ForestNavigator

D2.4 Demonstration of yearly updates in EU-wide and country GHG inventories

Report accompanying the demonstration

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Deliverable lead	Martin Herold (GFZ)
Authors	Alexandra Runge, Martin Herold (GFZ), Claudine Egger, Karl-Heinz Erb, Sarah Matej, Florian Weidinger (BOKU), Fulvio Di Fulvio, Andrey Lessa-Derci-Augustynczik (IIASA), Kevin Black (FER), Emil Cienciala (IFER), Roberto Pilli (RP)

Abstract

This report describes deliverable D2.4, which is a demonstration of yearly updates of EU-wide and country-level greenhouse gas emission inventories. The regional focus is on Ireland, Italy and the Czech Republic. A webinar was held on 23 February 2026 to present the results of this task. This report provides a brief summary of the datasets and methods presented in the webinar.

Keywords

Data integration, GHG reporting, Italy, Ireland, Czech Republic

Internal Technical Auditor	Name (Beneficiary short name)	Date of approval
Task leader	Alexandra Runge (GFZ)	04/03/2026
WP leader	Martin Herold (GFZ)	04/03/2026
Coordinator	Fulvio Di Fulvio (IIASA)	04/03/2026
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Abbreviations

ALS	Airborne laser scanning
CBM-CFS	Carbon Budget Model of the Canadian Forest Sector
CSO	Central Statistics Office
EO	Earth Observation
EFDA	European Forest Disturbance Atlas
EFFIS	European Forest Fire Information System
ESA	European Space Agency
EU	European Union
EUFo	Database of European forests
FAO	Food and Agriculture Organization of the United Nations
FI	Forest Inventory
FRA	Global Forest Resource Assessments
GEDI	Global Ecosystem Dynamics Investigation
GHG	Greenhouse gas
IPCC	Intergovernmental Panel on Climate Change
LiDAR	Light Detection And Ranging
LULUCF	Land Use, Land Use-Change and Forestry
NFI	National Forest Inventory
RADD	RAdar for Detecting Deforestation
SoEF	State of Europe’s Forests
WP	Work Package

1. Introduction

WP2, as part of the ForestNavigator project, is focusing on providing quality data and data-driven assessments towards the project objectives. The aim is to ensure that state-of-the-art and up-to-date, consistently integrated data streams are provided and used in data-driven analysis, greenhouse gas (GHG) inventory estimation, and in forward-looking models to enable transparent monitoring of progress towards the national and EU climate change mitigation targets.

The development of the Forest Navigator forest geodatabases has been performed and presented in deliverables D2.1, D2.2, and D2.3. The databases include an updated “picture” of the current and recent past on forest status and use. Generating the databases combined different data streams from remote sensing, statistics, and inventories for a consistent and comprehensive dynamic representation of forests for a spatially explicit assessment of forest changes, aboveground biomass/carbon stocks, forest age, and structural diversity.

D2.4 focuses on integrating different data sources for improving GHG inventories and supporting national estimation and reporting processes. Several key datasets coming from National Forest Inventories (NFIs), Earth Observation (EO) and statistics have been considered and are presented for country case studies in Ireland, the Czech Republic, and Italy. The D2.4 deliverable is a "demonstration” and includes two components:

1. A Forest Talks webinar ‘Integrating EO data in national forest monitoring and assessment’ demonstrating the country-specific analyses and assessments (organized on 23 February, 2026).
2. This short report providing the summary of the main demonstrations for the different country cases.

The presentation of the results is structured around the three partner countries Ireland, the Czech Republic, and Italy and across the integration of different datasets and objectives, such as NFI, EO, LiDAR, disturbances and biomass estimation. Additionally, a brief pan-European analysis of harvest levels and disturbances is included, placing the three case studies within their broader European context. For this purpose, the EUFo (Database of European forests), as reported in deliverables D2.2 and D2.3, provides data for comparison with Earth Observation-based disturbance data across 220 regions in Europe.

1.1. Relevant policies

The key EU policy underpinning these considerations is the Land Use, Land Use-Change and Forestry (LULUCF) regulation, which supports the EU's climate-neutrality goal. It was adopted under EU law in 2021 (Regulation EU 2021/1119) and commits the EU to achieving at least a 55% net reduction in greenhouse gas emissions by 2030 compared to 1990 levels.

More recently, the Council of the European Union and the European Parliament adopted a revised LULUCF regulation text, published as Regulation EU 2023/839 (19 April 2023, in force since 11 May 2023). This revision sets out the pathway for meeting the EU’s increased net-emission-reduction targets in the LULUCF sector. In particular, it establishes the Union's commitment to achieve net carbon removals of at least -310 Mt CO_2-eq. by 2030 and introduces binding national targets for Member States, which together represent a significant contribution to the climate-neutrality aim.

An important amendment supporting the development of adequately robust LULUCF inventories is the newly introduced text in Annex V, Part 3, of Regulation 2018/1999 on Methodologies for monitoring and reporting in the LULUCF sector (included as Annex V to EU 2023/839). This text provides key principles for monitoring systems underpinning GHG inventory reporting, including expanded use of Earth Observation datasets in several areas:

1. **Geographically explicit land-use conversion data**, enabling higher-tier Intergovernmental Panel on Climate Change (IPCC) approaches and improving transparency in tracking land-use change and area estimates.
2. **Spatial information to identify priority areas** with strong potential to support climate action, thereby strengthening the geographic evidence base for climate policy development.
3. **Improved monitoring of natural disturbances and impacts**, assessed in the context of managed lands, requiring identification of the location, type, and timing of disturbances, as well as evaluation of compensation potential for associated losses.
4. **Progress towards higher-quality carbon-stock estimates**, with IPCC Tier 2 as a minimum requirement from 2028 onwards and Tier 3 in specific areas (e.g. high carbon stocks, high climate risk).
5. **Increasing timeliness in data and estimates provision**, moving toward annual and more timely inventories, compliance checks, and closer alignment with policy implementation.

With these requirements in mind, the present work addressed several of the points listed above, considering country-specific settings and priorities.

1.2. Data

We used three distinct types of data in this assessment: (National) Forest Inventory (NFI), Earth Observation (EO) data, and the database of European forests (EUFo).

As part of ForestNavigator, and within this work package, Ireland, Italy, and the Czech Republic provided forest inventory (FI) data. Forest inventories systematically collect information on the location, composition, and distribution of forests and sometimes trees outside forested areas. They can combine multiple data sources, including field measurements and remote sensing, to estimate key forest characteristics at the national scale for specific points in time. NFIs enable the comprehensive assessment of forest resources and are widely used to evaluate biodiversity, soil conditions, socio-economic aspects of forest use, and carbon storage. The data is essential for evidence-based forest management, shaping national policies, and supporting international reporting (FAO, 2025).

We included a range of Earth Observation datasets in the analyses, most notably the European Forest Disturbance Atlas (EFDA). The EFDA is a Landsat-based (30 m spatial resolution) annual disturbance dataset that identifies forest disturbances at pixel level by disturbance year and disturbance agent, such as fires, windstorms and bark beetle infestation, harvest activities, and areas affected by multiple disturbance agents between 1985 and 2023. A forest land use mask, following the FAO definition as close as possible for EO and using a minimum mapping unit (MMU) consisting of 6 Landsat pixels (0.54 ha), was applied (Viana-Soto and Senf, 2025). The EFDA represents the most recent and comprehensive Europe-wide dataset, covering the longest continuous period of mapped forest disturbances. Since its first publication, this dataset has been updated temporally and methodologically to improve mapping accuracy and is expected to be updated annually, ensuring continued data availability. While national disturbance maps often offer higher accuracies, they typically vary in reference years and lack consistent time series. Therefore, EFDA provides the only consistent and uniform database suitable for comparable country assessments.

While EFDA relies on optical multispectral data, RADD-EU alert (RAdar for Detecting Deforestation) is a forest disturbance detection approach using Sentinel-1 radar data. Since radar satellite signals can penetrate clouds, Sentinel-1 provides consistent, gap-free observations every few days at 10 m spatial resolution, enabling near-real-time monitoring across Europe. The RADD alert forest disturbance detection algorithm was initially developed for tropical regions (Reich et al., 2021) but was recently adapted for temperate forests (van der Woude et al., 2026), providing a near-real-time disturbance time series for Europe between 2020 and 2023. RADD-EU's main advantages are its timeliness, independence from weather conditions, and high spatial resolution, which enable the identification of small-scale disturbances. However, its main disadvantage is the shorter temporal coverage compared to EFDA.

In addition to pixel-based image products, we also used Light Detection and Ranging (LiDAR) data. Airborne laser scanning (ALS) data were available for Ireland, Italy and the Czech Republic, while satellite-based LiDAR data were available for Czechia and Italy only. ALS data results from individual flight campaigns and therefore the acquisition time and specifications differ between the countries and sometimes even between ALS flight campaigns within one country. Here, we conducted a comparison of ALS-derived biomass data and NFI-based biomass data for Ireland, the Czech Republic, and Trento in Italy, following data availability. The Global Ecosystem Dynamics Investigation (GEDI) instrument is a full-waveform LiDAR installed on the International Space Station. It provides detailed observations of Earth's 3D structure, including forest canopy height, canopy vertical structure, and surface elevation. During its first acquisition period (December 2018-March 2023), GEDI acquired millions of individual 25 m footprint shots that enable the estimation and monitoring of forest biomass and carbon stock changes. GEDI's spatial coverage extends between ~ 52° N/S latitude; therefore, Ireland is not covered.

The European Forest database (EUFo) is a database of sub-national forest inventory data across Europe and is an achievement of WP2 in the ForestNavigator project. It was first described in D2.2, and offers information on forestry area, harvest, biomass stocks and increment for the period 1990/2000-2023 at (mostly) sub-national level. It was updated in Deliverable D2.3 and will be published in an upcoming paper. The EUFo database consists of two main components: the EUFo-reported dataset and the EUFo-harmonized dataset. The core of the EUFo-reported dataset consists of the collected primary data from National Forest Inventories (NFIs) and census statistics with additional national data from the State of Europe’s Forests (SoEF) (FOREST EUROPE, 2020) and the Global Forest Resource Assessments (FRA) (FAO, 2020) for the available reporting periods/years in the timeframe 1990-2023. Data was converted to common units, and national specifics regarding definitions were documented. The EUFo-harmonized dataset, in contrast, was established based on common definitions and by applying necessary adjustments and harmonization procedures on the reported values for the included indicators. Further, gap-filling was performed using appropriate methods for each indicator, like interpolation and modelling (with the CRAFT model), to establish a stock-flow consistent annual time series for forest harvest, area, growing stocks and increment for the timeframe 2000-2023.

2. Country case studies

2.1. Ireland

Ireland's greenhouse gas reporting framework combines harvest data from the National Forest Inventory (NFI) and the Central Statistics Office (CSO) for reporting annual harvest data (EPA, 2025) to the UNFCCC, FAO and EUROSTAT.

NFI data is collected from permanent sample plots, with the first cycle conducted in 2006 and subsequent measurements at 4-6-year intervals in 2012, 2017, and 2021. CSO data supports annual reporting to Eurostat, which is based on a statistical survey of the timber-milling sector. EO products, such as the EFDA, provide an alternative approach for estimating pixel-based identified forest disturbances by their disturbance year, disturbance agents and area impacted on an annual basis for the period 1985-2023.

In this study, plot-based harvest data from the NFI (2006-2021) were compared with Landsat-derived EFDA (2006-2022), and Sentinel-1 RADD-EU (2020-2023). The NFI is a detailed periodic survey of permanent forest plots based on a randomised systematic grid sample design with a density of 2 km x 2 km. This corresponds to 17,423 sample points nationwide in 2006, each representing approximately 400 ha. Each circular plot has a diameter of 25.24 meters, comprising 500 m^2. Repeated measurements enable estimation of harvest and disturbance areas and volumes at the national scale with a precision of +/- 5% at the 95% confidence level.

The use of Landsat data at 30 m spatial resolution (ca. 0.1ha) for assessing harvest is limited to clear-fell events, with a minimum detectable patch size of 0.09ha. In Ireland, the clear-fell patches have traditionally been restricted to less than 30 ha per clear-fell event; however, 11% of clear-fell areas are smaller than 0.1 ha and 50% are smaller than 1.2 ha (Figure 1, Phillips et al., 2021).

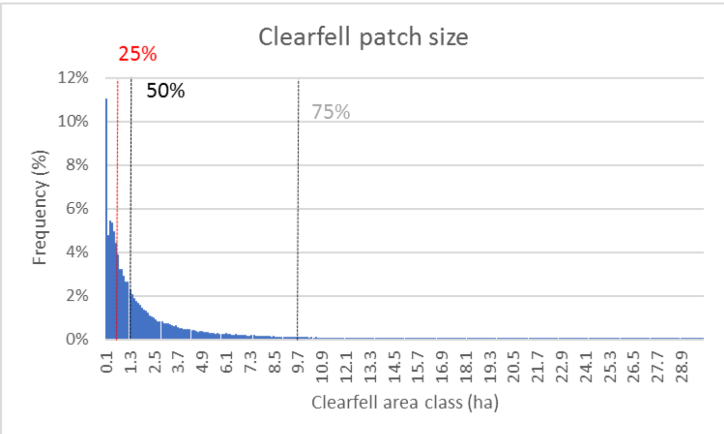

Figure 1: The frequency distribution with 25, 50, and 75 percentiles of clear-fell areas based on the all-Ireland timber forecast (derived from Phillips et al., 2021).

2.1.1. EO and NFI

Landsat-based Earth Observation disturbance products

Thinning harvest represents 50-70% of the total national harvest area for the period 2006-2021 (Figure 2) and would not be detected using the Landsat EFDA product. NFI data shows that clear-fell areas ranged from 5,200 ha in 2011 to 16,400 ha per year in 2014 (Figure 2). A comparison between EFDA-derived harvest estimates with clear-fell and NFI (Figure 2) shows that the EFDA underestimates harvest disturbances. The overall accuracy is below 6%, with a high omission error reflecting clear-fell events that are not detected. Moreover, the EFDA harvest area does not follow the temporal trend observed for NFI clear-fell data.

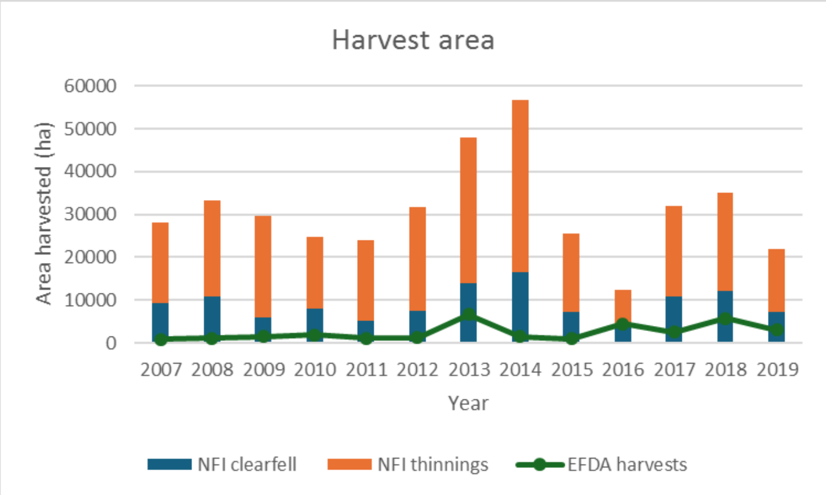

Figure 2: A comparison of clear-fell and thinning areas derived from the NFI with the total harvest areas detected by the EFDA product.

The underestimation of EFDA harvest areas may partially be attributed to the high occurrence of small clear-fell patch sizes in Ireland (Figure 1). If partial clear-fells in some EFDA pixels and pixel mixing effects could increase the resolution limit for detecting clear-fell harvest to 2 or 3 pixels, the detection limit using the EFDA data is more likely to be 0.18 to 0.23 ha. Based on the clear-fell patch-size distribution shown in Figure 1, EFDA data should be able to detect about 75% of the observed harvest in the NFI. The large omission rate, therefore, likely reflects additional factors, such as persistent cloud cover, misalignment in harvest-year dates, inconsistencies in forest-area definitions, and/or other EO classification or processing errors.

Sentinel-1-based Earth Observation disturbance products

The RADD-EU data have a higher spatial resolution (10m) and therefore may better resemble clear-fell harvest events. There is no NFI currently available to estimate harvests from 2020 onwards. However, the harvest area detected using the RADD data is within the historical range detected by the NFI (Figure 2 and Figure 3) and ca. 3-7 times higher than the EFDA estimate (Figure 3).

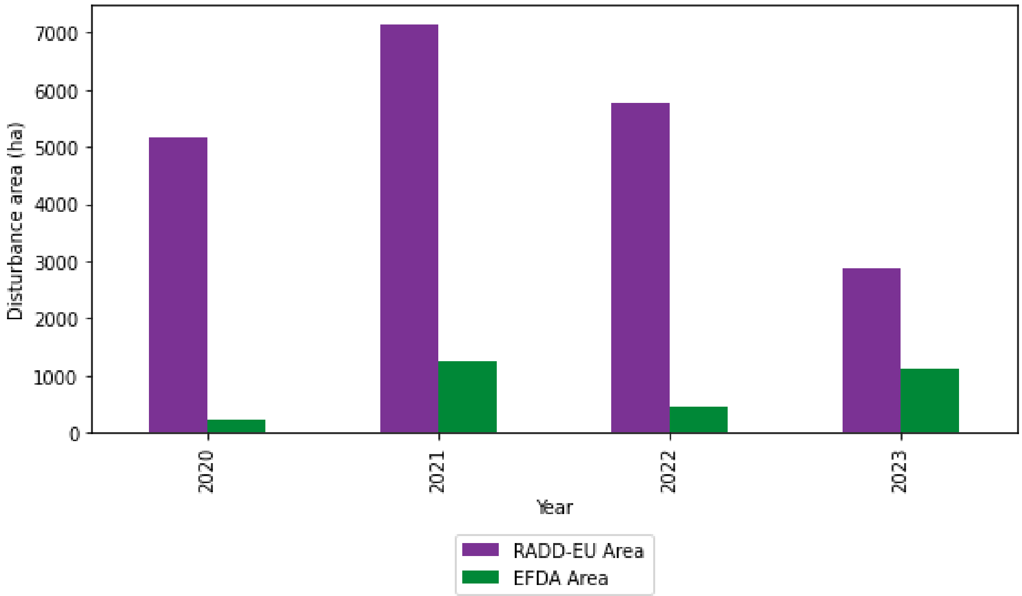

Figure 3: Comparison of disturbed areas detected using the RADD and EFDA data for the period 2020-2023.

2.1.2. Conclusion and Outlook

The discrepancy between EO data, at 30 m resolution limitation, high cloud cover and forest disturbance patch size in Ireland appears to be a major limitation. However, the use of a higher spatial resolution dataset may offer potential to track national forest harvest areas in the future.

2.2. Italy

2.2.1. Data Integration

In Italy, as in several other European countries, harvest statistics are partially incomplete or underestimated and do not fully capture recent national-level trends. Until 2012, annual removal statistics, compiled from regional data, were published by the National Italian Statistical Institute (ISTAT; Pettenella, 2024). From 2013 onwards, however, growing gaps in regional reporting increased uncertainty in the series, leading to the suspension of publication in 2015.

Meanwhile, two National Forest Inventories, formally attributed to 2005 and 2015, provide direct estimates of annual fellings at both regional and national scales. Concurrently, major disturbance events, such as windstorms and insect outbreaks, have underscored the need for a consistent national monitoring system (Pettenella et al., 2021).

When properly integrated with field measurements, remote-sensing data can help fill the data gaps and compensate for the lack of data collected at the national level. Based on a preliminary assessment of available data, we selected the following input data for our analysis:

1. **Amount of fellings from the Italian NFI 2005 and 2015**, scaled to NUTS2 level and including the confidence intervals reported for each region (Gasparini et al., 2011; Gasparini et al., 2022).

2. **Data from the European Forest Disturbance Atlas** (EFDA, Viana-Soto and Senf, 2025), a Landsat-based disturbance dataset, indicating pixel-based identified forest disturbances by their disturbance year (1985-2023) and disturbance agents, such as fires, windstorms and bark beetle infestation, harvest activities, and areas affected by multiple disturbance agents.
3. **Ancillary information**, including:
    i. areas affected by fires reported by EFDA and the European Forest Fire Information System (EFFIS, 2024),
    ii. area and volume affected by the major windstorm in northern Italy in October 2018, as reported by various data mostly collected at the regional level,
    iii. additional regional harvest statistics, where publicly available.
4. **Historical harvest statistics from the National Italian Statistical Institute** (ISTAT 2000-2015), used to support validation of the results.

The analysis was based on the integration of NFI and remote sensing data, combined at the NUTS2 level, and upscaled to the national level. While EFDA provides a long, consistent and yearly time-series, the NFI data report total fellings, based on direct ground measurements collected at the regional level, for two points in time.

As stressed by Viana-Soto & Senf (2025), the agent attribution provided by EFDA should be taken with caution, as reliable estimates of disturbance agent map accuracies are missing, and the quantification of disturbances and trends should rely on "manually interpreted sample" techniques. Based on that, we checked and preprocessed the EFDA dataset to identify missing data and observations affected by possible detection errors, mostly due to a misattribution of the area affected by fires and harvest disturbance events.

Before using NFI data, we performed (i) a comparison between 2005 and 2015 regional-level NFI data and (ii) an accuracy assessment of the NFI reference year, to correctly attribute the amount of fellings reported by NFI to the corresponding period. Based on our preliminary assessment of the actual survey dates, data reported by NFI 2005 were assigned to 2004, and NFI 2015 was assigned to 2018. Additionally, 2005 NFI data for two administrative regions and 2015 NFI data for three regions were excluded from the analysis because they were reporting null or inconsistent data.

If properly calibrated with NFI data reporting the total fellings that occurred within a certain period (Ti), the relative difference between the area affected by disturbance events in EFDA within the period Ti, and the following or preceding periods can be used to estimate the evolution of fellings within a certain time period (Figure 4). In Figure 4 the panels report the main methodological steps. Step 1: temporal evolution of the area affected by harvest according to EFDA (left axis) and total fellings (right axis) estimated by NFI 2005, assigned to 2004, and NFI 2015, assigned to 2018; Step 2: calibration of EFDA data series against NFI data; Step 3: final fellings derived by Fel_back_2005, Fel_forw_2015 and by combining Fel_forw_2005 with Fel_back_2015 with scaling weighting factors; Step 4: maximum and minimum amount of fellings as derived by NFI error intervals.

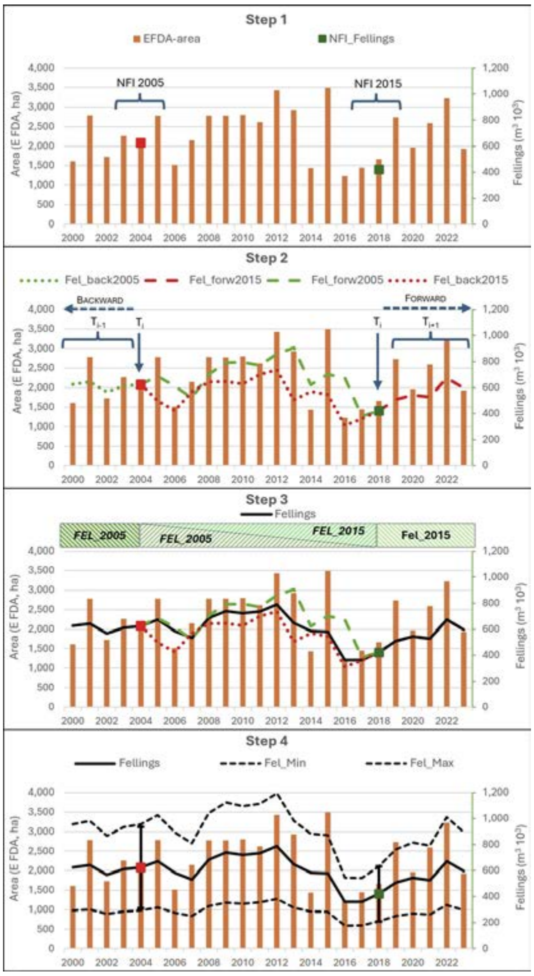

Figure 4: The panels report the main steps implemented, at the regional level, by our methodological framework.

A key requirement is that the share of different silvicultural practices determining the total fellings (e.g., thinning, final cuts, selective logging) remains stable over time, since EFDA does not detect thinning or selective logging. The further the assessment period lies from Ti, the greater the probability that silvicultural practices have changed, thereby increasing uncertainty in the results.

Given the availability of two NFIs reporting total fellings for 2004 and 2018, the data was divided to estimate the relative variations in fellings by applying each NFI within either a forward or backward calibration framework. For years prior to 2004, a backward approach was applied, starting from the amount of fellings reported by NFI 2005 (*Fel_back_2005*). For years after 2018, a forward approach was used, starting from the amount of fellings reported by NFI 2018 (*Fel_forw_2015*).

For the intermediate period (2005-2017), fellings were estimated by combining the two data series: decreasing correction factors were applied to the data series derived from NFI 2005, while increasing correction factors were applied to the data series from NFI 2015.

Using the standard error reported by NFI data, minimum and maximum felling estimates were calculated for each region based on NFI 2005 and NFI 2015. These were subsequently aggregated to derive corresponding national-level minimum and maximum estimates (Figure 5).

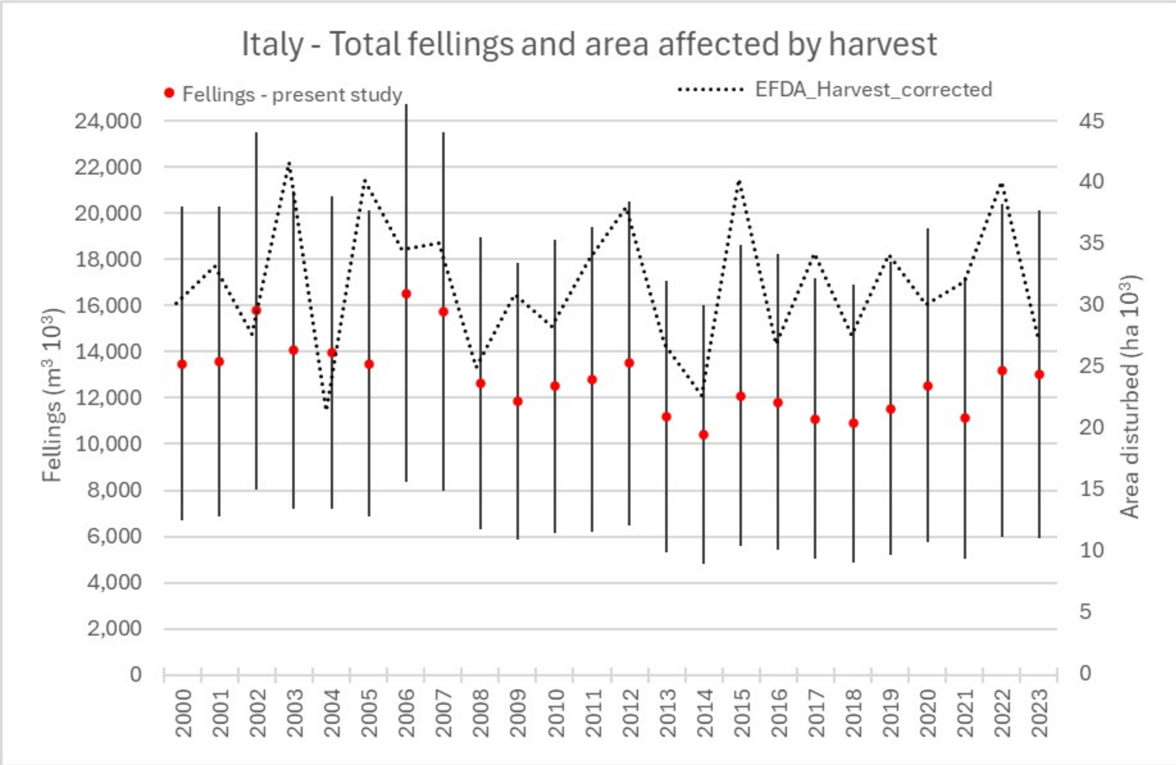

Figure 5: Total fellings estimated at national level from this study (red dots), including the corresponding confidence interval. The total area affected by harvest according to EFDA (black dotted line, right axis).

2.2.2. Conclusion and Outlook

We estimate that total fellings in Italy ranged from a peak of approximately 16.5 million m^3 in 2006 to a low of about 10.4 million m^3 in 2014 between 2000 and 2023. Due to uncertainties in all input datasets, however, national-level estimates of total fellings carry an uncertainty of about ± 50% for each period.

An in-depth analysis of all available data sources highlighted that none, when used in isolation, can provide a complete picture of the relative and absolute harvest levels, at the regional or national scale, or their evolution over time. Each dataset therefore requires critical evaluation, partial correction, and integration with ancillary information, including data collected at the regional level. When remote sensing data is used to quantify temporal evolution of disturbance agents (i.e. harvest), preprocessing of the original inputs is always needed. The criteria applied during preprocessing and quality screening can also influence the final results.

An accurate review of NFI ground data further highlighted that, when disaggregated to the regional level, some estimates are not fully consistent with other information sources. This may reflect sampling designs that are not sufficient to capture a rare phenomenon like harvesting. Moreover, we highlighted that the amount of fellings reported by NFIs cannot be directly attributed to the nominal NFI year (i.e. 2005 and 2015), instead, they should be attributed to the periods 2003-2004 and 2017-2019, for NFI 2005 and 2015, respectively.

The two main data sources integrated within this approach are available for most European countries. Consequently, we believe that our approach can be easily adapted across many EU Member States. The same approach can also support near real-time assessment of national harvest levels, an increasingly important capability for evaluating short-term changes in the forest carbon sink across Europe.

2.3. Czech Republic

In this country-specific study, we focused on forest disturbance monitoring, which is crucial for sustainable forest management and climate change mitigation. The Czech Republic is a country with a long forestry tradition. Despite numerous environmental and societal challenges in recent decades, the advanced silviculture and forest management in the country have resulted in one of the highest forest biomass, growing stock and annual increment per hectare in Europe (e.g., Avitabile et al., 2024). However, Czech forestry remains vulnerable to biotic disturbances. By the end of the 2020s, Czech forests experienced a historically unprecedented calamity, which was dominantly attributed to the exceptionally cumulated soil drought unforeseen in the region for the last 2100 years (Brázdil et al., 2023; Büntgen et al., 2021). Therefore, the topic of disturbance monitoring and the related challenges of quantitative assessment of the affected forest biomass and carbon sequestration capacity have become increasingly important.

There is a solid, centrally administered forest evidence system in place in the country. It annually collects information on forest disturbances using salvage logging data, which also distinguishes disturbance types such as wind, biotic, and others. However, spatially explicit information on affected forest areas is not readily available.

This study compares two entirely independent approaches for assessing forest disturbance areas in the Czech Republic: First, we used the Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3; Kull et al., 2019; Kurz et al., 2009). Second, we used the European Forest Disturbance Atlas (EFDA), a Landsat-based remote sensing mapping approach (Viana-Soto & Senf, 2025). The comparison exercise of independently estimated forest disturbance areas spans the period of 13 years, 2011-2023, across 14 NUTS3 regional units and a country-level aggregation.

2.3.1. CBM-CFS and EO

Methods

CBM-CFS3 Approach: A nationally calibrated forest carbon dynamics model accounting for growth, mortality, and disturbance processes specific to the Czech Republic forestry practices and conditions. The model was calibrated for the Czech forestry conditions at the NUTS3 regional scale (Cienciala & Melichar, 2024). Here, we use the most recent pilot model calibration (Augustynczik et al., 2025) using data and estimates of the National Forest Inventory (Kučera & Adolt, 2019; Máslo et al., 2023b, 2023a, 2024).

The essential input information used by the CBM-CFS3 model is the collected annual data on forest disturbance types in units of harvested volumes for planned and unplanned (salvage) forestry interventions, including thinning, final cut, and salvage logging as used in the Czech forestry in compliance with the mandatory forestry legislation (Czech Republic, 1995) and its later amendments. This information is centrally administered and made available by the Czech

Statistical Office (Czech Statistical Office, 2022) at the level of tree species and NUTS3 units and updated annually.

Using these data, the calibrated CFS3-CFS3 model can produce spatial estimates (in hectares) at the adopted aggregation level (NUTS3) and corresponding to individual disturbance types. A graphical excerpt of the essential input data used for CBM-CFS3 runs and analysis documenting the progression of the recent exceptional calamity in the country is shown in Figure 6.

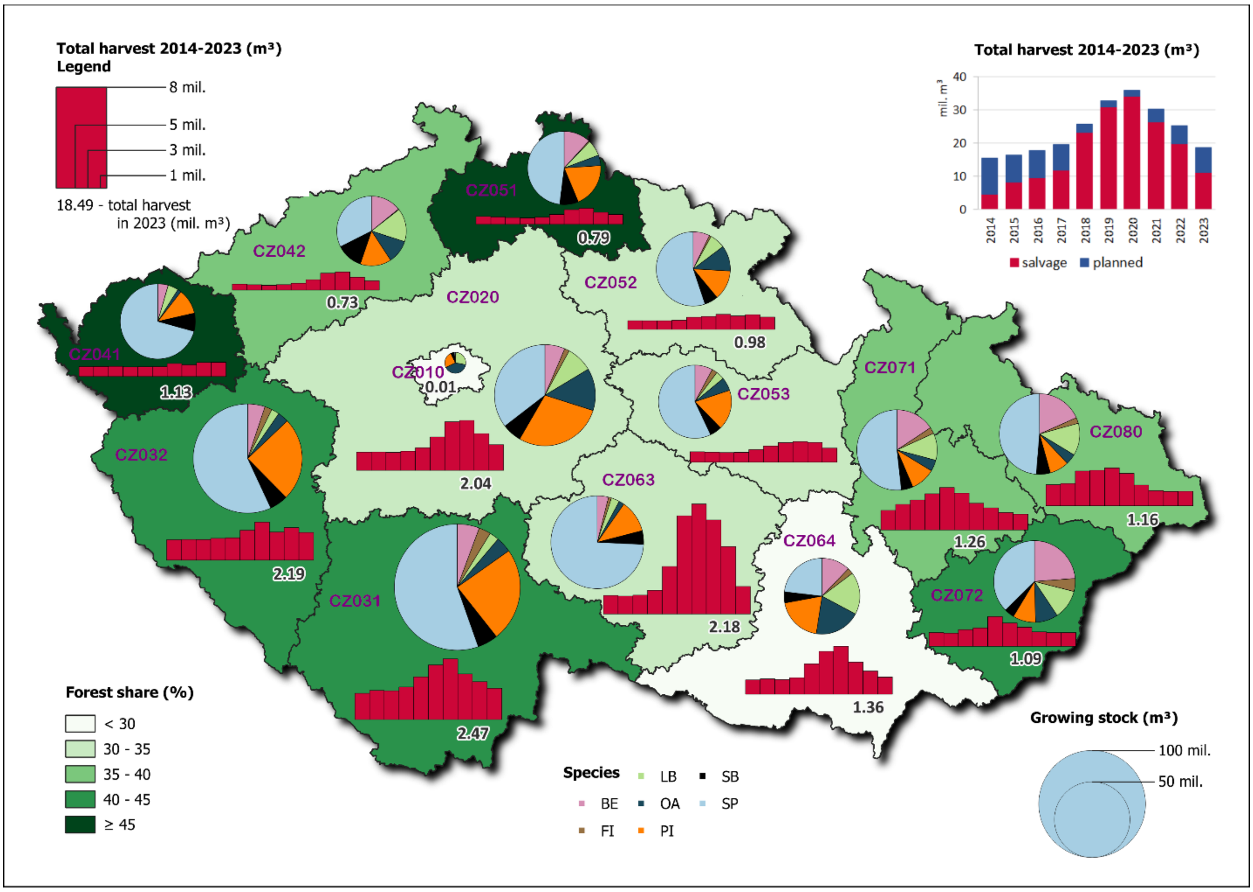

Figure 6: Czech NUTS3 regions and growing stock by tree species (BE – beech, OA – oaks, LB – long-lived broadleaves, SB – short-lived broadleaves, FI - firs, PI – pine, SP – spruce), forest share in regions, total wood volume harvest and total harvest.

EFDA Approach: Annual forest disturbance mapping based on Landsat satellite imagery using automated detection algorithms to identify disturbed forest areas (Viana-Soto & Senf, 2025). These data contain disturbance areas by disturbance agents categorized as: 1) wind and bark-beetle, 2) fire, 3) harvest (i.e., planned thinning, final cut, and salvage), and 4) mixed. For several reasons (apparent after initial data screening), we used these data as total annual values regardless of agent categorization.

Statistics: We applied ordinary linear regression analysis to assess correlations between the two approaches at the country and regional levels. Paired t-tests evaluated systematic differences in disturbance area estimates. Significance levels: ***p<0.001, **p<0.01, *p<0.05.

Results

The estimated country-level forest disturbance areas by the two independent approaches, namely CBM-CFS3 and EFDA, using their specific categorization, are shown in Figure 7. The pattern of total disturbance area differs substantially between the two approaches. The key difference is caused by areas of thinning, which are not discerned by the corresponding EFDA categories (Wind and bark beetle, fire, harvest, or mixed). Once thinning is excluded, the assessed total disturbance areas became similar between the two methods. Hence, the subsequent analyses compared the CBM disturbance areas excluding thinning, against the EFDA total as detailed below.

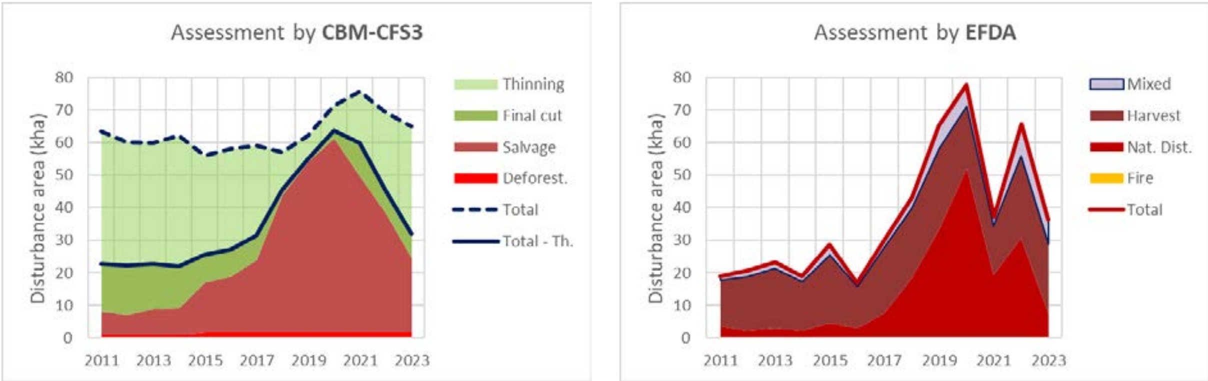

Figure 7: Country-level assessment of annual disturbance areas by CBM (left) and EFDA (right) using their specific categorization. Nat. Dist. for EFDA means wind and bark-beetle disturbances. Fire category for EFDA is low and practically invisible in the graph.

At the national scale, the assessment area by CBM-CFS3 (excluding thinning) and EFDA showed a strong correlation ($r = 0.883$, $p < 0.001$), indicating good agreement in temporal trends of forest disturbance (Figure 8). At the same time, a paired t-test revealed no significant difference for annual disturbance estimates between the two methods ($p > 0.05$), suggesting comparable overall magnitude assessments.

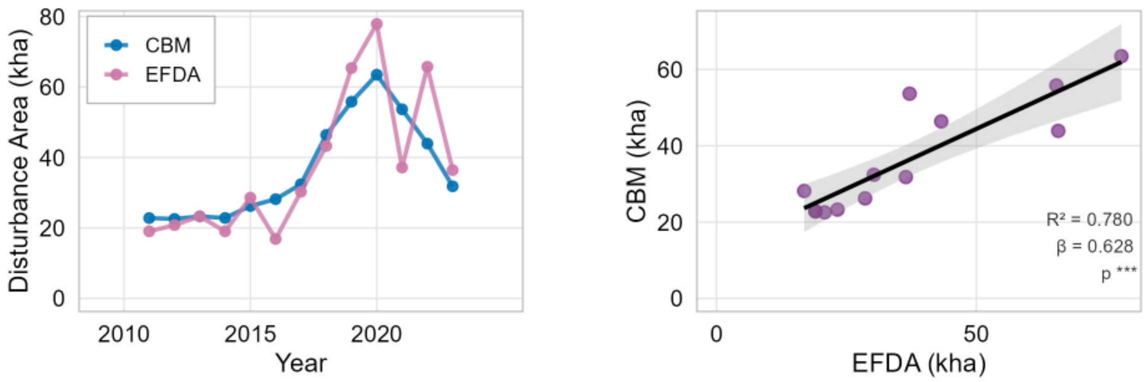

Figure 8: Country-level assessment of forest disturbance areas by CBM-CFS3 (note -excluding thinning) and EFDA (left) and the scatter graph and statistics of the relationship between the two independent assessments (right).

At the regional (14 NUTS3 units) scale, 12 showed significant correlations between CBM-CFS3 and EFDA approaches, demonstrating robust spatial consistency across most regions. As for differences in magnitude, for 10 regions the annual disturbance estimates matched well, while for four regions the estimates differed locally due to methodological differences. The temporal pattern of the estimates for NUTS3 regions is shown in Figure 9. The corresponding scatter and regression statistics are shown in Figure 10.

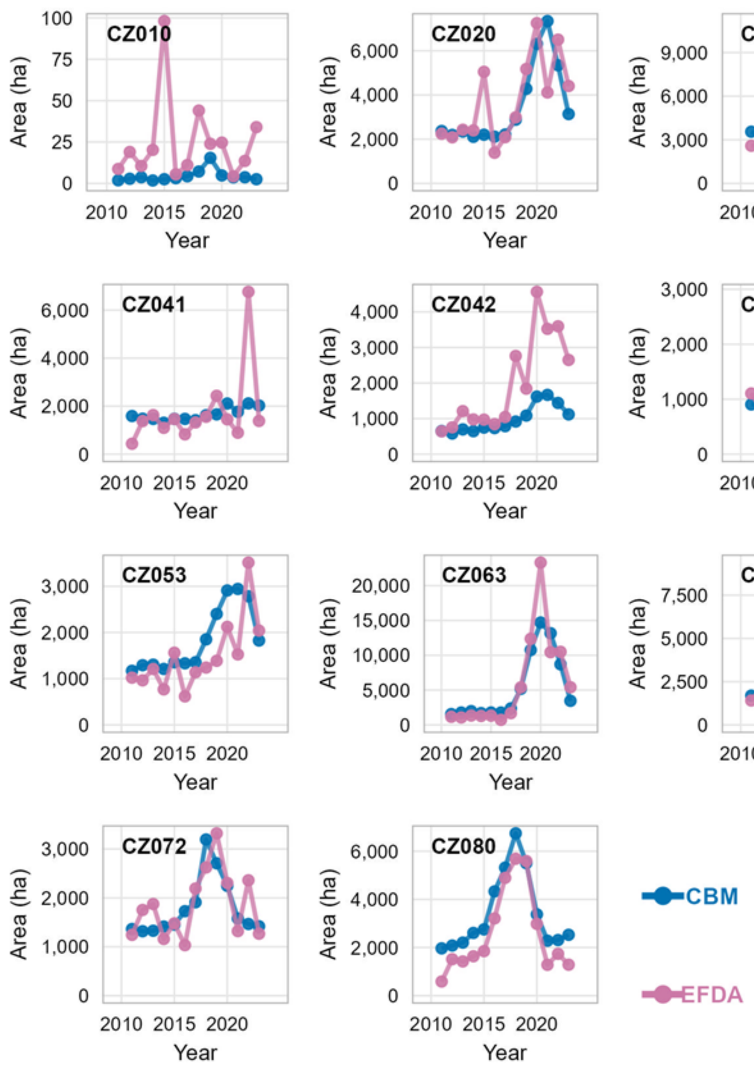

Figure 9: Temporal quantitative correspondence of the assessed disturbance areas by CBM (excluding thinning) and EFDA.

Interpretation

The estimated disturbance areas by the two independent approaches show a rather good match, provided that thinning is excluded from CBM-CFS3. These observations are encouraging considering the observed good quantitative match at both the country and regional levels. This gives confidence to both empirical approaches represented by CBM-CFS3 to estimate disturbance areas based on forestry evidence (affected wood volumes by tree species and spatial attribution), as well as to EFDA estimates that represent an entirely independent geographically explicit quantitative approach.

On the other hand, thinning disturbance was not adequately captured by EFDA. Specifically in the Czech conditions, thinning represents a relatively major reduction in volume (20-30%) and capturing this change in forest structure remains evidently challenging for earth-observation based approaches.

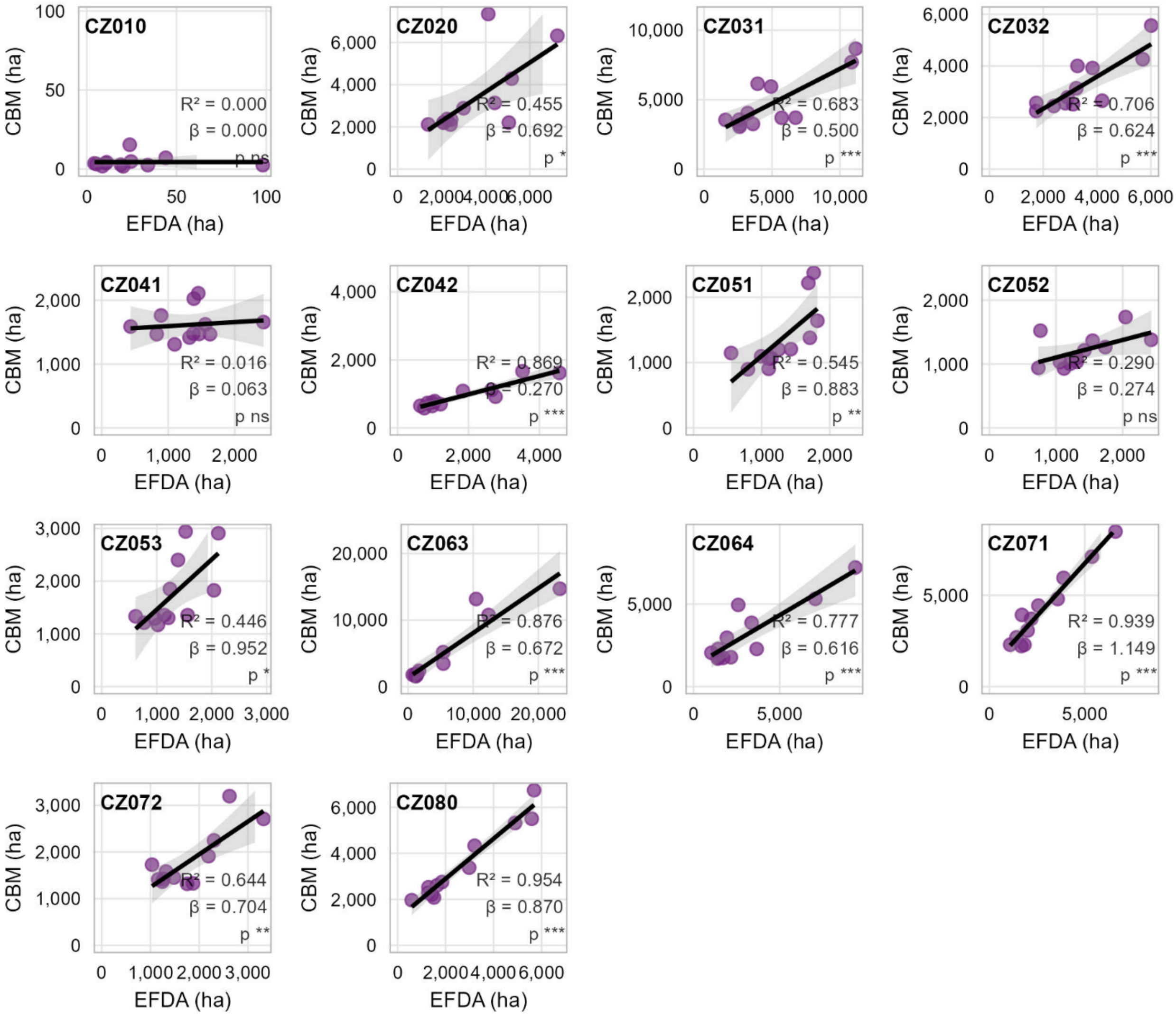

Figure 10: Regional (NUTS3) level comparison of the assessed disturbance areas by CBM (excluding thinning) and EFDA, together with the regression statistics (R2, slope parameter, and significance level).

2.3.2. Conclusion and Outlook

This case study demonstrated a) the benefits and importance of forest inventory data as well as the value of carbon budget models; b) the limitations of multispectral EO disturbance datasets, which primarily identify canopy disturbances; and c) the first 'quantified' underestimation of EO-based disturbance datasets resulting from undetected thinning activities. The comparison between CBM-CFS3 results and EFDA initially showed little agreement, but excluding thinnings, responsible for about 20-30% reduction in volume, from the CBM-CFS revealed similar trends and good agreement in observed disturbance areas both at national and NUTS3-levels.

This highlights that EO data can be used to fill data gaps in a canopy disturbance time series. However, additional data or other EO-based disturbance products, such as active radar disturbance datasets, are likely necessary to capture the full range of forest disturbances and changes reliably.

3. Forest Inventory and LiDAR integration

3.1. FI and ALS

The objective of this work is to establish national biomass estimation using NFI/national research plots and airborne laser scanning (ALS) data. We processed the national ALS surveys to derive high-resolution canopy height models (CHM) at 1-4 meters. Then, NFI plots and CHM are co-registered both spatially and temporally (acquisition year difference ≤ 2). Multiple canopy height metrics (mean μ_H, median $\widetilde{H}$, maximum H_m heights, height standard deviation σ_H, and the ratio of tree-covered area r) of NFI plots are then derived from CHM maps. Then we trained with 80% and tested with 20% of the data three machine learning models on the curated NFI-ALS dataset for the Autonomous Province of Trento in Italy, Czechia, and Ireland.

The results show the R^2 scores of the biomass estimation range from 0.31 to 0.48, except for Czechia, where the scores were 0.17 or lower (Table 1). The low correlation is explained by the low point density (<1 ppsm) of the acquired ALS in Czechia. Additionally, it is discovered that plot location is crucial for modeling. When moving the research plot coordinates around the original plot (maximum 26 m away in x/y direction) to find the best FI-ALS match, the R^2 scores increased significantly. This study demonstrates the great potential of ALS for national biomass estimation, particularly considering the vast amount of available ALS data across European countries.

Table 1: R^2 scores of biomass estimation results for test set (20%)

	R^2 before location correction			R^2 after location correction		
	Trento, Italy	Ireland	Czechia	Trento, Italy	Ireland	Czechia
$\log B \sim (\log \mu_H)$	0.48	0.31	-0.02	0.92	0.68	0.40
$\log B \sim (\log \mu_H, \log \sigma_H, \ldots)$	0.41	0.47	0.11	0.92	0.51	0.48
$B \sim \mu_H$	0.47	0.42	0.17	0.92	0.57	0.47

3.2. FI and GEDI

Forests play a critical role in the global carbon cycle, yet carbon removals in Europe are declining due to increasing wood demand, natural disturbances, and a growing share of ageing forests. Sustaining and enhancing forest carbon sinks requires a better understanding of forest structure complexity, which underpins accurate carbon estimates and aligns with emerging EU policy priorities such as identifying old-growth, natural, and even-aged forests.

Forest inventory (FI) surveys provide essential ground-based information for evaluating forest structure complexity. Remote sensing data enables large-scale assessments in a consistent and timely manner. Therefore, our objective is to assess the applicability of integrating FI and GEDI data for characterising forest structure complexity, particularly for distinguishing low and high structural complexity forests. For this, we evaluate the availability and suitability of matched NFI plots and high-quality GEDI shots, derive a forest structure complexity measure from integrated FI and GEDI variables, and demonstrate a machine learning model trained on FI-GEDI data to classify forest structure complexity. This study is conducted for the Czech Republic, Italy, and Spain, representing temperate, mountainous, and Mediterranean biomes across Europe. These countries were selected due to the availability of forest inventory data and their location within GEDI's latitudinal coverage (~52° N/S).

We initially identified about 34,000 FI plots (Italy, Spain, and the Czech Republic) that had a geographic match with almost 90,000 GEDI shots (from a total of ~64,000 FI plots available and ~200,000,000 GEDI shots in Spain, Italy, and the Czech Republic). Rigorous GEDI quality filtering and additional matching criteria, such as at least two GEDI shots per NFI plot and excluding plots on terrain steeper than 15 degrees, reduced the dataset to a total of 2,509 FI plots and 5,488 corresponding GEDI shots. This is equivalent to 7% of the NFI plots and 6.5% of the geographically matched GEDI shots. The final dataset includes 66 FI plots in the Czech Republic (11% of the available Czech FI plots). From Italy, 272 NFI plots are included (4% of the 3rd NFI cycle). From Spain, 2,122 NFI plots remained (4% of the 4th NFI cycle). This shows that NFI plots and GEDI shot acquisitions geographically match, but further highlights that data quality requirements reduce the number of matched plots and GEDI shots drastically. Therefore, the database for assessments of individual countries is low, and a pan-European assessment is favourable.

Forest structure complexity was derived at the plot level using variability in diameter at breast height (DBH), tree height (THT), and species richness, combined into an equally weighted structure complexity score. Low variability indicated even-aged, single-species stands, whereas high variability reflected diverse, multi-aged, structurally complex forests. We selected the NFI plots within the lowest and highest 25 % structure complexity score for low and high structural complexity, respectively (Figure 11).

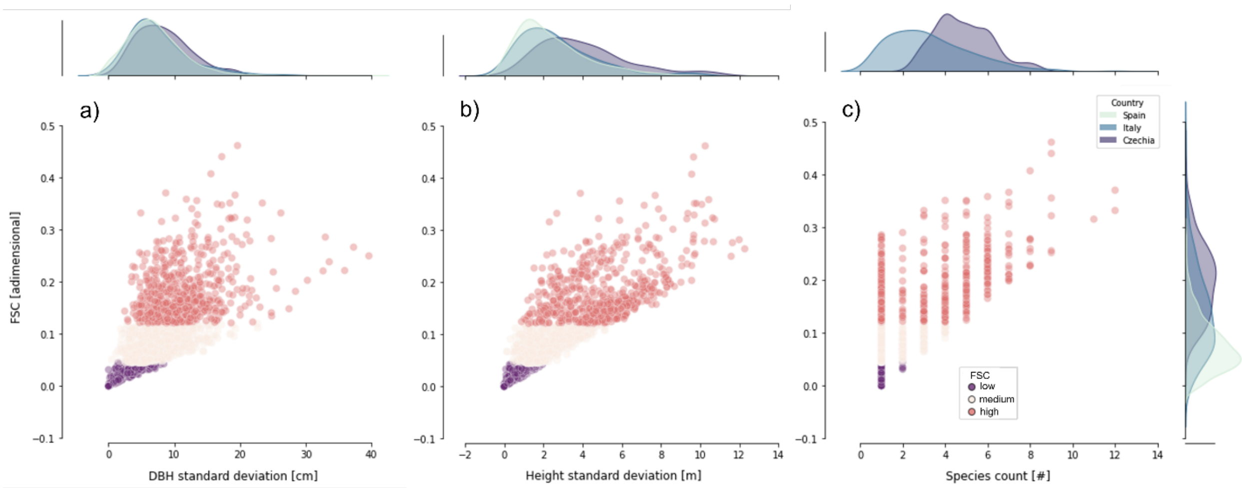

Figure 11: The scatter plots indicate the NFI plot distribution according to a) std of DBH, b) std of tree height, and c) the species count per plot and the associated FSC measures as 25%-lowest/highest values. The variable spread by country.

Training a Support Vector Machine (SVM) with GEDI data to differentiate between low and high structural complexity, as derived from the FI-based score, resulted in a GEDI-based model accuracy of 0.81. Restricting the evaluation to the predictions with probabilities > 80% increased the accuracy to 0.94. Applying this model to high-quality GEDI shots in Italy, the Czech Republic, and Spain highlights the country-wide occurrence and distribution of low and high-structural complex forests. A first assessment indicates that 86%, 65%, and 26% of the forest areas are associated with high structural complex forests in the Czech Republic, Italy, and Spain, respectively.

These results demonstrate the potential of integrating invaluable ground-based observations with spaceborne LiDAR to characterise forest structural complexity at large scales. Even relatively simple structural scores and models provide a reliable representation of the distribution of structural complexity across Europe.

This approach provides a new basis for improving forest carbon estimates, monitoring structural changes driven by disturbances and other dynamics, and supporting EU forest policy targets related to biodiversity, climate resilience, and sustainable forest management.

4. Pan-European analysis of disturbances and harvest

The assessment of the three case study countries in Ireland, Italy and the Czech Republic presented in Chapter 2 was complemented by a pan-European analysis of harvest levels and disturbances. To assess the direction and strength of the relationship between harvest and disturbed area, we compared NFI, census data, and EFDA data.

Annual harvest levels were compiled from NFIs and census data and harmonized in the EUFo database and are available for 220 regions in Europe. From the EFDA database, we aggregated forest areas that were disturbed by windthrow, bark beetle infestation, and harvest per region. To assess the direction and strength of the (linear) relationship between harvest and disturbed area, we calculated the Pearson correlation coefficient (Figure 12).

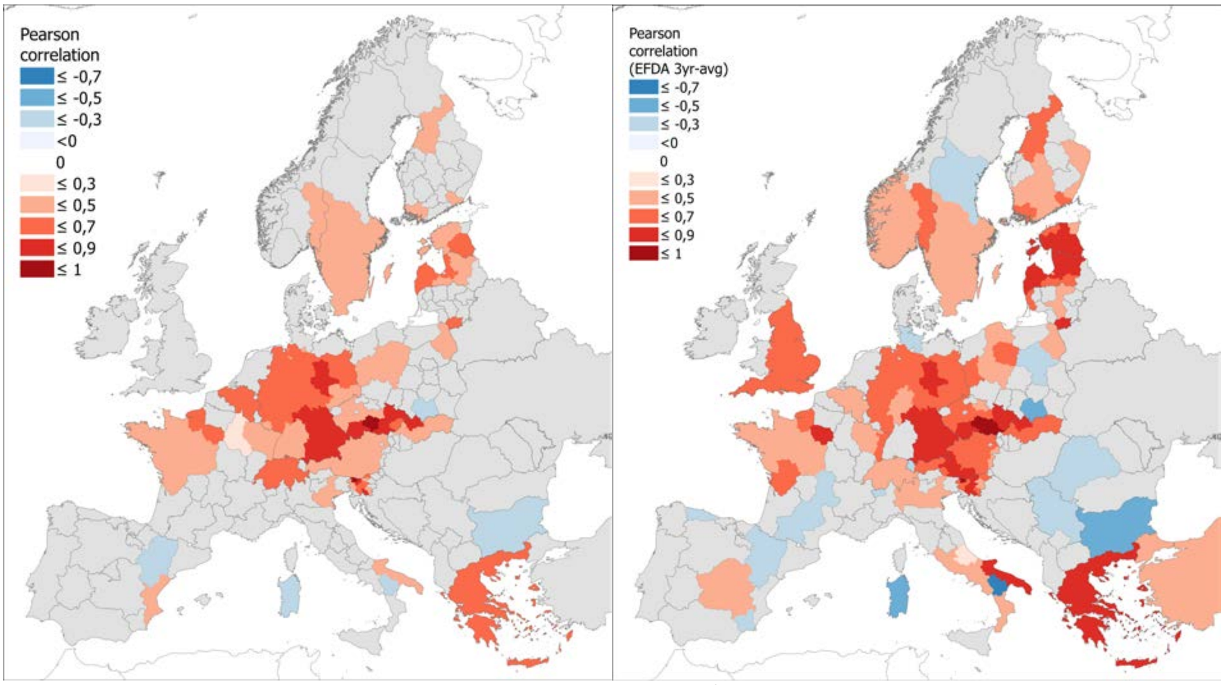

Figure 12: Pearson correlation between annual EUFo harvest volumes (m^3 roundwood under bark) and forest area (ha) disturbed by wind, bark beetle or harvest from EFDA (left: annual, right: 3-year rolling average) from 1990-2022. Grey = no correlation.

In 34% of the regions, corresponding to 26% of the European forest area, we find a positive Pearson correlation coefficient (significance level α=0.1) above 0.3. In 13% of the regions (8% of forest area), the correlation coefficient between disturbed forest area and harvest levels is higher than 0.5, with the maximum coefficient of 0.95 in the Czech region Kraj Vysočina (CZ063) (Figure 13). In 2% of the regions (3% of forest area), the Pearson correlation coefficient is negative and between –0.3 and –0.5, indicating that harvest levels increase with decreasing disturbed forest area (Figure 14).

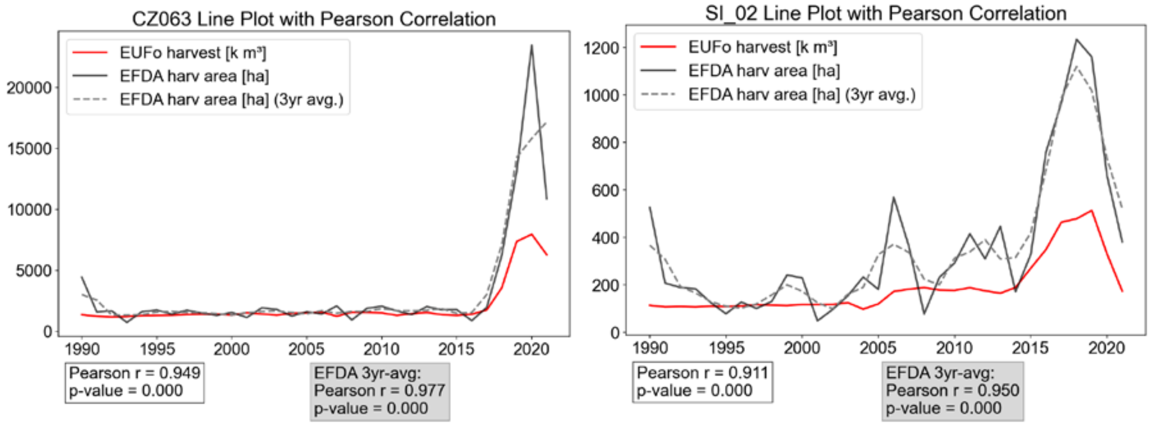

Figure 13: Example regions exhibiting a strong positive correlation between disturbed forest area and harvest levels for the Vysočina region in the Czech Republic (CZ063) and the Bled region in Slovenia (SI_02).

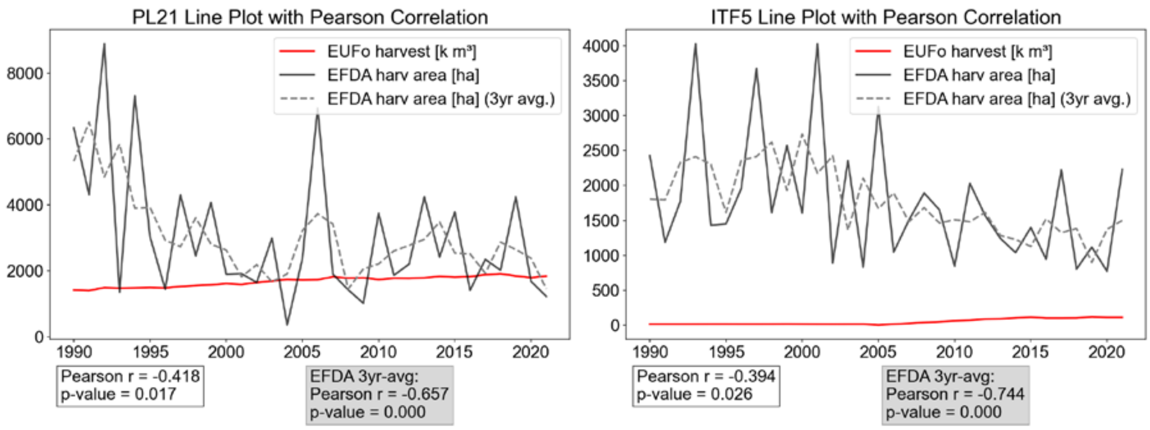

Figure 14: Example regions exhibiting a strong negative correlation between disturbed forest area and harvest levels for the Małopolskie region in Poland (PL21) and the Basilicata region in Italy (ITF5).

Because data uncertainty and time lags between disturbance events and subsequent harvests may influence the relationship, we also calculated a three-year rolling average of EFDA disturbance area. Comparing this smoothed time series with EUFo harvest levels yields an overall improved fit, with stronger correlations observed in 80% of regions.

Using the three-year EFDA average, 47% of regions (representing 44% of forest area) show a significant positive Pearson correlation coefficient above 0.3, while 8% or regions (10% of forest area) exhibit a significant negative Pearson correlation below -0.3. Correlations exceed 0.5 in 28% of regions, corresponding to 16% of the total forest area.

5. Synthesis

5.1. EO vs field-based data: opportunities and limitations

Forest inventories have a long history and are an essential component for assessing forest conditions and status, especially because the surveys are grounded in statistically robust sampling designs, which enable reliable upscaling and stock estimation across different scales. However, conducting forest inventory surveys is time- and labour-intensive and therefore not carried out frequently enough to fully capture current disturbance regimes and climate change-induced

changes. Earth Observation (EO), by contrast, provides more timely information and has the potential to support annual assessments and detect changes, even in near real-time.
There are clear opportunities to integrate NFI and EO data, but limitations related to sensor specifications, data availability, and environmental circumstances indicate that no single solution fits all. For example, the Irish case study showed that small forest and disturbance patch sizes are not fully captured by EO products with a 30 m spatial resolution, and that the limited GEDI spatial coverage constrains data integration options. The Czech case study demonstrated limitations of specific sensor systems and challenges in capturing all changes on the ground. In particular, detecting thinning interventions, which are common forest management practices that partially reduce growing stock density and crown cover, remains challenging for EO approaches. Lastly, the Italian case study highlighted the importance of reliable and continuous (national) statistics, as well as the difficulties that arise when time series are interrupted.

The range of integration opportunities is expected to increase in the future with the availability of longer time series from existing sensors (e.g. Sentinel-1, GEDI) and the deployment of new sensors (e.g. NASA EDGE, VeggieH). Furthermore, closer coupling of ground surveys with satellite missions and ALS is essential to ensure temporal alignment between datasets. For example, the Sentinel-1 time series began in 2015, GEDI acquisition cycles span 2018-2023 and 2024-present, and ALS data are typically collected during individual flight campaigns. So far, there has been limited temporal overlap between the national forest inventory cycles in Italy, the Czech Republic, and Spain and GEDI data, and only partial temporal overlap with Sentinel-1.

Current EU policies, particularly the LULUCF Regulation, emphasise the need for improved monitoring of natural disturbances and their impacts, as well as timely GHG reporting through a transition towards annual inventories. Achieving these objectives requires the integration of forest inventories and EO data. While no single approach currently fits all countries or regions, several general integration strategies have emerged that move in the right direction and may require only country-specific adjustments.

5.2. Uncertainties

Using remotely sensed tree cover change as a proxy for the volume of felled trees carries substantial uncertainty. Remote sensing alone struggles to distinguish between different drivers of land change, such as planned harvests (fellings) versus natural disturbances, and misses thinning in general. For example, the Italian case study suggests that approximately 6.6% of areas affected by "wildfires" were misclassified as "harvest".

Uncertainty is further compounded by limitations in official national statistics, which in some cases tend to underestimate harvest levels because they do not fully capture wood used for energy (fuelwood). NFI data also introduce temporal uncertainty: measurements attributed to a specific reporting year may reflect harvesting that occurred up to 24 months earlier, as observed in Italy.

Finally, uncertainty increases as the assessment period diverges from the calibration years. This reflects the difficulty of detecting changes in silvicultural practices, such as thinning or selective logging, through remote sensing, as these practices may evolve over time and remain only partially observable in satellite-based indicators.

Uncertainties of harvest data from the EUFo database

In D2.3, we showed that, at the aggregated EU-26 level (excluding Malta), harvest estimates derived from harmonized NFI and census data (constructed by calculating roundwood under-bark timeseries from reported data using expansion factors and interpolation) are broadly aligned with SoEF harvest statistics and show no systematic bias. At the national level, however, notable differences remain, with some countries consistently reporting higher or lower harvest levels than SoEF.

Here, we extend this assessment by analyzing country-level alignment between NFI/census-based estimates and SoEF (Figure 9). For each country, we plot the mean harvest ratio (EUFo / SoEF) against the Pearson correlation coefficient over the period 2000-2023. This representation shows systematic differences in average harvest levels (bias) compared to differences in annual variability and trend. The results reveal substantial cross-country variation. Notably, NFI-derived harvest estimates tend to be systematically higher than SoEF values, while census-based estimates show a wider spread around SoEF. A notable example is Germany, where NFI-based estimates indicate declining harvest levels, whereas SoEF reports an increase, resulting in a negative correlation.

For the final EUFo harvest estimates used in the pan-European analysis of disturbances and harvest in Chapter 4, we therefore applied the average of SoEF and NFI/census-based estimates to account for these uncertainties. Although this analysis cannot identify the specific sources of disagreement (such as accounting methods, imprecise implementation of definitions, or the application of expansion factors), it can indicate that countries showing closer agreement across data sources (i.e. those located near the middle top in Figure 15 can be considered to have more robust estimates (The mean ratio (EUFo / SoEF) indicates bias, while the Pearson correlation coefficient quantifies alignment in variability between the two time-series. Countries in the middle top therefore have a good alignment between EUFo to SoEF data while countries further away from this point have either a systematic bias and/or low alignment in variability. Point size reflects primary data availability, and color denotes data source (NFI or census)).

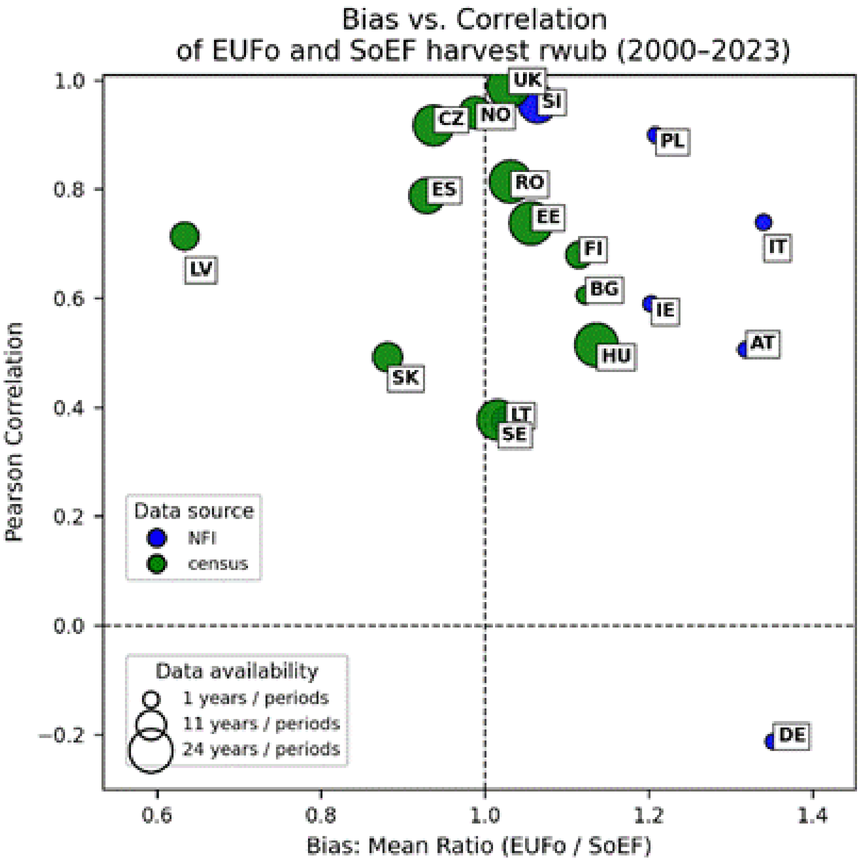

Figure 15: Bias–correlation comparison between EUFo and SoEF national harvest estimates (2000–2023). Each point represents one country from the EUFo database for which NFI or census harvest data was collected. The mean ratio (EUFo / SoEF) indicates bias.

6. Demonstration

A demonstration for this deliverable was done as part of the established Forest Talks webinar series. On 23 February 2026, we hosted the Forest Talks webinar on '[Integrating EO Data in National Forest Monitoring and Assessment]' with up to 110 participants attending online.

The webinar included a brief overview of ForestNavigator, WP2, followed by extensive demonstrations of the three country case studies and their results, which are also outlined in this documentation. Additionally, Thomas Pugh (Lund University), representing the project ForestPaths, presented his work on 'Carbon Balance in European Forests: Exploring Past Trends', as well as Murali Thoppil (University of Bristol), representing the project PathFinder, who presented 'An EU Reporting and Accounting Framework for the LULUCF Sector'. The webinar concluded with a Q&A session and a short interactive survey lasting approximately 20 minutes.

The interactive survey included four questions (Figure 16). First, we were interested in the area of expertise of the webinar participants (Figure 16, question 1). Most attendees were from modelling, Earth Observation and National Reporting, with fewer stakeholders from Forest Policy and Forest Management. The attendees identified forest cover/area, disturbances, biomass/carbon stocks, tree height and species as the most promising forest variables for forest inventory and Earth Observation integration (Figure 16, question 2). The main added value of EO in forest-related GHG estimation and reporting lies in its spatial coverage, timeliness, comparability (between countries, regions), consistent assessment, and long time series (Figure 16, question 3). In a final open-ended question, we asked about the key challenges to enhancing forest inventory and EO data integration. Common responses included consistency, cooperation/collaboration, financing, data access, especially regarding harvest, as well as several individual suggestions (Figure 16, question 4).

Figure 16: Results from the Interactive Survey conducted using Mentimeter. About 45 webinar attendees completed the interactive survey.

7. Outlook

D2.4 is the final deliverable of WP2 for ForestNavigator. Within this work package, we have compiled and harmonised NFI and EO datasets and explored their integration for improved temporal and spatial forest monitoring and GHG reporting.

The EO datacube (forest4model) and EUFo database have been and will be taken up by other work packages and projects. The forest4model datacube is featured on the [ForestNavigator Data Explorer]() by WP9 and will be presented to the stakeholders in a stakeholder engagement workshop organised by WP1 in April 2026. Furthermore, the results from WP2 are taken up by WP8 T8.3 and T8.4. We are currently working on integrating the data results from WP2 into the policy pathways of WP8, which will also be addressed in a white paper on data, models and pathways.

Besides this, members of this work package are currently working on publications featuring the findings, such as ‘NFI and ALS comparisons across Europe’, ‘Integrating forest inventory plot and GEDI data for forest structure complexity assessment’, and ‘Consistent Forest statistics for Use Intensity Analyses Across Europe (2000-2023)’. Similarly, results of this work package will be presented at national and international conferences, such as the EGU 2026.

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