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Copernicus for monitoring European forests: strengths, challenges and potential

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ABSTRACT
Copernicus is the European Union's Earth Observation program, offering forest-related maps through its High-Resolution Layers (HRL). Corine Land Cover (CLC) and the Japan Aerospace Exploration Agency (JAXA) also provide map-based products on European forests. However, these maps are difficult to use due to the lack of aggregated statistics, and their consistency with official forest statistics from national forest inventories compiled by the Food and Agriculture Organisation (FAO) remains unclear. This study explores the potential of Copernicus ready-to-use data for simplified forest statistics, temporal consistency, and alignment with external and validation sources. First, Copernicus data were integrated with European Local Administrative Units (LAUs) to produce comprehensive information on forest cover and density at the local scale. Second, forest area estimates from HRL, CLC, and JAXA pixel counts were compared with FAO statistics at the country level. Results indicate that changes in methodologies and spatial resolution of the source data used in Copernicus HRL over the past decade affect the reported statistics. Copernicus HRL data show significant discrepancies compared to FAO data, while JAXA and CLC data are more aligned. These findings highlight the need to integrate better, present, and homogenize European forest information tools to ensure practical and accessible data.

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Forest type; tree cover density; satellite data; local administrative units; forest change; earth observation

HIGHLIGHTS

- Copernicus forest data are assessed and compared for 2012, 2015, and 2018.
- Multitemporal statistics on forest area and tree cover density are provided for each local administrative unit.
- Copernicus, JAXA Forest/Non-Forest map, and EEA Corine Land Cover-derived forest statistics are compared.
- Official forest area estimates from the FAO Forest Resource Assessment are used as a reference.
- The strengths, weaknesses and potential of Copernicus in forest monitoring are identified and discussed.

Introduction

Earth Observation (EO) provides essential data for monitoring and assessing forest ecosystems, making it an indispensable tool for verifying the effect of policies and planning sustainable management (Corona et al., 2023; Drusch et al., 2012; Reid & Castka, 2023; L. Wang et al., 2020; Woodcock et al., 2008; Wulder et al., 2022). EO data are available through many public-domain platforms provided by government agencies and support the production of forest datasets (Jutz & Milagro-Pérez, 2020; Reid & Castka, 2023). Several initiatives support the development and updating of EO data platforms worldwide; in the European Union (EU), this role is filled by the Copernicus program.

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With the partnership of the European Environment Agency, Copernicus provides free and accessible data for forest monitoring, including the High-Resolution Layers (HRLs). HRLs are a collection of geospatial data about five specific land cover features, including forest area by leaf type and tree cover density. They potentially represent an important information product for forestry, nature conservation, rural development, and ecosystem accounting (Congedo et al., 2016; Dostálová et al., 2021; Drašković et al., 2021). Currently, the data delivered by Copernicus are based on the Sentinel-2 satellite mission with a spatial resolution of 10 meters and on other complementary European and non-European contributions from medium- and high-resolution satellite platforms. Until 2015, the main medium-resolution data sources were Landsat 5–7–8, SPOT 5, and Resourcesat-1–2 satellites, all resampled to a spatial resolution of 20 meters. The high-resolution data sources were GeoEye-1, WorldView-2–3, Deimos-2, and SPOT 6–7 (Copernicus Land Monitoring Service, 2015, 2018). Technological advances and changes in satellite platforms over the years have led to differences in spatial resolutions and inconsistencies in the Copernicus processing steps, and therefore in the derived products and information (Copernicus Land Monitoring Service, 2018). To our knowledge, a comprehensive account of the state of European forests from Copernicus HRLs data covering all reference years is lacking. To this end, the analyses reported here were conducted at both national and Local Administrative Unit (LAU) levels, as the latter represents an information layer for aggregating and providing accessible, easy-to-use forest statistics, particularly useful for supporting operational forestry, nature conservation, rural development and ecosystem accounting (D'Agata et al., 2024).

Other map-based forest datasets available for EU are the Forest/Non-Forest (FNF) map by JAXA (Shimada et al., 2014) and Corine Land Cover (CLC) also from Copernicus. The JAXA FNF is a global product generated by classifying SAR images, while the CLC has European coverage and is based on manual delineation of different satellite missions (Caffaratti et al., 2021; Copernicus Land Monitoring Service, 2021; L. Wang et al., 2020). Together with HRLs, these maps are valuable sources of spatial information (e.g. forest area at various administrative levels) to support research, planning and policy applications (Francini et al., 2022). However, map-based estimates, performed through pixel counting, represent a biased approach (Olofsson et al., 2014; Waldner & Defourny, 2017) as classification errors tend to be systematic in EO-derived maps and there is no compensation between commission and omission errors, i.e. areas of land-cover type A incorrectly mapped as land-cover type B are not compensated for by areas of land-cover type B incorrectly mapped as A (Corona, 2010). On the other hand, reliable estimates of EU forests are produced by the individual countries' national forest inventories (NFIs) and are summarized in the FAO Forest Resource Assessment (FAO FRA). FAO FRA national estimates from 2015 and 2018 are available for comparison with the map-based datasets mentioned above.

Comparing forest area estimates from different ready-to-use mapping products is inherently challenging due to differences in input data, processing methodologies, classification approaches, and spatial resolution (Araza et al., 2022). The Copernicus HRL forest products have evolved significantly over time, with different sensor sources (e.g. Landsat before 2015, Sentinel-2 from 2018), spatial resolutions (20 m in earlier products, 10 m in 2018), and classification methods (e.g. Random Forest models in 2018 vs. threshold-based approaches before). CLC, while part of the Copernicus program, relies on a semi-automatic interpretation of multiple satellite sources with a coarser resolution (25 ha minimum mapping unit), making its thematic accuracy highly dependent on expert interpretation (Copernicus Land Monitoring Service, 2021). Finally, the JAXA FNF map, based on SAR data, is less affected by cloud cover but operates a simpler binary classification of forest presence, which can lead to misclassification in heterogeneous landscapes (Shimada et al., 2014). Each of these datasets has its strengths and limitations, influencing their comparability and reliability in forest estimations across Europe (Gschwantner et al., 2016). To the best of our knowledge, a comprehensive analysis has not yet been conducted to assess the discrepancies between FAO FRA forest area estimates, which is considered the benchmark, and the pixel counting estimates from HRL, CLC, and JAXA.

In the light of this, the objective of this study is to explore the potential of Copernicus ready-to-use data, and similar map-based products, as base information layer for generating simple and practical statistics on European forests. Accordingly, we aim to illustrate the possibilities and consistency of using Copernicus data for change detection in forest statistics at the local administrative scale, as well as their alignment with external validation sources. To achieve this, the study consists of two main parts. First, forest area and tree cover density statistics were accounted for by HRL forest products for each LAU in EU for 2012, 2015 and 2018, and changes were identified and analysed at the LAU and country levels. Second, to assess which changes might be related to actual changes in the state of forests and which might be due to inconsistencies in mapping over time, we compared the Copernicus HRL pixel count estimates of forest area with FAO FRA statistics, to identify differences and similarities associated with the map-based dataset compared to the NFI reference data. This analysis was also performed for CLC and JAXA map-based datasets. It is important to emphasize that our focus is on comparison, specifically examining the statistics that can be extrapolated from different products across available years. This study does not conduct a formal accuracy assessment but rather evaluates the consistency and differences among these datasets to identify systematic biases and trends over time. The comparison was made at the country level, as the FAO FRA statistics do not provide data at the LAU level.

Materials and methods

Study area

This study focuses on the geographical area of the EU (Albania, Austria, Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom). Forests are unevenly distributed across EU, reflecting bioclimatic variation from boreal conditions in the north, through Atlantic climates in the midwest, to temperate and Mediterranean regions in the south-central (Gschwantner et al., 2022; Mason et al., 2022). The high diversity in terms of climate and biomes makes European forests important for biodiversity (Paillet et al., 2010). Considering the ongoing processes driving changes in forest composition and structure, including climate change, human impact, and ecological succession, European forests can be summarized as follows (Hinze et al., 2023). Boreal forests are found in high latitudes and mountains where coniferous trees such as spruce and Scots pine are common. Deciduous trees such as oaks and beech are typical of temperate forests in the central and southern parts of the continent (Barbati et al., 2014; Brockerhoff et al., 2017).

To define the study area, aggregate forest data and provide forest statistics in an easy-to-use format, we referred to the local administrative units (LAUs). LAUs are the low-level administrative divisions of European countries used by Eurostat to provide statistics for different purposes. The LAUs cover the entire territory of the EU Member States and the United Kingdom, including statistical regions for EU candidates and European Free Trade Association countries. They are the constituent elements of the Nomenclature of Territorial Units for Statistics (NUTS), which is a hierarchical classification of statistical regions in Europe. In general, LAUs are the smallest administrative units within each NUTS and can include municipalities, communes, districts, counties or other similar administrative units (Figure 1). One of the key functions of LAUs is to provide a consistent framework for the collection and analysis of statistical data at the local level. This includes data on the degree of urbanization (DEGURBA), which classifies LAUs as cities, towns suburbs, or rural areas based on a combination of geographical contiguity and population density.

Data description and processing

Full details of the data used in this study are provided in Appendix A, while key information and methods implemented are summarized here and in Figure 2.

Forests HRLs (Appendix A.1) consist of three types of status layers, with a three year update cycle. Data is available for 2012, 2015, and 2018. The two primary status layers (Appendix A.1.1) are the Dominant Leaf Type (DLT) and Tree Cover Density (TCD) layers which provide pixel-wise percentage estimates of broadleaved and coniferous fractions and tree cover density (0–100%). DLT and TCD are the input data for the third status layer, i.e. Forest Type (FTY) which identifies areas that meet the Global Forest Resources Assessment (FAO, 2020) definition of forest (Appendix A.1.2). As such, it is the only layer explicitly designed for forest-specific applications, using a minimum mapping unit of 0.5 hectares and a canopy cover threshold greater than 10%. TCD refers more generally to vegetated areas with tree canopy cover and

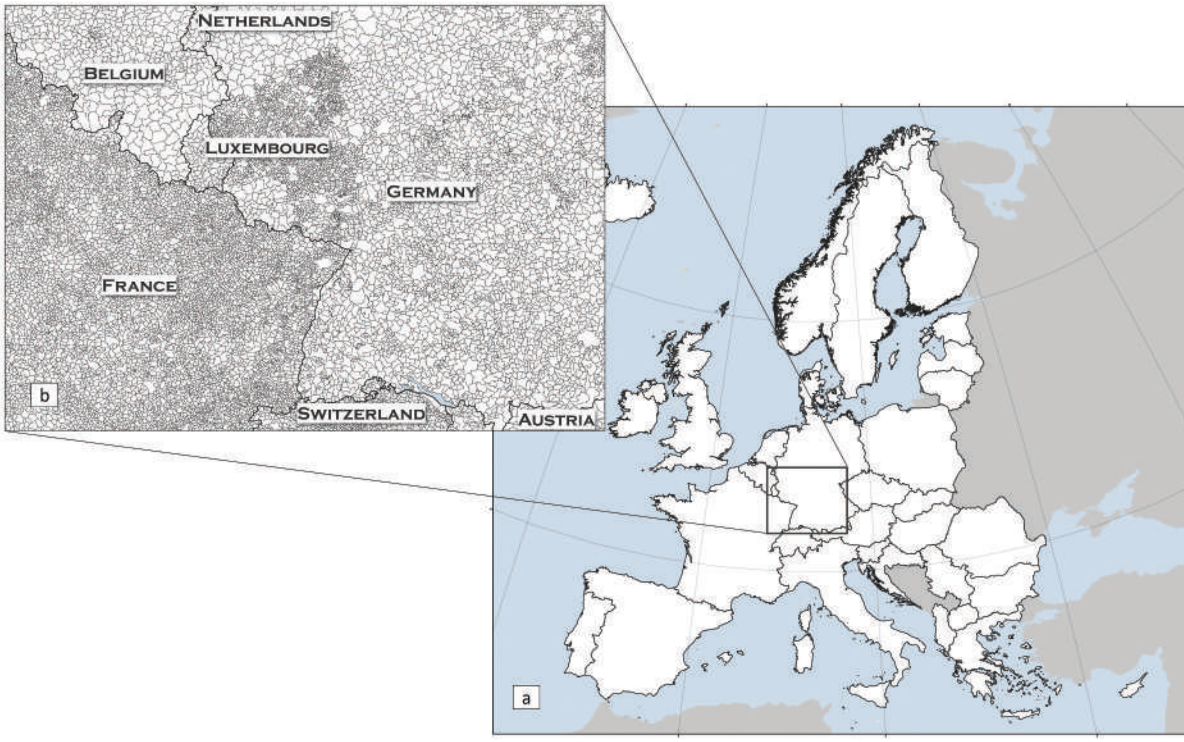

Figure 1. (a) Countries considered in the study area, within which LAUs are located; (b) examples of different sizes and patches of LAUs in some countries of central Europe.

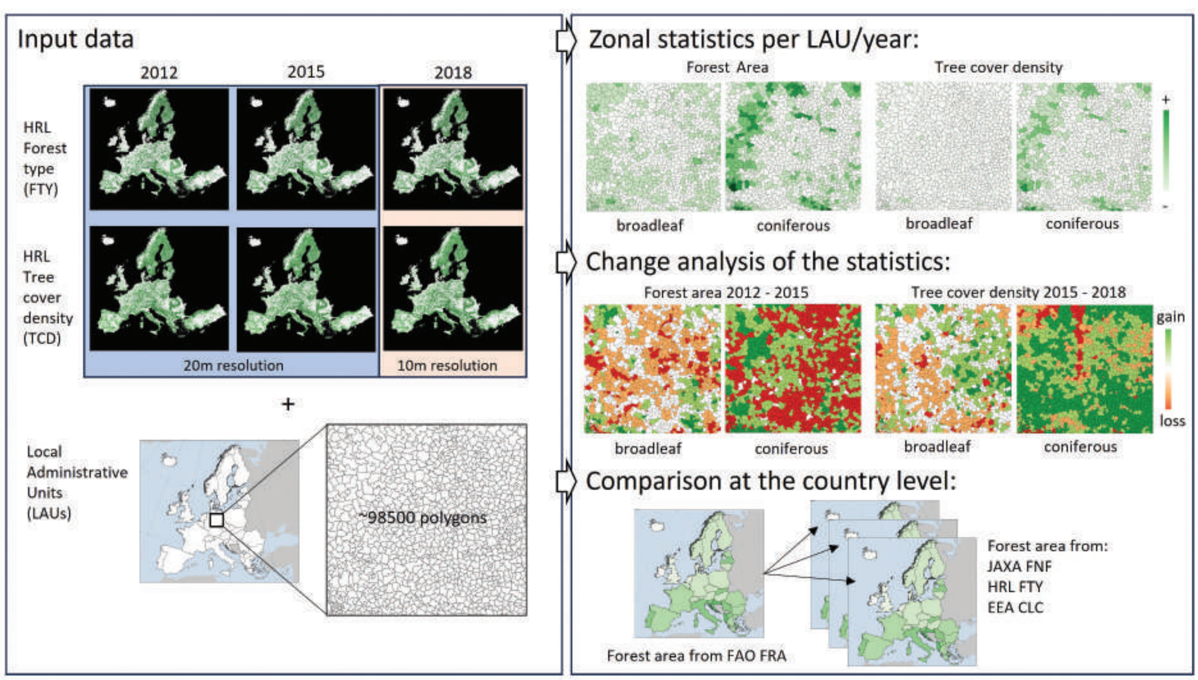

Figure 2. Workflow diagram showing the HRL data used to account for LAU level statistics, analysis of changes between reporting years and comparison between map-based datasets (HRL FTY, JAXA FNF, CLC) and FAO FRA reference data.

does not necessarily meet any definition of forest. For this reason, in this study, non forest areas were masked from TCD using FTY. Both FTY and TCD were available at a spatial resolution of 20 meters for 2012 and 2015 and 10 meters for 2018. The FTY and TCD time series consisting of three dates were analysed at the LAU and country levels, to identify annual statistics and to assess changes, therefore detect gain or loss in forest area and in tree cover density. Finally, to correctly interpret forest statistics and changes according to the altitude and the degree of urbanization, we used the Global 30 m Digital Elevation Model (DEM GLO-30, Appendix A.1.4) and the DEGURBA classification included in the LAU dataset. The altitudinal belts were selected based on those proposed by Kottek et al. (2006) for the Alpine region.

Forests statistics from FTY and two other available EU map-based datasets covering EU area were compared with (i) the Forest Resource Assessment (FRA) by FAO (Appendix A.2.3), (ii) the Global Forest/Non-Forest map (JAXA) by Japan Airspace Exploration Agency (Appendix A.2.1) and (iii) the Corine Land Cover (CLC) by Copernicus itself (Appendix A.2.2). This comparison was carried out at the national level, based on the type and years available. More specifically, JAXA FNF maps are available for 2015 and 2018, as well as FAO FRA datasets, while CLC datasets are available for 2012 and 2018. The differences between country-level statistics deriving from the four datasets were assessed in terms of mean bias error (MBE, Hu et al., 2021). The MBE highlights the similarity of the datasets: values close to 0 indicate that the differences among the two compared datasets are minimal, while values consistently greater or smaller than 0 indicate that there is an over- or underestimation, respectively (Urquhart et al., 2013).

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(d1_i - d2_i)$$

Where *d1* and *d2* are the statistics derived from the data set considered, *i* is the reference country and *n* is the total number of countries.

Results

Comparisons between datasets

Comparison between FAO statistics and those derived from the map-based datasets (FTY, JAXA and CLC) revealed large discrepancies. These results are also reported in Appendix C, Figures A1–A5. Negative MBEs indicate that FTY and JAXA overestimate forest area for both 2015 and 2018 compared with FAO data, with the overestimation reaching 16% and 17% for FTY (Figure A1a) and 11% and 6% for JAXA (Figure A2a–b). Although FAO FRA and CLC can be only compared for 2018 as this is the only year for which they both provide data, they provided the most similar statistics, with an MBE of 4.5% and with a per-country percentage deviation almost always lower than 5% (Figure A3a).

Figure A3–A5 also shows the results of the cross-comparison between FTY, JAXA and CLC. The MBE indicates that JAXA underestimates the forest area compared to FTY for both years, specifically by 5.4% for 2015 (Figure A4b) and 10.4% for 2018 (Figure A4a). However, compared to CLC, JAXA overestimates forest area with a negative MBE of 10.5% (Figure A3b). Finally, FTY overestimates CLC of 21.1% for 2018 (Figure A5a) and 17% for 2015 (Figure A5b). All the MBEs values of the comparisons carried out are summarised in Table 1.

In Figure 3 the average deviation of the comparisons is ranked by each country to assess which country has the largest differences between the datasets under comparison. The mean deviation across all countries is 12.2% with a standard deviation of 4.2%.

Table 1. Summary of MBEs (with standard deviation, SD) from forest area comparison by Copernicus FTY, JAXA, FAO FRA and CLC dataset for the available years.

Dataset 1	Dataset 2	Year	MBE [%]	SD [%]	Figure
FAO FRA	JAXA	2018	−6.25	±8.26	8a
FAO FRA	JAXA	2015	−10.79	±8.58	8b
FAO FRA	FTY	2018	−16.84	±5.57	9a
FAO FRA	FTY	2015	−15.82	±6.49	9b
FAO FRA	CLC	2018	4.54	±4.90	10a
CLC	JAXA	2018	−10.46	±7.80	10b
JAXA	FTY	2018	−10.38	±6.19	11a
JAXA	FTY	2015	−5.36	±8.03	11b
CLC	FTY	2018	−21.11	±6.78	12a
CLC	FTY	2012	−17.01	±7.63	12b

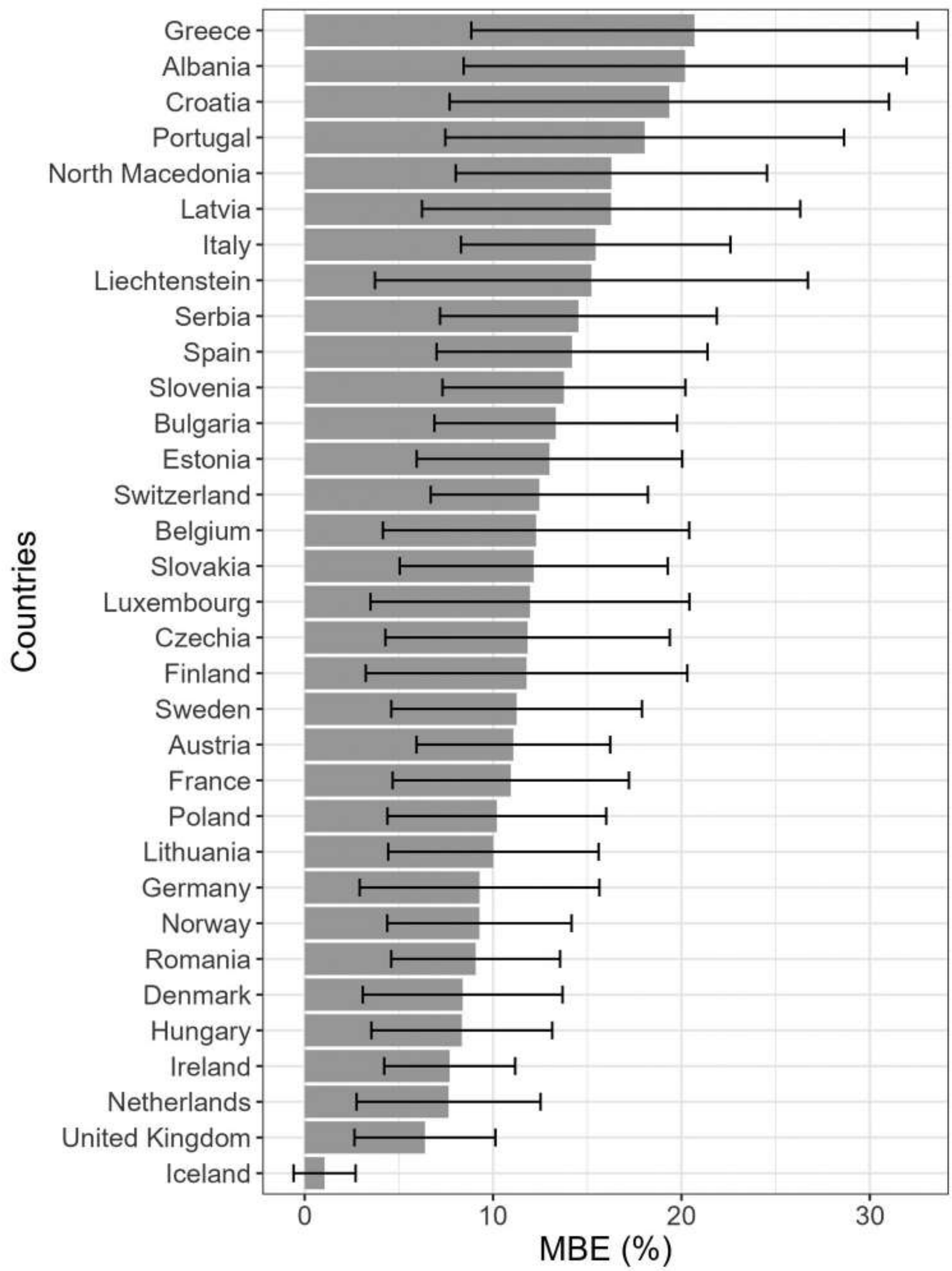

Figure 3. For each country, the MBE% and its SD% are shown from table 2. Mediterranean countries generally show higher values of MBE%, while lower values are reported for countries with high forest cover.

HRIs derived statistics and changes

According to Copernicus FTY, from 2012 to 2015, forests increased by 3%: the average change per LAU was 3.7% while the median was 2.3% (Table 2). From 2015 to 2018, however, the increase was consistently more limited (0.6%), with an average change per LAU near 0 and a median change of 0.6. Forests in urban areas experienced the largest contraction by LAU, going from 39% in 2015 to 26% in 2018 (Figure 4a–c). Broadleaves loss was the main factor (Figure A6b–f) since coniferous did not decline significantly (Figure A6a–e).

Forests remained in a stable condition for all altitudinal belts with a slight decrease in both conifers above 1730 m a.s.l. and broadleaves between 1190 and 1730 m a.s.l. from 2015 to 2018 (Figure 5a–c).

While conifer forests have gradually increased over time, from 2015 to 2018 the increase in broadleaves forests dropped by 0.2%, with a change per LAU of −0.3% (Table 2). The decrease of broadleaves forests in EU has been concentrated in very small and specific areas (Figure 6).

Table 2. Summary Copernicus FTY forest area and TCD tree cover density statistics.

					Δ2012–2015 per LAU		Δ2015–2018 per LAU	
		2012	2015	2018	mean	median	mean	median
FTY	Tot forests	2 357 068 km^2 47.6%	2 510 127 km^2 50.6%	2 538 819 km^2 51.2%	3.7%	2.3%	0%	0.6%
	Coniferous	905 511 km^2 18.3%	937 830 km^2 18.9%	978 565 km^2 19.7%	0.6%	0%	0.2%	0%
	Broadleaves	1 451 557 km^2 29.3%	1 572 297 km^2 31.7%	1 560 253 km^2 31.5%	3.1%	1.8%	−0.3%	0.4%
TCD	Tot forests	22.0%	23.8%	21.3%	1.8%	1.2%	−2.5%	−1.7%
	Coniferous	6.9%	7.5%	6.9%	0.6%	0%	−0.6%	0%
	Broadleaves	15.1%	16.3%	14.4%	1.2%	0.8%	−1.9%	−1.2%

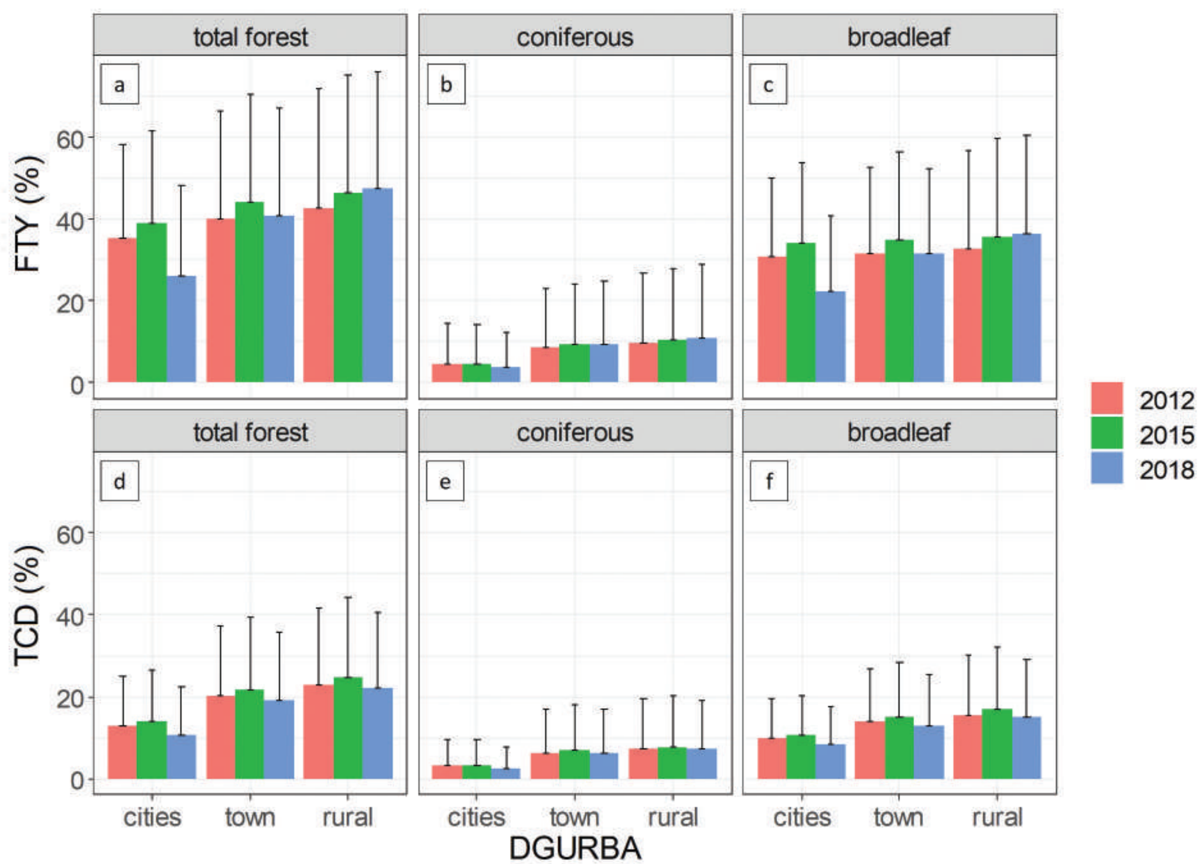

Figure 4. Histograms of average FTY forest area and TCD tree cover density by LAU represented by DEGURBA classes (cities, towns and suburbs, and rural areas) and reference years. From 2015 to 2018, the average forest area per LAU showed a decline in cities and in towns, while it slightly increased in rural areas (a), more in line with broadleaf (c) than with coniferous (b). The tree cover density, however, increased in 2015 and decreased in 2018 in all DEGURBA classes, considering all forests (d) and exclusively coniferous (e) or broadleaved (f) forests.

According to Copernicus TCD, from 2012 to 2015, the tree cover density of the LAU increased by 1.8% on average and by 1.2% on median. Between 2015 and 2018, however, it decreased on average by −2.5%, with a median of −1.7%. In particular, from 2015 to 2018, broadleaves tree cover density decreased by −1.9% on average and by −1.2% on median (Table 2). While the decrease in broadleaves forest areas between 2015 and 2018 was concentrated in very limited portions of the EU (Figure 6), tree cover density decreased almost everywhere between the same years (Figure 7).

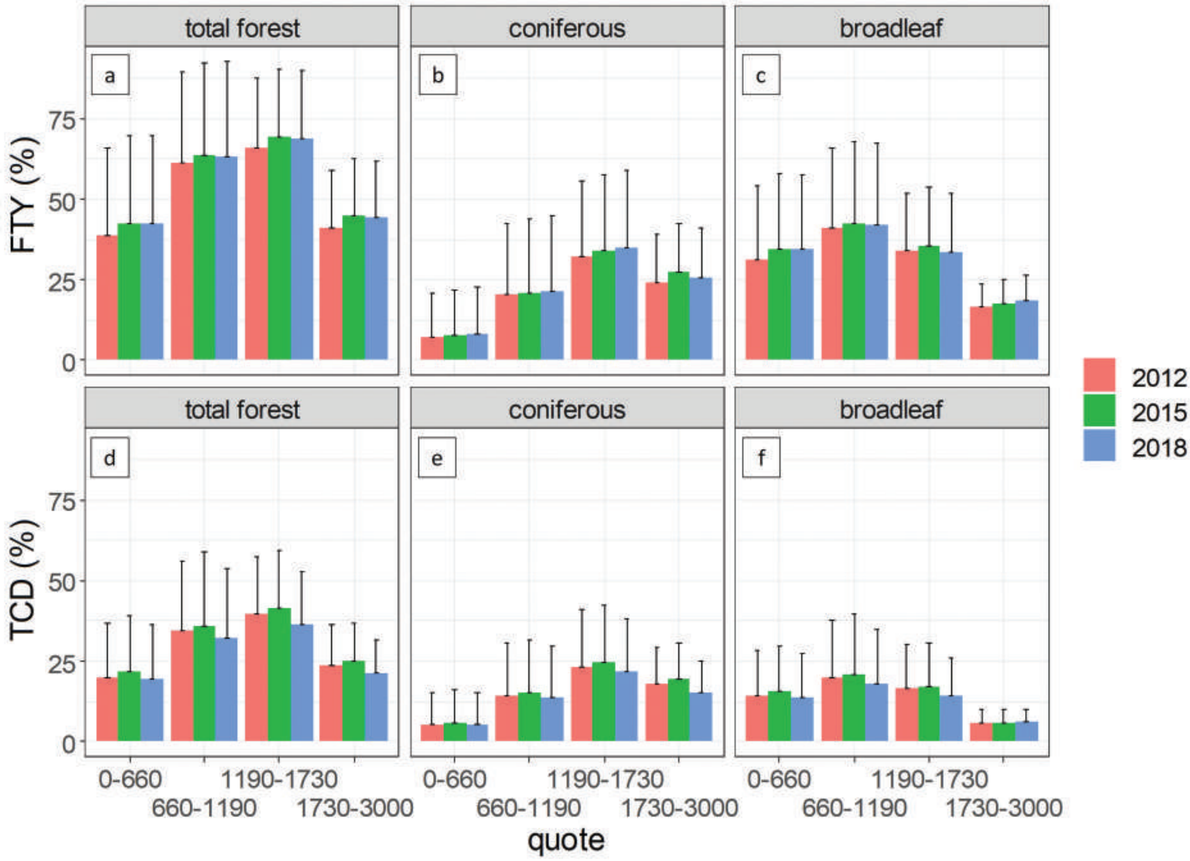

Figure 5. Histograms of average FTY forest area and TCD tree cover density by LAU and by altitudinal belts and reference years. From 2015 to 2018 the average tree cover density per LAU had an overall contraction for both broadleaf and coniferous in the whole altitudinal belts (e,f). The forest area increased for coniferous between 1190 and 1730 m asl and decreased above 1730 m asl (b). Broadleaf remained more or less stable for all altitudinal belts, with a slight decrease between 660 and 1730 m asl (c). In general, results suggest that the altitude didn't have relevant influences on the overall forest area (a) and tree cover changes (d) over time.

From the DEGURBA classification, (i) cities, (ii) towns and suburbs, and (iii) rural areas recorded a decrease in tree cover density from 2015 to 2018 of 3.4%, 2.8%, and 2.5%, respectively (Figure 4d). Losses were particularly evident for broadleaf, especially in cities (Figures 4f, A7b–f) while they were less pronounced for conifers (Figures 4e, A7a–e). Tree cover density had an overall contraction for both broadleaves and conifers across the entire altitudinal range, between 2015 and 2018 (Figure 5d–f).

Discussion

Copernicus EO data are designed to play a key role in continuous forest monitoring, offering broad spatial coverage and high multi-temporal resolution (Apicella et al., 2022). However, the Copernicus system is not the only one providing data on EU forests, as official statistics from NFIs are provided by FAO and other map-based spatial datasets exist such as CLC and JAXA FNF. Despite this wide availability, a comprehensive simple comparative analysis of these sources of information on EU forests had not yet been carried out.

Forest area estimates from HRL, JAXA FNF and CLC, were compared with FAO FRA country-level data to assess their divergence from official NFI forest statistic. In this sense FAO FRA statistics are taken as validation reference at country level, since they are not available at LAU scale. It's important to underline that in this study the focus is on the possibilities related to the usage of Copernicus ready-to-use data, and the other map-based product, as they are provided in the official platform, without additional correction (Avitabile et al., 2024). The observed discrepancies among HRL, CLC, and JAXA forest estimates and FAO

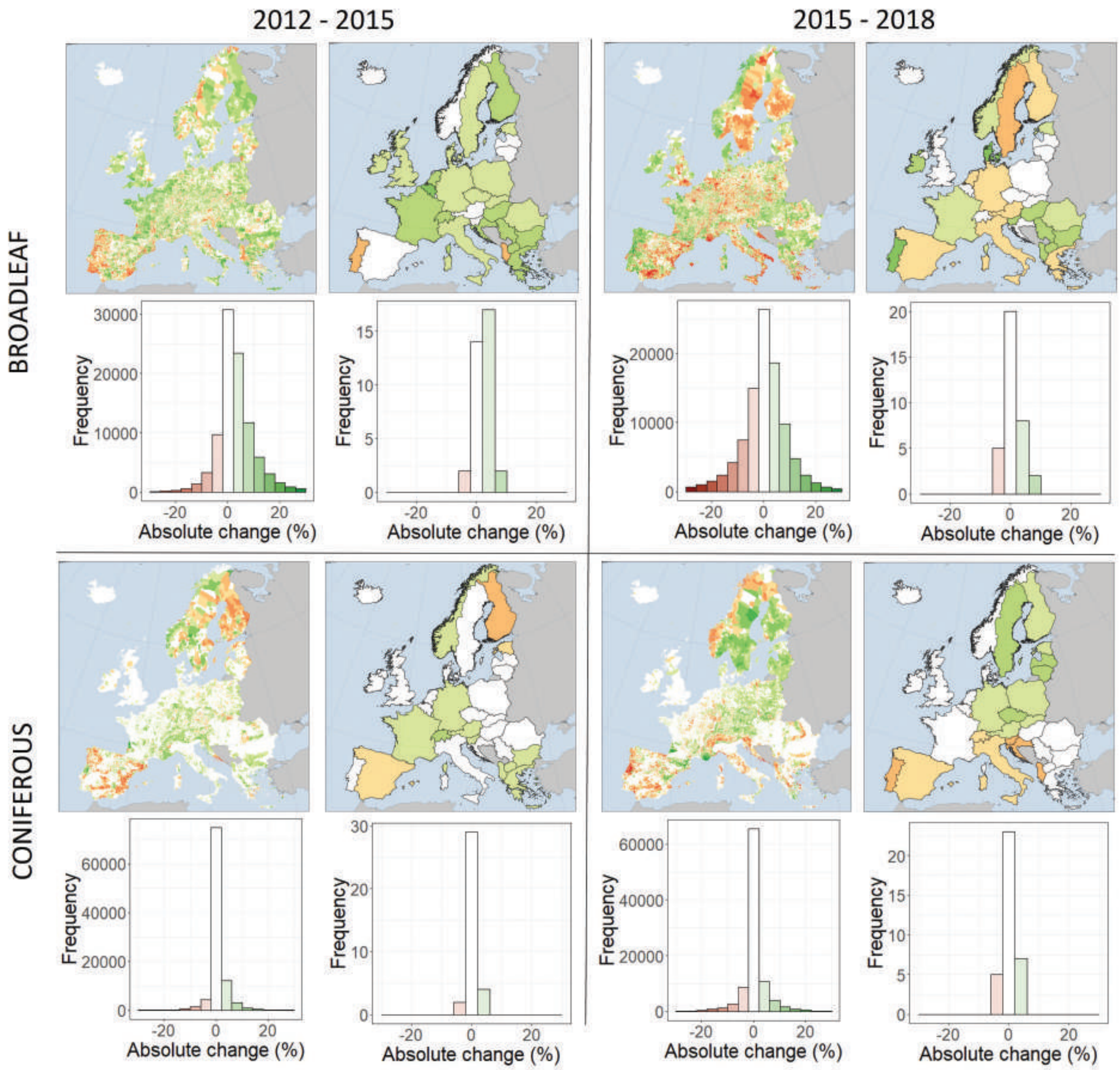

Figure 6. Maps and histograms of forest area change between 2012 and 2015 (left panels) and between 2015 and 2018 (right panels) at both the LAU (left) and country (right) levels.

FRA statistics can be attributed to fundamental differences in their data sources, processing methods, and spatial resolutions. Relevant differences were found between HRL FTY statistics and FAO FRA data, rather than with the other available map-based datasets (Table 1). While JAXA and CLC provided fairly similar forest area estimates to FAO FRA (MBE of −6.2% and + 4.5%, respectively for 2018), compared to FTY, MBEs were high for both years available for comparison (−15.8% for 2015 and −16.8% for 2018). FAO FRA and CLC produced the most similar datasets in terms of MBE, probably because CLC also includes field data and expert validation to supplement maps (Appendix A.2.2.). Compared to FAO FRA, JAXA has an MBE of −10.8% in the 2015 product, revealing higher discrepancies rather than 2018. The JAXA and FTY datasets also showed similarities, which may be due to the fact that both are based on satellite data, albeit from different sensor types (SAR and optical). On the other hand, significant differences persist, and while the MBE% for 2015 was around −5.4%, in 2018 it more than doubled, reaching over 10%. Finally, FTY and CLC, probably because of the presence of validation field data in the latter, produced the most different datasets in terms of MBE, which was −21.1% for 2018 and −17% for 2012.

The forest estimates form HRLs were assessed over 2012, 2015 and 2018 focusing on changes at the LAU and country level. Copernicus HRL products have shown inconsistencies over time, with processing

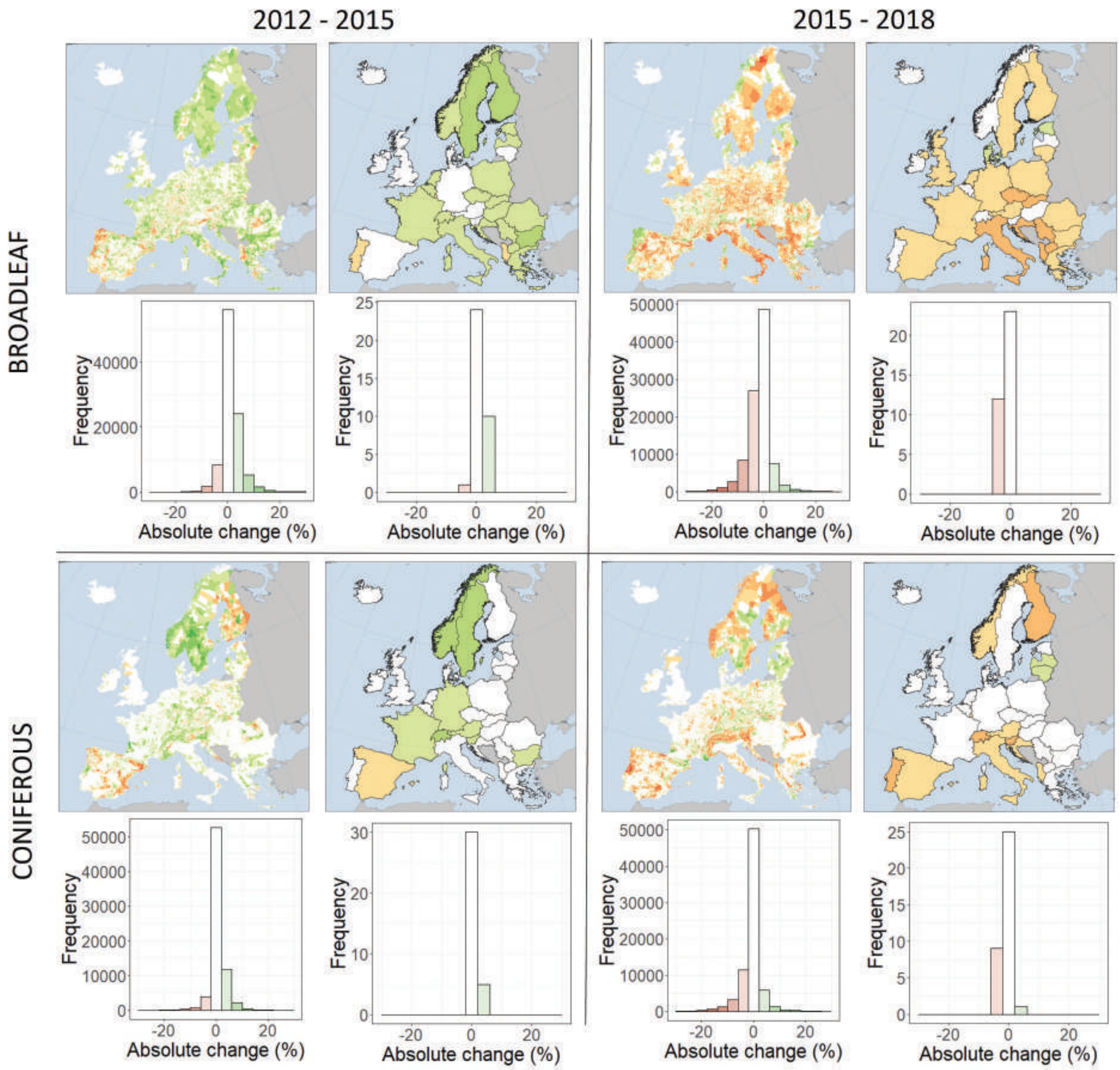

Figure 7. Map and histograms of the percentage change of tree cover density at both the LAU and country level by leaf type and reference years.

methodological changes and sources affecting their comparability across different years. HRLs data has highlighted a reversal of the trend in forest area and tree cover density over the years. In particular, the average area change of LAU in broadleaves forests between 2012 and 2015 was + 3.1%, while between 2015 and 2018, it was −0.3%. The tree cover density also decreased by −1.9% for broadleaves and −0.6% for conifers from 2015 to 2018. Considering the evolution of the imagery from HRL satellite, the changes observed in EU forest area may be mainly attributed to artefacts rather than to actual environmental changes: in particular, the differences between the statistics accounted for over the years suggest that changes in data resolution and processing methods of HRL have played a negative role in the consistency of the data. Indeed, the data source platforms used to produce HRLs have changed continuously over the reporting years. In 2012 and 2015 HRLs had a spatial resolution of 20 meters and were built mainly using the Landsat 5–7–8 satellites, but also SPOT 5 and Resourcesat-1–2. Starting from 2018, HRLs are instead fully based on Sentinel-2. As a result, HRLs spatial resolutions changed from 2012–2015 to 2018 from 20 to 10 m, implying a different ability to detect forest area and tree cover density. At coarser resolutions (20 m), mixed pixels that partially include other land cover can still be classified as forest. However, at finer resolutions (10 m), the same area is represented by a greater number of smaller pixels, some of which may no longer meet the criteria for forest classification: this pixel-splitting effect may lead to a more fragmented map and lower forest area estimates, even when the actual land cover remains unchanged. In fact, looking at 2018 HRLs data, forest detection performed better than the previous data from 2012 and 2015 for land use types related to heterogeneous contexts, leading to a contraction of forest area and tree cover density statistics in 2018. More specifically, the forest trees more accurately predicted in 2018 are included in rural areas with olive groves and fruit trees (Figure A8b), vineyards (Figure A8c), but also poor and densely wooded areas at high altitudes and mountains (Figure A8e) and mixed deciduous and evergreen forests (Figure A8d) and gardens and urban parks in cities and towns (Figure A8a) were more accurately predicted in 2018. Overall, the main differences from 2012–2015 to 2018 were detected in Mediterranean regions, northern Scandinavia, mountain environments and urban green areas (Figure 6).

The methodology and products of Copernicus Land Monitoring Service (2015, 2018) are obviously influenced by the availability and quality of imagery, climate conditions and extreme weather events (Khanal et al., 2020; Notti et al., 2018; Sagan et al., 2020; Zhang et al., 2023). The availability of satellite data is still limited in some regions (Francini et al., 2023), such as northern Scandinavia (Bartsch et al., 2023). Constraints related to satellite platforms (now primarily Sentinel-2) and cloud cover are known to affect the quantity and quality of available satellite observations (Tarrio et al., 2020; Zekoll et al., 2021). Although this study does not directly quantify the relationship, areas with persistent cloud cover are likely more susceptible to misclassification and inconsistencies in forest estimates. Cloud masking issues lead to artefacts in the data, especially in areas with frequent cloud, haze and/or snow cover (Thaler et al., 2023; J. Wang et al., 2021). Furthermore, the terrain correction algorithm used alters the spectral characteristics of tree-covered pixels, making tree cover detection and leaf type differentiation more difficult, particularly in mountainous regions (Feng et al., 2023; Ma et al., 2023). Geometric shifts over time in the multi-temporal coregistration of Sentinel-2A and 2B images further affect the derived statistical features (Gascon et al., 2017; Languille et al., 2015; Rufin et al., 2021). As with other EO systems, all this implies that it is not possible to guarantee with certainty that a particular pixel consistently observes the same landscape feature during an observation period (Axelsson et al., 2021; Yan et al., 2018).

In areas with high spatial heterogeneity, detection of small linear features and sparse tree cover is particularly challenging (Biermann et al., 2020; Deng et al., 2022; Ying et al., 2019). Northern Scandinavian and Alpine regions face challenges due to short growing periods, long-lasting snow cover and distinct topography (Largeron et al., 2020; Radočaj et al., 2020; Udali et al., 2021). Another main uncertainty factor for forest maps based on passive satellite sensors is long-term climate conditions as well as seasonal or exceptional weather events (Sturm et al., 2022), such as in the Mediterranean region regarding the effects of frequent drought phenomena (Mathbout et al., 2021; Tramblay et al., 2020). The over-radiation effect of bright surfaces with sparse tree cover has an impact on the tree cover detection, as the respective areas show almost no spectral signals characteristic of tree cover (Stocker et al., 2019; von Keyserlingk et al., 2021). Drought negatively affects tree cover detection and TCD values as heat and drought stress cause premature leaf discoloration and drop (Anderegg et al., 2019; Descals et al., 2023). The decrease in spectral signal hinders tree cover detection and leads to lower tree cover density values than expected under normal conditions (Senf et al., 2020; Wu et al., 2022). This situation makes additional post-processing steps necessary to compensate for the lack of spectral information in dry regions (Konings et al., 2021; Roushangar et al., 2020).

Conclusion

Approaches for forest monitoring and assessment are rapidly evolving as new information needs emerge and new techniques and tools become available. However, their effective utilization and integration into decision-making processes should be based on validated and reliable data sources to ensure transparency and accountability (Corona, 2018). In this study, we used Copernicus HRL forest products to deliver multi-temporal forest statistics at the LAU level, aiming to assess whether Copernicus provides simple, uniform, and practical data on the state of forests. Copernicus currently offers powerful products for deriving forest-related information at various administrative levels across EU countries, which could be instrumental in guiding forestry, environmental, and rural policies in Europe.

However, our analysis has revealed certain limitations in using these statistics. Specifically, our comparisons have shown significant discrepancies between Copernicus data and FAO FRA statistics, as well as other map-based products such as JAXA FNF and CLC. Moreover, Copernicus forest HRLs do not yet constitute a fully uniform system. Their statistics vary over time due to changes in image sources and processing methods, and they lack smart access to local-level data. This highlights the need for further efforts toward developing a single, comprehensive EU forest monitoring system.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

All the data used in this study is open access. If the readers need support they can contact saverio.francini@unibo.it or http://lorenzo.cesaretti@uniroma1.it.

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