023, representing a reduction of about 59%.

Harvest per forest area shows a spatial pattern broadly similar to that of growing stock density, with high values concentrated in central Europe. However, relatively high harvest intensities in 2023 are also observed in regions with low to medium stock densities, such as Portugal, Galicia in Spain, and parts of southern Scandinavia. Changes in harvest are more heterogeneous than changes in forest area or growing stock. In northern, central, and eastern Europe, harvest per area increased consistently across most regions. In contrast, western and southern Europe show a mosaic of trends, including increasing, stable, decreasing, and fluctuating harvest intensities. Declines are most prominent in regions of France, Spain, and Greece, while stable and fluctuating patterns are found in parts of Spain, Germany, and the Balkans. Overall, total harvest of roundwood under bark increased from approximately 2.3 million m³/yr in 2001 to 2.8 million m³/yr in 2023, corresponding to an increase of about 22% over the study period.

Figure 5 summarises the agreement between national-level EuFor-harmonized estimates and SoEF data for forest area, growing stock, and harvest removals. For harvest, the “EuFor-estimate” version was used rather than the harmonized estimate, as described in Table 1. At the aggregate level, agreement between the two datasets is very high for all indicators. For forest area, the EuFor total is about 1% larger than SoEF-derived forest area, with a Pearson correlation coefficient of $r = 0.985$. For growing stock and harvest, the EuFor totals are each about 4% higher than the corresponding SoEF totals, with correlations of $r = 0.940$ and $r = 0.949$, respectively.

However, the country-level analysis reveals substantial heterogeneity, as shown by the spread of countries across the agreement scatterplots in Figure 5a–c. Across all countries, mean relative deviations between EuFor and SoEF were lowest for forest area (3.2%), followed by growing stock (7.4%), and highest for harvest (14.5%). Similarly, mean temporal correlations across countries are highest for growing stock ($r = 0.872$), followed by forest area ($r = 0.743$), and lowest for harvest ($r = 0.654$). This indicates that agreement is substantially weaker at the country level than at the aggregate level for all indicators, suggesting that aggregation masks underlying discrepancies among countries.

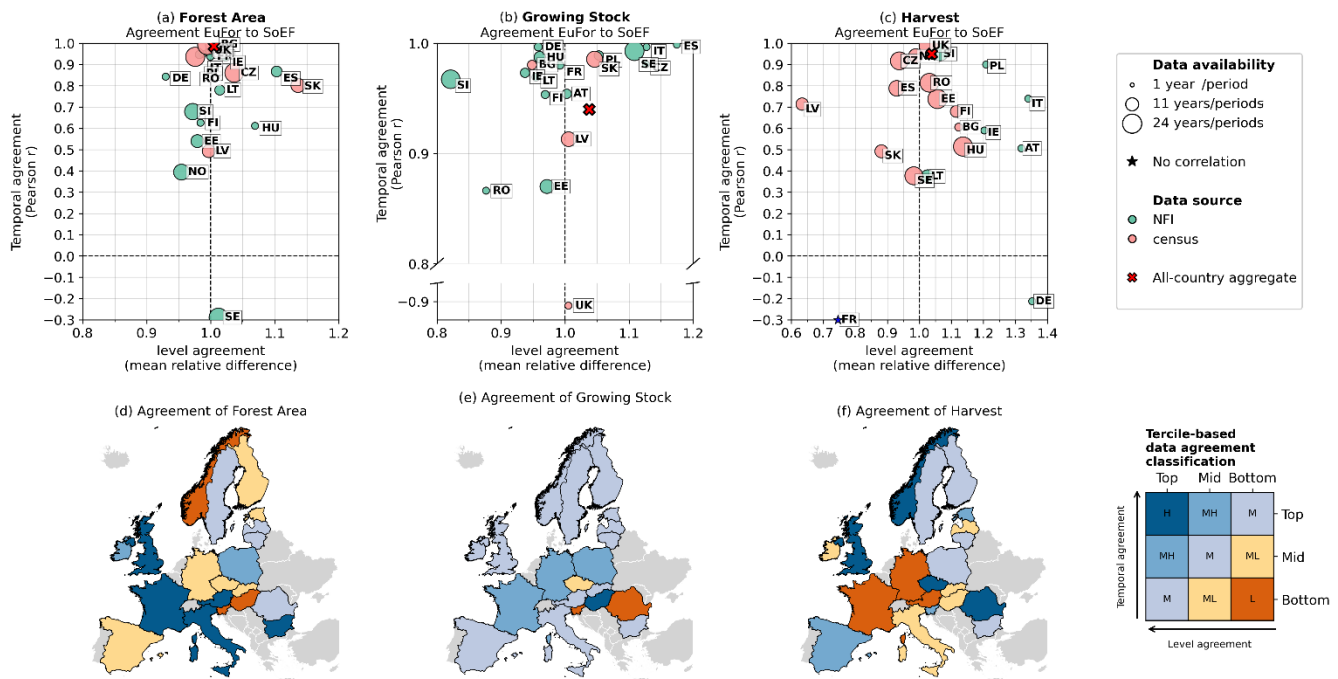


Figure 5 Data agreement of EuFor-harmonized relative to SoEF data. Scatterplots show national-level agreement between EuFor and SoEF estimates for (a) total forest area, (b) growing stock (roundwood over bark), and (c) harvest (roundwood under bark). Agreement is expressed as the mean ratio (level agreement) versus the Pearson correlation coefficient r (temporal agreement). Points represent countries and are coloured by data source, with point size indicating data availability. Countries were classified into five agreement classes (H: High, MH: Medium-high, M: Medium, ML: Medium-low, L: Low) based on terciles of both metrics across countries. These terciles reflect relative agreement and are visualized in the maps shown in panels (d), (e) and (f). Countries not included in the analysis are displayed in grey.

Countries were grouped into five relative agreement classes: High, Medium-high, Medium, Medium-low, Low, following the approach described in Methods Section 2.4.1 Calculation of Data Source Agreements between EuFor and SoEF. This classification enables comparison of data-source agreement between countries without relying on fixed thresholds (Figure 5d-f). The simplified agreement patterns (see Table S15) show that no country has uniformly high agreement, corresponding to a score of 6, or uniformly low agreement, corresponding to a score of 0, across the indicators. Instead, most countries show mixed agreement patterns. The highest overall agreement (score = 5) is observed for Poland and the United Kingdom. Both countries show high agreement for forest area and growing stock, and medium agreement for harvest. Intermediate scores (3-4) dominate and include countries such as Austria, Ireland, Italy, Estonia, Spain, and Norway, reflecting combinations of high, medium, and low agreement across indicators. Lower scores of 2 or below, indicating more pronounced inconsistencies, are found for Germany, Hungary, Czechia, Slovenia, and Slovakia. Overall, the results show that discrepancies between EuFor and SoEF vary within countries across indicators rather than forming uniform country-specific patterns.



3.2 Spatial and Temporal Patterns of Forest-use Intensity in Europe

Distinct subnational patterns and dynamics were observed across the four forest-use intensity indicators calculated from EuFor-harmonized (Figure 6): (i) harvest per area, (ii) harvest per NAI, (iii) harvest per growing stock, and (iv) harvest per NPPpot across 38 European countries.

Harvest per forest area (Figure 6a) follows a spatial pattern similar to growing stock densities (see Figure 4b). High values are concentrated in central Europe, moderate levels occur across other temperate regions, and lower intensities in northern and southern Europe. Increases above 150% occurred in 11 regions, including Región de Murcia, Sardinia, Albania, parts of Czech Republic and the Netherlands, southwestern Norway and northern Estonia. Strong decreases below -50% were limited to Italy and southern Spain (Figure 6e). Temporal patterns (Figure 6i) show predominantly increasing trends in central and eastern Europe, while other regions exhibit a mixture of increasing, decreasing, stable and fluctuating dynamics. Overall, annual roundwood under bark harvest per area rose from 2.3 to 2.7 m³/ha/yr, corresponding to an increase of 15%.

Harvest per growing stock (Figure 6b) displays a different spatial pattern than harvest per area. The central part of Europe still exhibits relatively high intensities, but this dominance is less pronounced. Additional high-intensity regions occur in Portugal, Aquitaine, Ireland, Scotland, and southern parts of Sweden and Finland. Low intensities remain concentrated in southern Europe and northern Norway. Regions with strong increases broadly overlap with those identified for harvest per forest area, but decreases are more widespread and extend beyond Spain and Italy (Figure 6f). This is also reflected in the temporal patterns (Figure 6j), which show mostly decreasing trends in northern, western, and southern Europe, mixed trends in central Europe, and increasing trends in eastern Europe. Overall, annual harvest per growing stock remained almost unchanged, increasing only marginally from 18.8% to 18.9%, corresponding to an increase of less than <1%.

Harvest per NAI (Figure 6c) shows a pattern broadly similar to harvest per growing stock (Figure 6b), but with important regional differences. For example, Pays de la Loire and Rhône-Alpes show higher intensities, while Aquitaine shows moderate values. Southern Sweden and Finland display lower intensities, whereas northern German regions show comparatively higher values. Spatial patterns of strong increases and decreases (Figure 6g) are more differentiated than for the other intensity indicators, with more regions showing substantial changes in both directions. The temporal patterns (Figure 6k) show predominantly increasing trends in central and eastern Europe, alongside a substantial number of regions with fluctuating levels of harvest per NAI dynamics. Overall, annual harvest per NAI increased from 61% to 73%, corresponding to an increase of around 21%.

Harvest per NPPpot (Figure 6d) shows a spatial pattern broadly consistent with harvest per area (Figure 6a), although with some regional deviations. In particular, the United Kingdom, Ireland, and Portugal show comparatively higher harvest



intensities relative to NPPpot than relative to forest area. Regions with the strongest increases and decreases (Figure 6h) largely coincide with those identified for harvest per forest area. However, temporal patterns are more heterogeneous, with central Europe no longer showing uniformly increasing trends (Figure 6i). Overall, annual harvest per NPPpot increased by 22%. Absolute values are not reported because the unit (m^3/tC) has limited interpretability.

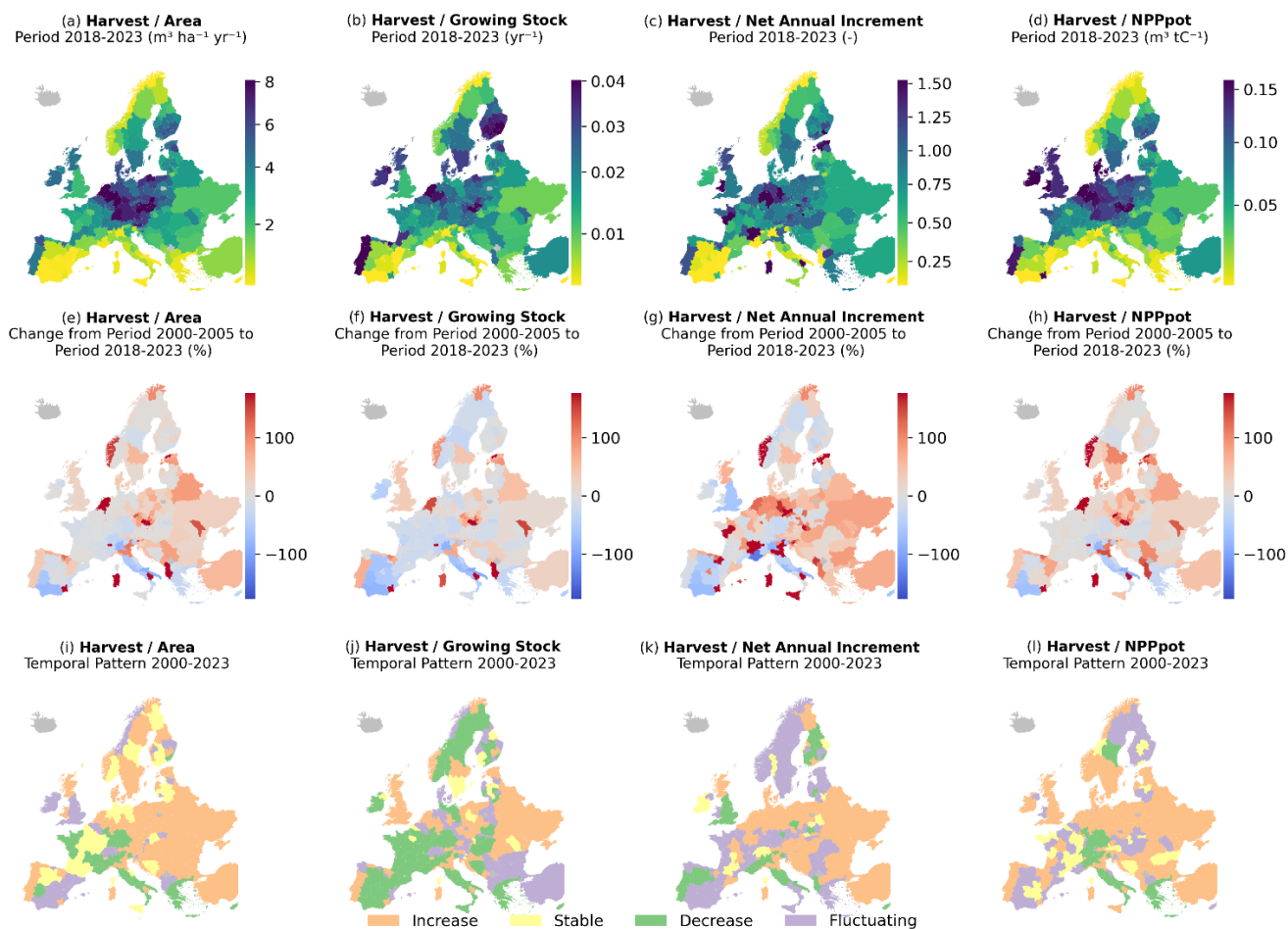


Figure 6 Spatial patterns of forest-use intensity across 38 European countries, based on the EuFor-harmonized database subset. The four indicators are harvest per forest area, harvest per growing stock, harvest per net annual increment (NAI), and harvest per NPPpot. Status maps (a–d) show mean values for 2018–2023, using indicator-specific colour scales normalized to the 5th–95th percentile range and centred on the median, allowing European-wide comparison across the four indicators. Relative change maps (e–h) show changes between the periods 2000–2005 and 2018–2023. Temporal trend maps (i–l) classify regions into increasing, decreasing, stable, or fluctuating dynamics over 2000–2023. Regions with no data are shown in dark grey.

Taken together, these results show that forest-use intensity patterns depend strongly on the baseline used to contextualise harvest. Area-based indicators emphasise production pressure relative to land area, whereas stock- and NAI-based indicators capture harvest relative to existing biomass stocks and annual forest growth. In contrast, the NPPpot-based indicator relates



harvest to potential ecosystem productivity, providing a measure of human pressure on the biophysical productive capacity of forest ecosystems. As a result, the four indicators reveal complementary, but not always concordant, spatial and temporal patterns of forest-use across Europe.

We further investigated those different patterns in Figure 7, which shows spatial patterns of agreement in forest-use intensity changes across the four indicators between the periods 2000–2005 and 2018–2023. The classification approach is described in Methods Section 2.3.3 Synthesis of Change Agreement between Forest-use Intensities. The underlying country- and indicator-specific intensity changes are presented in Figure S6, while the region-level agreement classifications are provided in Tables S16 and S17.

Agreement of forest use intensity change across indicators (2000–2023)

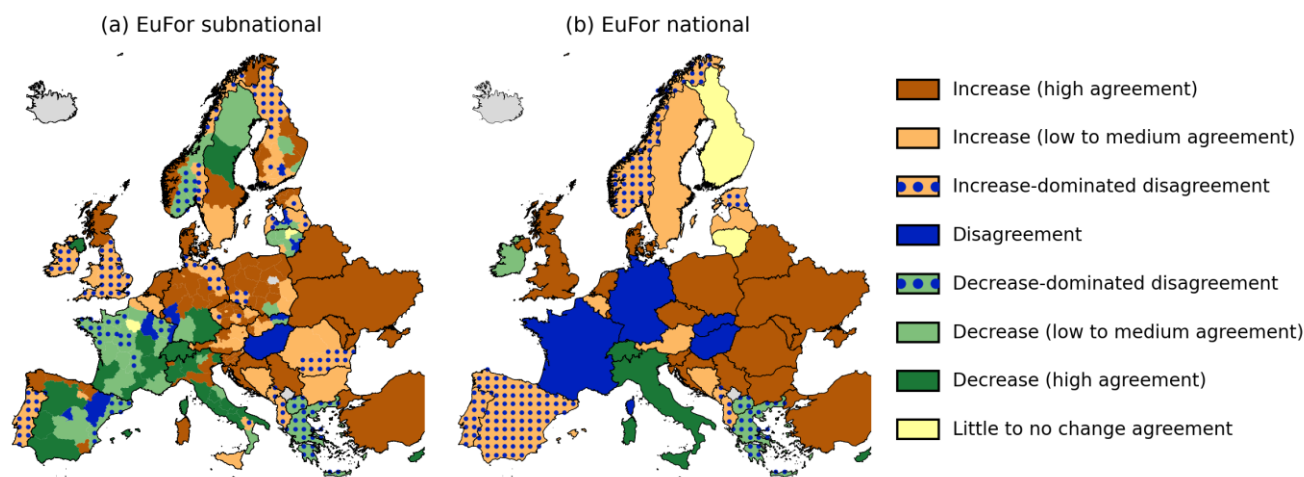


Figure 7 Agreement in forest-use intensity change across indicators in Europe, based on EuFor-harmonized. Indicators include harvest per forest area, harvest per growing stock, harvest per net annual increment (NAI), and harvest per NPPpot. Changes are calculated between the average values for 2000–2005 to 2018–2023. Panel (a) shows subnational agreement in forest-use intensity change across 214 regions, while panel (b) shows national-level aggregates for 38 countries. Regions with no data are shown in grey.

Strong agreement among indicators on increasing forest-use intensity is observed across large parts of eastern Europe, both at the national and subnational levels. In other parts of Europe, no clear macro-regional pattern of cross-indicator agreement emerges. However, the apparent consistency in eastern Europe may partly reflect a scale effect, because several countries in this region are represented by relatively few subnational units in EuFor (see Figure 2) and are therefore characterized mainly by national-level data.

Across a substantial share of Europe’s forest area, the forest-use intensity indicators disagree on the direction of change. This means that at least one indicator shows an opposite direction of change to the others, as shown by the blue areas and dots in



Figure 7. Such disagreements occur on 24% of forest area at the subnational level and 33% at the national level. This highlights that spatial aggregation can mask contrasting regional trajectories and alter observed patterns of agreement and disagreement.

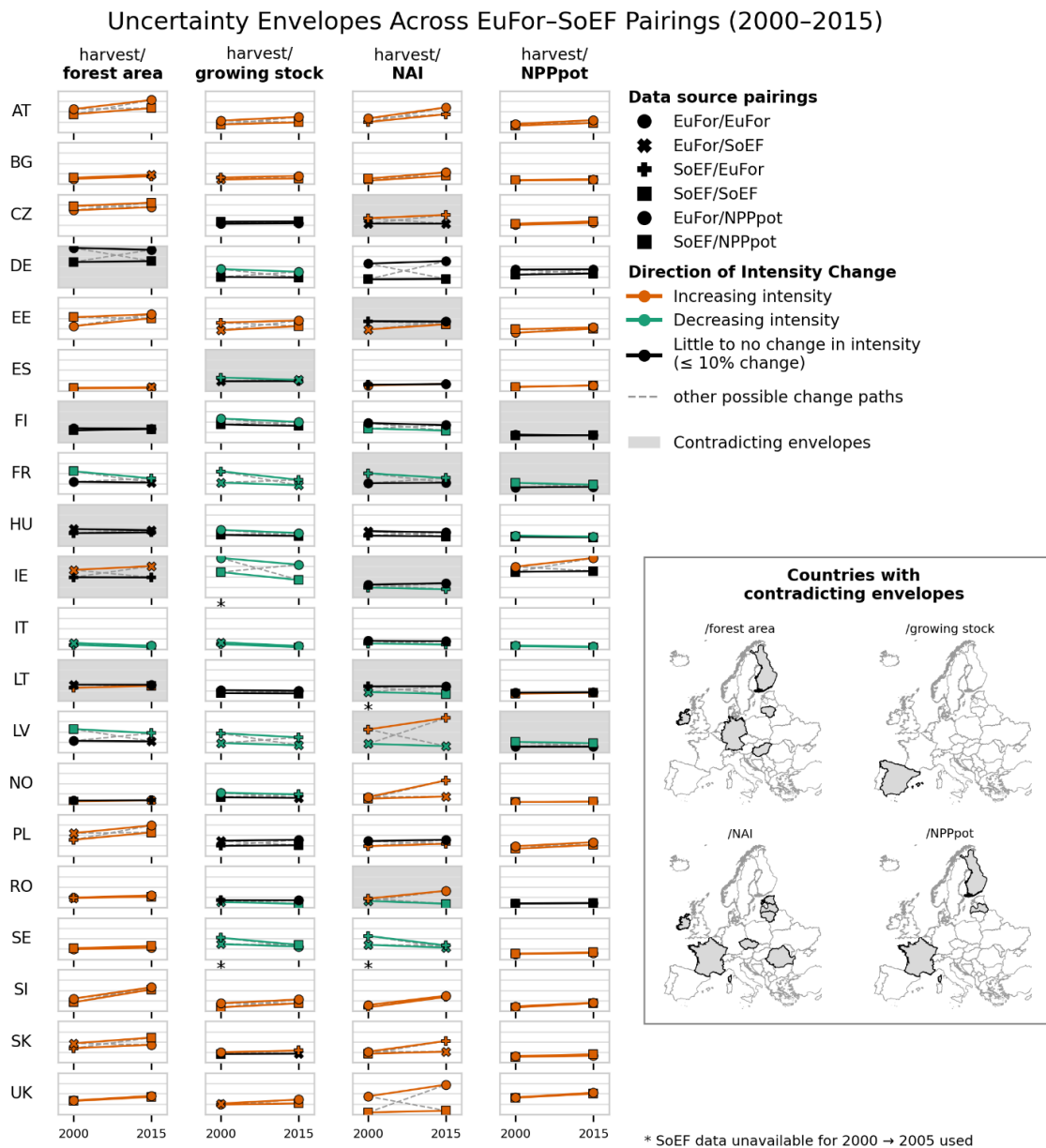
More broadly, the limited agreement among indicators across Europe suggests that forest-use intensity is best understood as a multidimensional phenomenon rather than as a single underlying process. Because the indicators capture different aspects of forest use, they may respond differently to changes in management, ecosystem dynamics, disturbances, and data uncertainties. Consequently, uncertainty in forest-use intensity assessments arises not only from differences among data sources, but also from the choice of indicator itself. Alternative indicators can imply different trajectories of forest-use change even when derived from the same harmonized database.

To assess the role of data-source uncertainty on forest-use intensity change, we constructed uncertainty envelopes from all possible combinations of EuFor and SoEF estimates for harvest and for the denominator variables: forest area, growing stock, NAI, and NPPpot. This analysis was conducted for the 20 countries for which NFI or census data were collected (Figure 8).

Contradictory uncertainty envelopes, where the lower and upper bounds indicated opposite directions of change, occurred in 16 of the 80 cases, corresponding to 20% of all country-indicator combinations. These 80 cases represented 20 countries and four forest-use intensity indicators. Contradictory envelopes affected 11 of the 20 countries analyzed. Such cases indicate particularly high uncertainty, because the direction of change cannot be determined robustly. No country showed contradictions for more than two indicators.

Contradictions were most common for harvest intensity relative to NAI, occurring in seven countries. This was followed by harvest per forest area, with contradictions in five countries; harvest per NPPpot, with contradictions in three countries; and harvest per growing stock, with contradictions in one country. The high frequency of contradictions for harvest per NAI likely reflects the combined propagation of uncertainties in both harvest and NAI estimates. In addition, NAI data reported to SoEF by countries are known to differ in underlying definitions and reporting practices, and these differences are not always fully harmonized within international reporting frameworks (Gschwantner et al., 2024), introducing further inconsistencies between datasets.

Most contradictory envelopes occurred where changes in forest-use intensity were small. Among the 16 contradictory cases, four had envelope bounds that fell within the little-to-no-change category, despite indicating opposite directions of change. In 10 cases, one bound indicated little-to-no-change, while the other indicated either an increase or a decrease. Only two cases showed substantial contradictions, where both bounds changed by more than 10% but in opposite directions.



765 **Figure 8** Changes in harvest-intensity uncertainty envelopes across EuFor–SoEF dataset pairings for 2000–2015 in countries where
 NFI or census data were collected. Analyses were conducted at the national level to match the spatial resolution of SoEF data. Panels
 show changes in the lower and upper bounds of uncertainty envelopes derived from all combinations of EuFor and SoEF estimates
 for harvest and denominator variables, including forest area, growing stock, NAI, and NPPpot. Where SoEF data for 2000 were
 770 unavailable, 2005 values were used instead, marked by an asterisk. Panels with a white background indicate envelopes whose lower
 and upper bounds move in the same direction. Grey-shaded panels denote contradictory envelopes, where the lower and upper
 bounds move in opposite directions. Inset maps identify countries with contradictory envelopes for each forest-use intensity
 indicator.



Applying a stricter contradiction criterion increased the number of contradictory cases to 51 of 80 (Figure S7). This included cases where the envelope prevented a clear classification of forest-use intensity change, even when both bounds shifted in the same direction. Under this criterion, every country exhibited at least one contradiction across the four indicators, highlighting the uncertainties in forest-use assessments arising from differences among forest data sources.

3.3 The EuFor Database: Compilation, Uncertainties, Best Practices, and Applications

The EuFor database consists of two subsets: EuFor-reported and EuFor-harmonized. EuFor-reported contains the compiled source data, including variables that could not be retained in the harmonized dataset, such as species-specific information, forest area classes, and harvest categories. EuFor-harmonized provides consistent, annual time series of forest area, harvest, and growing stock for 214 regions across 38 European countries for 2000–2023. Further details on the compilation, harmonization, and database structure are provided in the Methods section. Both database subsets are openly available; data access is described in the Data Availability section.

The creation of EuFor-harmonized required the integration of highly heterogeneous data sources and reporting systems. Although initiatives such as the Forest Information System for Europe (FISE) have improved access to national forest information, identifying and obtaining relevant datasets remains challenging. Data are distributed across numerous national portals, often with limited documentation, in different languages, and frequently embedded in PDF reports rather than provided in machine-readable formats. As a result, data extraction, quality control, and harmonization require considerable effort, hampering straightforward analyses. Our assessment reveals that improving the accessibility of forest statistics through English-language documentation, providing machine-readable data formats and comprehensive metadata, for example by following the FAIR data principles (Wilkinson et al., 2016), is an urgent prerequisite to establish transparency, interoperability, and reproducibility of forest information in Europe.

Forest area and harvest categories reported in NFIs and census showed substantial variation in definitions and terminology across countries, while growing stock and increment appeared more consistent. However, this apparent consistency partly masks differences in NFI definitions and methodologies, as highlighted by previous harmonization efforts (e.g., Gschwantner et al., 2019, 2022). A further source of uncertainty was that growing stock was not always reported for total forest area, but sometimes only for used forests. This was particularly relevant in northern countries with large shares of unused forests. Additional uncertainty arises from the expansion and correction factors used to harmonize reported volumes. While some factors could be derived directly from NFIs, most data-harmonization steps had to rely on values reported in the literature only. In some cases country-specific estimates were unavailable, thus regional or European averages had to be used, introducing further uncertainties. Although recent studies have improved the availability of such factors (e.g., Avitabile et al., 2024; Pilli et al., 2024), incomplete coverage remains a key limitation for pan-European assessments. Consistent reporting of expansion and conversion factors would help reduce the substantial uncertainties documented here.



The reconstruction of growing stock using the CRAFT model (Le Noë et al., 2020) generally produced plausible results and enabled the creation of complete annual time series. Nevertheless, the model occasionally generated strong increases in growing stock where recent observations were unavailable, particularly when initial stock levels were low. This behaviour was most apparent in Spain, where stock data were missing for the later years of the study period. The results demonstrate that timely growing stock assessments are essential for deriving reliable near-real-time estimates and supporting up-to-date forest monitoring.

In general, users of the EuFor database should explicitly consider the uncertainty assessments presented in this study when working with the EuFor database. The observed differences between data sources and indicators demonstrate that uncertainty can affect both estimated values and the interpretation of changes in forest-use intensity across Europe. We therefore recommend that users take these uncertainties into account when selecting variables, designing analyses, and interpreting results.

Users should also exercise caution when using the annual time series provided by EuFor-harmonized. Many NFIs report observations for inventory periods rather than individual years, which required interpolation and extrapolation during time-series construction. Depending on the application, multi-year averages or moving averages may therefore be more appropriate than analyses focused on single-year fluctuations, particularly for harvest data. Users should also consider the calculation flags included in the database. These flags indicate whether values were directly reported, interpolated, extrapolated, or derived from other variables, and can therefore help assess the reliability of individual observations.

The EuFor database enables analyses that go beyond the forest-use intensity assessment presented here. In particular, it provides opportunities for investigating data uncertainties across forest reporting systems. Similar to the harvest uncertainty assessments conducted for Italy by Pilli et al. (2025), EuFor can support analyses of discrepancies between international datasets (e.g., SoEF, FRA, and FAOSTAT) and national forest statistics such as NFIs and census data. An annual country-level comparison between data sources has already been carried out within the ForestNavigator project and is presented in the annex of Work Package Deliverable 2.3 by Runge et al. (2025a). Such analyses can contribute to improving the consistency and transparency of forest reporting in Europe.

EuFor can also serve as a basis for deriving biomass carbon indicators, including forest biomass carbon stocks. These can be estimated using biomass expansion and conversion factors, for example from Pilli et al. (2024) or derived from international datasets. However, preliminary analyses within the ForestNavigator project revealed substantial discrepancies among resulting estimates, as well as differences relative to estimates from authoritative datasets such as the JRC dataset (Avitabile et al., 2024)



840 and FRA (FAO, 2025). These comparisons are also documented in ForestNavigator Deliverable 2.3 (Runge et al., 2025a). Further research is therefore needed before robust biomass and carbon assessments can be derived from EuFor.

Beyond forest statistics, EuFor is well suited for integration with remote sensing products. In ForestNavigator Deliverable 2.4 (Runge et al., 2025b), EuFor was combined with the European Forest Disturbance Atlas (EFDA) (Viana-Soto and Senf, 2025).
845 In addition, a project within the Young Scientists Summer Program (YSSP) at IIASA linked EuFor with the forest management maps from Scherpenhuijzen et al. (2025) (Weidinger, 2025). Although these applications were exploratory, they demonstrate the potential of EuFor to support integrated assessments of forest change, management, and resource use across Europe.

4. Data Availability

The EuFor database is publicly available at <https://doi.org/10.5281/zenodo.20815146> (Weidinger et al., 2026). The
850 Supplementary Information (SI) and Supplementary Dataset (SD) are available through the publication page accompanying this paper.

5. Conclusions

Understanding forest biomass dynamics is increasingly important as Europe faces rising biomass demand and growing ecological pressures. Robust, comparable, and detailed estimates of forest-use intensity are therefore essential for evidence-
855 based decision-making. EuFor addresses this need by compiling and harmonizing subnational and national forest statistics into an annually resolved, stock-flow consistent time series covering 2000–2023. The open-access database contains annual data on forest area, growing stock, and harvest, providing a ready-to-use resource for Europe-wide assessments of forest-use intensity and related applications.

860 At the same time, inconsistencies among existing forest statistics remain substantial and require careful interpretation. The comparison with SoEF confirms that EuFor successfully reproduces major European forest statistics at the aggregate level while revealing important country-level discrepancies, particularly for harvest estimates. Beyond providing harmonized data, EuFor therefore offers a framework for identifying, quantifying, and investigating inconsistencies among European forest statistics and their implications for forest-use assessments.

865 The analyses further highlight several priorities for improving forest monitoring and reporting to enable consistent assessments of forest resources and forest-use intensity across Europe. Substantial reductions in uncertainty will require harmonized key forest statistics to be produced and reported directly by the responsible national institutions at the national and subnational levels, as they are best placed to apply country-specific expertise. To ensure pan-European comparability and reduce



870 uncertainty, harmonization procedures, conversion factors, and the underlying methods should be systematically and
 comprehensively documented, thereby enabling the use of country-specific information instead of generalized assumptions,
 as in our case.

Beyond data availability and uncertainty, further work is needed to strengthen the conceptual understanding of forest-use
 875 intensity. Rather than representing a single metric, forest-use intensity is a multidimensional concept, with individual indicators
 capturing different aspects of human influence on forests and often showing contrasting spatial and temporal patterns.
 Evaluating the suitability of individual indicators, or their combinations, for informing biodiversity conservation, climate
 change mitigation, and sustainable forest management, provides a tangible frontier for future research. EuFor provides a
 foundation for such analyses across Europe.

880 **Author Contribution**

F.W.: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization,
 Writing (original draft)

S.M.: Conceptualization, Data curation, Methodology, Writing (reviewing & editing)

C.W.: Conceptualization, Data curation, Writing (reviewing & editing)

885 S.G.: Conceptualization, Writing (reviewing & editing)

L.R.: Data curation

E.L.: Data curation

M.H.: Conceptualization, Writing (reviewing & editing)

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890 F.F.: Conceptualization, Supervision, Funding acquisition, Writing (reviewing & editing)

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895 E.V.: Data curation, Validation, Writing (reviewing & editing)

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Competing Interests

900 The corresponding author declares that none of the authors has any competing interests.

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 905 Austrian Academy of Sciences (ÖAW), the Austrian National Member Organization of IIASA. ChatGPT (OpenAI) was used to assist with text revision and the development of Python scripts. All outputs were reviewed and verified by the authors.

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