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Integration of high-resolution data for a complementary assessment of forest dynamics in Europe

Benjamin Labohm [a,*], Manuel Wolff [a,b,*], Dagmar Haase [a,c,*]

[a] Department of Geography, Lab for Landscape Ecology, Humboldt Universität zu Berlin, Unter den Linden 6, 10117 Berlin, Germany
[b] Department of Urban and Environmental Sociology, Helmholtz Centre for Environmental Research – UFZ, Permoserstraße 8 15, 04318 Leipzig, Germany
[c] Department of Computational Landscape Ecology, Helmholtz Centre for Environmental Research – UFZ, Permoserstraße 15, 04318, Leipzig, Germany

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ABSTRACT

This study addresses the need for a cohesive pan-European forest monitoring system by developing a methodological framework to generate and provide spatially explicit and complementary indicators of forest dynamics. Utilizing Copernicus High-Resolution Layer Tree Cover Density data, we operationalize two key indicators—forest extent and condition—essential for robust forest monitoring across Europe. Our multi-step data processing methodology enhances data interoperability and usability, mitigating biases. By integrating both, changes in forest area and canopy density between 2012 and 2018, our approach provides nuanced insights into forest dynamics. These indicators offer robust monitoring supporting the assessment of forest resilience amidst climate change impacts and other stressors. This paper contributes a ready-to-use dataset on European forest dynamics, leveraging advanced technologies and big data availability to support sustainable forest management and the evaluation of Agenda 2030 goals.

- Development of spatially explicit indicators for forest extent and condition.
- Integration of Copernicus HRL TCD data using a standardized processing framework.
- Application of multi-step data processing to ensure data quality and reliability.

Specifications table

Subject area:	Earth and Planetary Sciences Earth and Planetary Sciences
More specific subject area:	Forest monitoring, geographic data analysis
Name of your method:	Development of spatially explicit indicators for forest extent and condition
Name and reference of original method:	If applicable, list the full bibliographic details of any key reference(s) that describe the original method you customized
Resource availability:	https://www.r-project.org/ https://land.copernicus.eu/en/products/high-resolution-layer-tree-cover-density https://github.com/blabohm/forest_dynamics

Background

With over 200 million ha, forests in Europe cover more than one third of the continent [1]. Forests provide multiple ecosystem services, involving the regulation of climate conditions and biophysical processes such as oxygen or nutrient cycling, the supply of timber, the provision of freshwater and clean air, and the contribution to human health and recreation [2,3]. Thus, forests play one

* Corresponding authors.
E-mail addresses: benjamin.labohm.1@hu-berlin.de (B. Labohm), manuel.wolff@hu-berlin.de (M. Wolff), dagmar.haase@ufz.de (D. Haase).

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central role for achieving the multiple goals and targets of the 2030 Agenda for Sustainable Development [4] - most prominently SDG 15 (life on land).

However, forests in Europe are subject to constant changes. Climate change impacts and associated other key drivers such as pests, diseases, extreme weather events and forest fires threaten forest's biodiversity and multi-functionality [5]. Pressure by air pollution, land abandonment and land consumption results in higher tree mortality, which in turn shapes forest structure, biomass and resource availability [6]. There is growing evidence that these combined effects are increasing forest disturbance impacts in Europe [7–9]. Forests are at risk to lose their capacity to maintain their structure, functions and services [9–11].

Forest area gain is associated to tree regeneration after logging or natural disturbances and tree planting on former arable land while forest losses are an effect of wildfires, windthrow, or bark beetles with subsequent forest clearing, as well as land grab by buildings or infrastructure development [9,12,13]. Considering the rapid changes in forest disturbance regimes, robust forest monitoring is required to understand and model forest dynamics and detect hotspots for adapted management and protection strategies to increase forest resilience [14]. Forest data availability across Europe is improving in the last decade. But the lack of a consistent and comprehensive pan-European forest monitoring service currently hampers the effective use of all available forest information. National Forest Inventories largely face disparate methodologies, high data collection costs, difficulties to access timely data. Earth observation like the Copernicus program provides a range of (spatial) information on forests. However, this data lacks proper integration into management practice and interpretation – it is hardly usable for non-experts [15].

This paper aims to fill this gap a) by proposing two key indicators to assess changes in the overall forest dynamics across Europe: forest area (growth and decline of forest extent) and forest condition (health and vitality as indicated by canopy density), and b) providing a workflow of handling imagery data to create the two indicators [16]. The two indicators provide spatially explicit information on forest dynamics in Europe between 2012 and 2018 based on accessible and reliable high-resolution data at European scale. This allows for effective and consistent use of the available information with existing services and strengthen general forest monitoring, while ensuring applicability on future data releases.

State of the start

There are a multitude of approaches and products suitable for forest monitoring available on global, European and regional scales [13,16–19]. The standard reference for global forest resource information, the FAO's global forest resource assessment (FRA), uses a land use based forest classification in their 5–10-yearly report (FAO / FRA) [16]. The FRA has some limitations, including inconsistent methods between countries, changes in forest definitions between reports, and reporting only net area changes [19]. Hansen et al. (2013) highlight forest change detection issues of a land-use based definition and emphasize discrepancies when comparing tabular data with differing criteria. Additionally, they introduce the Global Forest Change (GFC) product, using the FAO forest definition, with a 50 % tree cover threshold per 30 m raster cell. Forest loss, in this case, is a change from > 50 % to 0 % tree cover. Forest gain is a crossing of the threshold in the other direction [19]. A threshold based classification is highly dependent on the choice of threshold values and class boundaries (MOD44B_User_Guide_V61) [20]. The GFC product annually presents a global forest loss and gain classification since the year 2000. However, Hansen et al. acknowledge challenges, especially in European data, with the GFC product showing the least correlation with the FAO FRA in Europe [19,21]. These challenges might be attributed to the land-use focused FAO forest definition - a biophysical change in forest cover might not reflect a change in land-use [19] (Hansen et al. 2013 supplementary material).

To address these issues, the MODIS Vegetation Continuous Field (VCF) product (MOD44B) was created [17]. The MODIS VCF product has a spatial resolution of 250 m, representing a percentage of tree cover per raster cell. The product is based on the global 16-day MODIS satellite data composite. The VCF product may in theory allow the computation of the combined tree cover density and net-area changes of forests if aggregated to a lower spatial resolution. However, a 250 m resolution might enable global monitoring on a high temporal resolution but may not be suitable to detect small patches of trees, especially in complex environments with a more mosaic structure like e.g. cities [20,22].

One of the more recent and advanced methods regarding the monitoring of forest dynamics in Europe was developed by Senf and Seidl. In their report, Senf and Seidl focused on forest disturbance in continental Europe from 1986 to 2016. They rely on Landsat data and a time-series segmentation approach called LandTrendr. Their approach allows for the detection of disturbance events on a temporal as well spatial scale. Consecutively enabling insight over the frequency and scale of disturbance events in European forests [9]. In another paper, Senf et al. described canopy mortality as any loss of canopy, based on spectral reflectance properties. With this approach, they were able to detect trends in canopy mortality, as well as the share of young forests in Europe [23].

To complement these disturbance and mortality based approaches, we use a combination of forest extent and condition, based on high resolution Tree cover density (TCD) data for Europe as part of the high resolution land-cover (HRL) product of Copernicus. The HRL is produced in a 3 year cycle on a pan European scale. The TCD product represents the "vertical projection of tree crowns to a horizontal earth's surface" [22,24]. The TCD products are delivered in a 20 m and a 10 m resolution, which is 2.25 to 9 times higher than Landsat, respectively. Sentinel's 10 m resolution gets close to identifying individual trees and might perform better in urban and peri-urban areas. Further advantages of a higher resolution are that the raster data can be better matched with vector data, since the raster cells can represent complex shapes in better detail [25].

Method details

By combining forest area and forest density, we aim to provide spatially explicit and ready-to-use Earth-observation data to foster a robust and comprehensive European monitoring system on forest dynamics.

Indicators

Regarding objective a, we have compiled two indices for tree cover changes in continental Europe. Forest area change is a quantified measure of forest change. It mirrors the pure forest stock and is used as a proxy for afforestation/deforestation, the role for biomass and ecological connectivity, as well as for several other regulating ecosystem services [26–28]. Tree cover density changes indicate the ecological quality and health of forest ecosystems while negative changes indicate disturbance [29–31].

Input data

For our analysis, we used a high-resolution dataset on tree-cover-density for the reference years 2012 and 2018 [22]. These products are derived from high resolution satellite imagery via random forest classification and multiple linear regression. Values represent the percent of ground area of a raster cell covered by tree crowns ranging from 0 to 100.

The 2012 TCD product has a spatial resolution of 20 m and is based on multi spectral high-resolution (HR) satellite data complemented by very-high-resolution (VHR) satellite or aerial ortho-imagery data as reference data (Sentinel 2A, Landsat 8, SPOT-5, ResourceSat-2). The VHR and ortho-imagery was visually interpreted on a point grid. Tree cover density values were then transferred to the HR data using a multiple-linear-regression estimator. Thematic accuracy was reported to be at least 90 % in users and producers accuracy and was assessed using internal and independent validation approaches [24].

The TCD 2018 product is based on 10 m resolution Sentinel 2A and 2B time series data. The satellite data is complemented with training and validation data from the LUCAS 2018 database, LPIS data, OSM data, VHR satellite data, as well as previous HRL products. Processing of the Tree Cover Density product entails multiple steps using random forest classification, a multi-linear regression model and rule-based plausibility checks . The HRL 2018 products have a robust validation approach using a total of 9695 100 × 100 m plots, which were filled with a 5 × 5 point grid and manually interpreted [22]. Copernicus overall / user / producer accuracies for forest / no-forest classes are all well above 90 %, most are above 95 %. In comparison, the MODIS VCF product was only validated with two validation sites [20]. Hansen et al. (2013) used only a portion of validation data in temperate forests (n = 298), as compared to the TCD data set. Hansen reports very high overall accuracies for forest change in the temperate zone, but user and producer accuracies for loss and gain are lower (Loss: PA: 93.9, UA: 88.2; Gain: PA: 76.5 %, UA: 62. %). These classes also express very high standard errors (partly > 14 %) [19]. Even though the validation approaches in the GFC, MODIS VCF and TCD production process may differ, we conclude that the amount of training and validation data used for TCD production provides the most robust information on data quality.

Data processing

Regarding the second objective (b), we developed a workflow to create the two indices:

Forest area change product: First, we quantified the change of forest area in Europe by aggregating the HRL TCD data of each time step to a spatial resolution of 1 km. For each resulting raster cell, we calculated the relative forest coverage. Subsequently, we calculated the change between 2012 and 2018 (Δforest area in%-points, see Fig. 1A).

Forest condition change product: To avoid biased results for tree cover density changes in areas with expanding or declining forest areas we considered only forest area that was existing both in 2012 and 2018, by masking stable forest in both time steps (see Fig. 1B). We aggregated the stable tree cover to 1 km resolution, averaging the values in each cell and calculated the change between time steps (ΔTCD in %-points). By aggregating both indices to a 1 km grid, we avoided several uncertainty constraints of the high resolution TCD data (data quality chapter, JRC user manual) and ensured compatibility with other European data sets that align with the INSPIRE grid [32]. As a further quality measure, we excluded any of the resulting 1 km raster cells that contained NA values in the original data. All analyses were performed using R Statistical Software, specifically relying on the *terra* package for raster processing [33–35] (Table 1).

Table 1
Overview of the 1 km^2 resolution raster layer products covering continental Europe.

Indicator	Layer	Value range	Description
Forest area	2012 2018	0 to 100	Share of raster cell area covered by forest; max = 100 % = 1 km^2 forest area
	change	−100 to 100	Forest area change in percent
Forest condition	2012 2018	0 to 100	Average canopy density of forest area in raster cell; max = 100 % = Ground in raster cell is fully covered by tree canopy
	change	−100 to 100	Canopy density change in percent

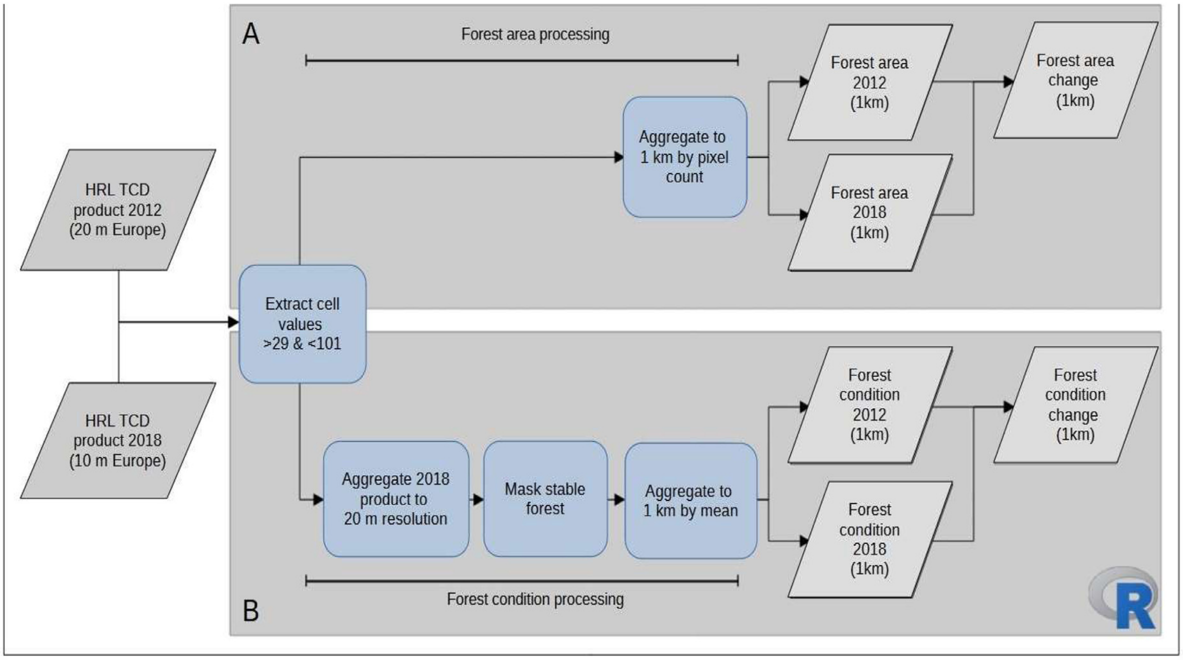

Fig. 1. Processing scheme for the creation workflow of forest area and forest condition change products, including intermediate steps and products.

Data quality check and sensitivity analysis

Data uncertainties

Since the HRL TCD products are based on satellite data, some data constraints apply including a) reduced data availability due to frequent cloud cover e.g. in Scandinavia or the French overseas; b) topographic over-correction at north and northwest oriented slopes and certain reliefs; c) multi-temporal co-registration errors affecting reliability at areas with high spatial heterogeneity e.g. tree lines, alleys, small tree patches, urban tree cover, sparse canopies with bright surface like olive groves. Most of these constraints have a higher impact on areas with sparse tree cover, such as in southern parts of Spain, Italy, Greece as well as parts of Portugal, Scandinavia and the Balkan. Furthermore, climate conditions also impact the observed trends of the data. The 2018 drought in particular might impose a systematic bias in large parts of Europe as drought in general can expose bright dry or bare soil surfaces at areas with sparse tree cover, especially in the Mediterranean. However, we feel encouraged to use the data considering that climatic extremes are predicted to occur more frequently in the near future [1] (Forest Europe, 2020) and also due to the fact that it is the most recent data which allows an estimation of tree cover density. Finally, areas with short growing periods like alpine regions or northern Scandinavia might be unreliably represented due to the shorter time frame for vegetated satellite image acquisitions.

Due to the high probability of a systematic error in areas with sparse tree cover we exclude all raster cells below a threshold of 30 % tree cover density following recommendations during the validation process of the data in order to increase the products accuracy [22,24]. To assess the general impact of this decision, we conducted a sensitivity analysis comparing the full data set to the one which we applied the threshold to.

Sensitivity analysis

As we see in Fig. 2A, the 2012 TCD product has a higher share of tree cover values below the 30 % threshold (see above), i.e. a share of raster cells that will be excluded from index calculation. Possible reasons for this effect are i.) the lower spatial resolution of the 2012 TCD product leading to lower sensitivity to smaller forested patches, ii.) higher data availability due to the availability of Sentinel 2B, resulting in better vegetation detection in the 2018 TCD product [25]. In general, the percentage of raster cells (x-axis) that are excluded by the application of the threshold is relatively low. As shown by the plot on the right side, there is no obvious systematic error visible (e.g. a peak in the higher percentages), as well.

Applying the 30 % threshold slightly increases the change of forest area values and decreases forest density values (see Fig. 2B). The share of excluded raster cells with low TCD values is higher in 2012 (see Fig. 2A). Thus, the application of the threshold leads to an increase of the average of the remaining values in 2012. In consequence, the average change between the years 2012 and 2018 must drop. Looking at the forest area, we see the opposite effect (see Fig. 2B). A higher share of removed raster cells decreases the

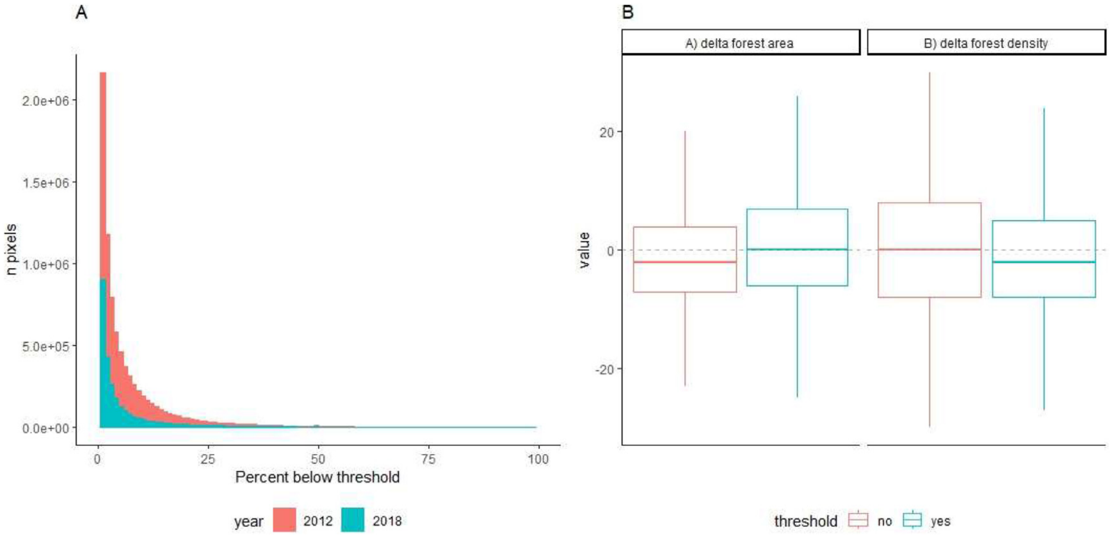

Fig. 2. Distribution of the share of input raster cells below the 30 % TCD threshold in the 1 × 1 km raster cells of the output products per year (A). Impact of the threshold application on the distribution of index values (B). Distributions are shown for forest area (left) and forest density (right) with and without the 30 % threshold applied (blue and red, respectively).

raster cell count per 1 × 1 km raster cell (i.e. the area) in 2012. Thus, leading to a larger decrease of the average area per raster cell in 2012. In turn, the average change in forest area must increase.

Still, the overall impact of implementing the 30 % threshold on the distribution of the index values is low. However, systematic errors due to the effects elaborated above are minimized and, in turn, increases the robustness of the change detection.

The first row in Fig. 3 focuses Southern Italy. The heel of the Italian boot shows a comparatively high share of raster cells below the threshold in 2018. Nonetheless, except for some small scale increases, there is no larger-scale impact on the forest condition index visible in this area (i.e. stable forest condition remains the same). The forest area index, on the other hand, shows a large-scale

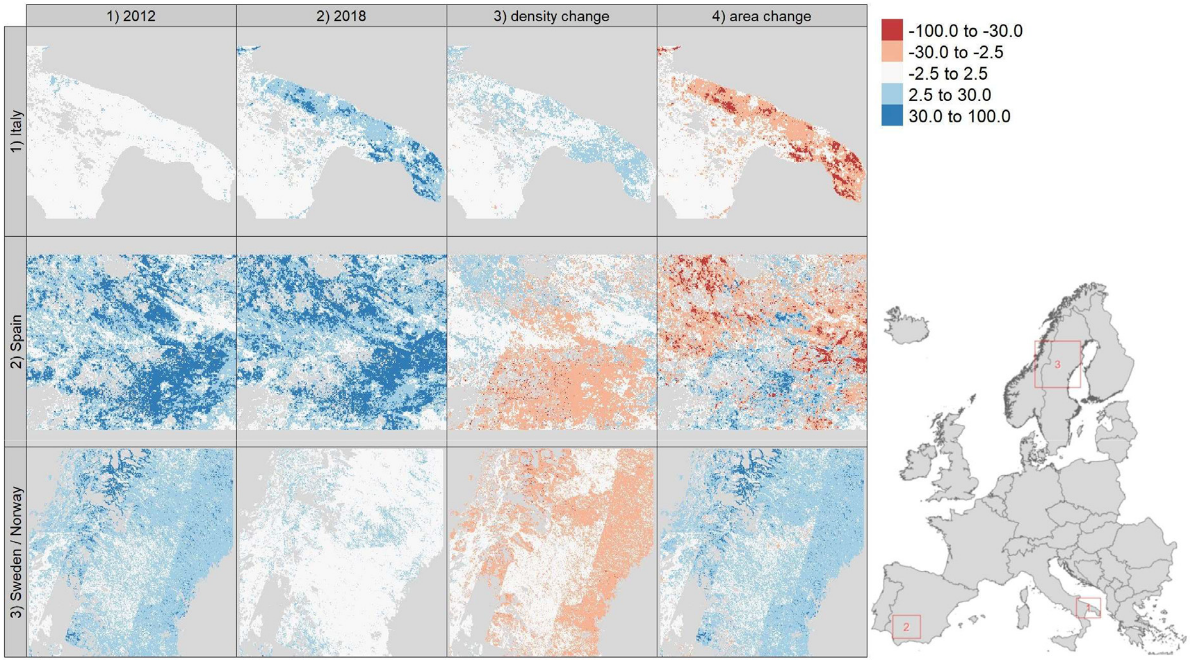

Fig. 3. Spatial distribution of the share of raster cells below the 30 % threshold per 1 × 1 km raster cell in the years 2012 (left) and 2018 (center left). The two right rows show the change in index values due to threshold application on forest condition (center right) and forest area (right). A lowering impact is depicted in blue, an increase in red.

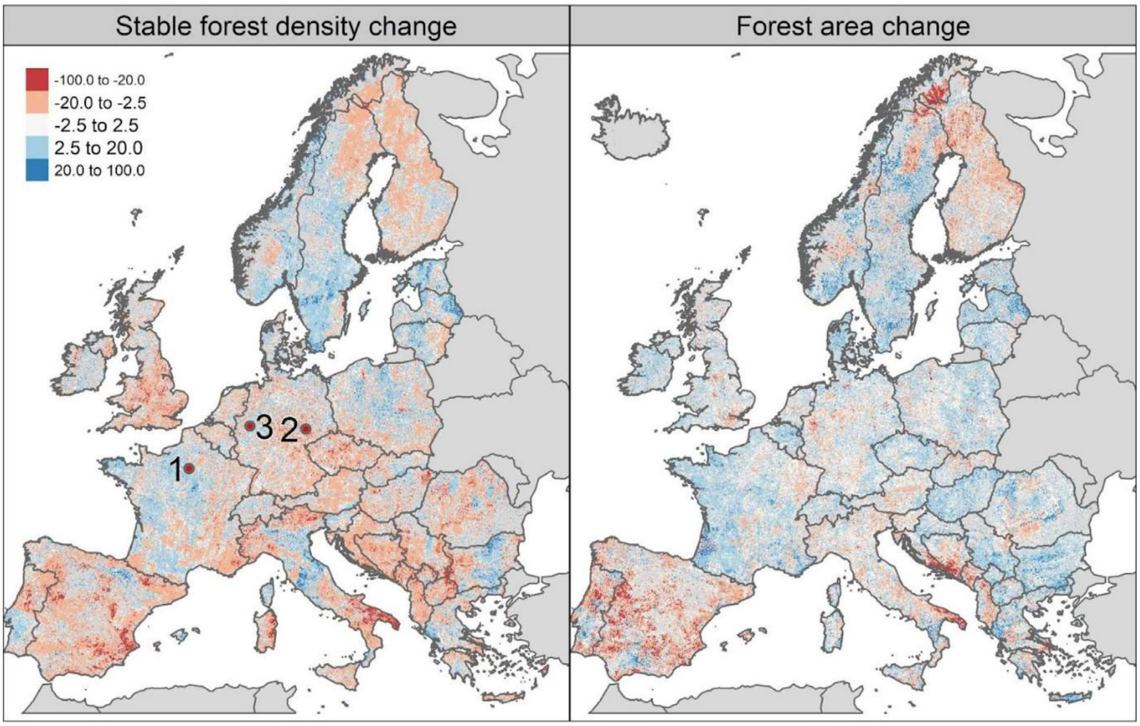

Fig. 4. Stable forest density change (left) and the forest area change (right) in continental Europe. Red colors indicate forest density decline/forest area loss. Blue colors indicate forest densification/forest area gain. The demonstration cases of Fig. 5 are highlighted and numbered.

decrease of index values (probably due to excluded raster cells, i.e. smaller area per 1 × 1 km cell). This already demonstrates the complementary nature of the two indices.

The second row in Fig. 3 shows a scene from Southern Spain. This plot exemplifies the generally low density of the vegetation coverage in parts of the Mediterranean region. Similar spatial patterns of raster cells below the threshold value are visible in both time steps. Consequently, applying the threshold results in more complex spatial patterns. Here, we see that threshold implementation lowered forest condition change values in the south of the plot and increased them in the north-west. Again, forest area change values express the opposite behavior, the overall impact on the area index is much stronger though. Towards the east / north-east there are large patches of a strong lowering impact of the threshold on forest area change.

The third row in Fig. 4 is a scene from Northern Scandinavia. The left tile shows clearly visible geometric patterns / stripes in the spatial distribution of the share of excluded raster cells. In addition, there are large swaths of areas with masked NA values (gray) that are mostly aligning in parallel to the geometric patterns in the share of excluded raster cells. These patterns are likely artifacts of low input data density in 2012. The two right hand side plots show the effects on the index values in this area. While the index for change in forest condition is generally decreased, the forest area values are mostly increased due to the threshold application. This perfectly aligns with the findings from above (less low values raster cells increase average of remaining raster cells in 2012, leading to a lower change value; more excluded raster cells lead to lower area values in 2012, leading to larger area changes). Thus, any increase in forest condition, as well as decreases in forest area in this region should be treated with caution (see Fig. 2B).

Method validation

In Fig. 4, we demonstrate forest density change and forest area change between 2012 and 2018. The average density of stable forest in Europe was 69.73 % in 2012 and 68.22 % in 2018. The total forest area was 1722,005 km^2 in 2012 and 1795,904 km^2 in 2018. The average density of European forested area has decreased by 1.51 % in the six-year period, while the forest area has increased by 73,899.09 km^2 or 4.29 %.

There are several consistent patterns between the two indicators. In northern Scandinavia there is a general decrease in both density and area. Towards southern Scandinavia, however, both indicators tend to be positive. In southern Europe, forest density and area also show overlapping negative patterns (e.g. in Spain, southern Italy, the Adriatic coast of the Balkans). In Central Europe (e.g. Belgium, Netherlands, Germany, Poland, Czech Republic) forest density is generally decreasing, while forest area is mostly increasing.

In Fig. 5, we demonstrate how the forest density and area products that we devised can be used to detect forest dynamics in urban to rural ecotones. We do so by comparing the indicators to a forest density change product derived from 250 m resolution MODIS VCF products from comparable time steps (MOD44B 2012 & 2018, tiles: h18v03 / h18v04) [17].

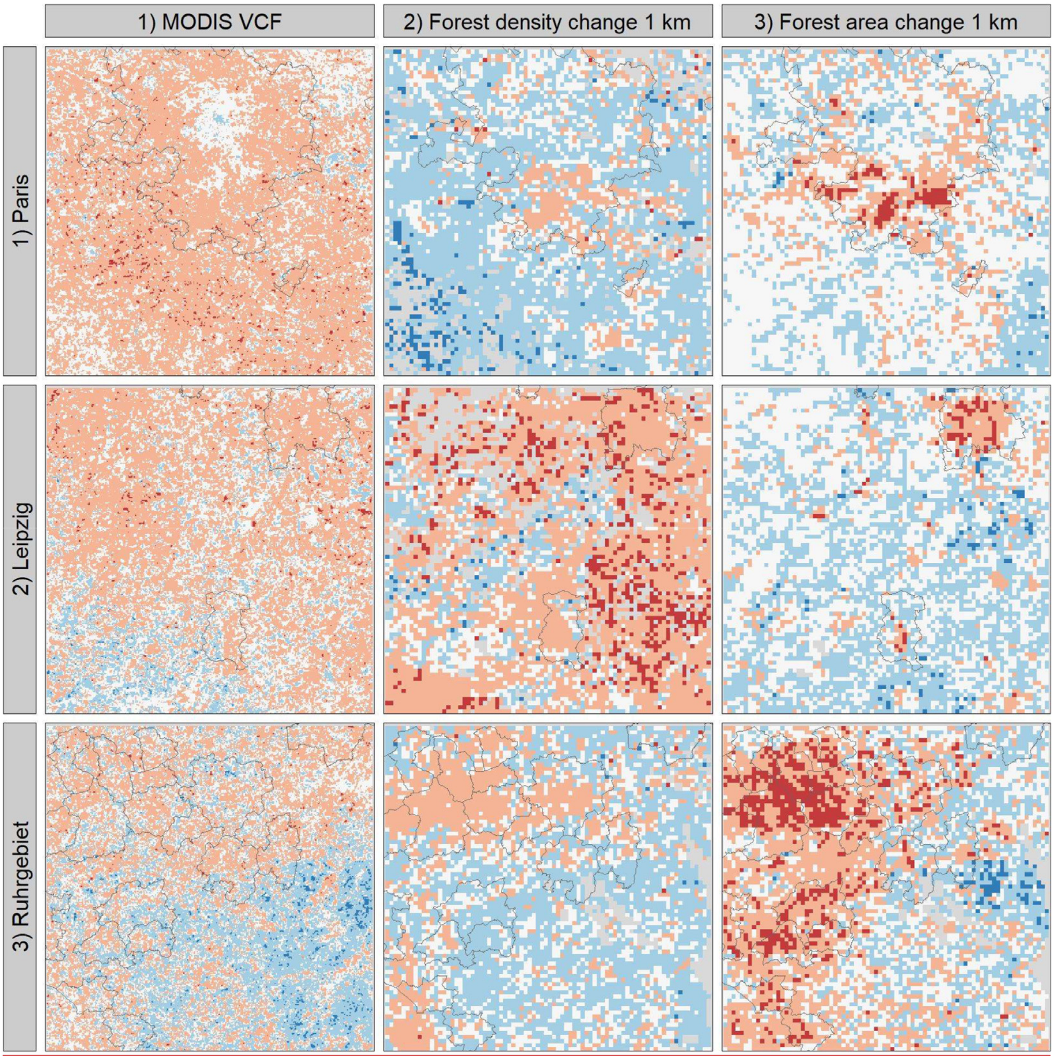

Fig. 5. Comparison of data products: delta forest density in 250 m (based on MODIS VCF 2012 - 2018) and 1 km (based on the aggregated TCD product) resolutions. Blue colors indicate an increase in density, red colors indicate a decrease, white indicates no change; gray indicates no forest. The columns show three example locations shown in the Europe map (Fig. 4).

The first row shows the city of Paris in France. The MODIS product (top left) detects a widespread slightly negative density change, with small areas of higher negative change to the south of the city boundary. In the center of Paris, as well as to the east of the city, we see areas with no change or a slight increase in forest density. The density change product derived from the TCD products gives a different picture. Here we see a general slight increase in density, with larger increases in the south-west. There are areas of small negative density change in the southern city and in smaller areas across the central to north-eastern map. On the other hand, the forest area change product shows a more mixed picture for Paris. The city center, where there is no or slightly positive area change, is surrounded by a ring of slight area loss. The southern part of the city even shows larger losses of forest area.

The second row shows the area between the cities of Leipzig and Gera, Germany. Again, the MODIS VCF derived product shows a general decrease in (floodplain) forest density with a larger area of density increase in the southwest. The TCD derived density product also shows a general decrease in density in this area. Here we see a larger band of negative density changes scattered across the northern and eastern parts of the map. The forest area change product shows a small overall increase in area. The cities of Leipzig and Gera and the villages below the city of Halle are major exceptions, showing regions with low to high decreases in alluvial forest area.

The third row shows the eastern Ruhr area in western Germany. The map shows the large conglomeration of cities along the northern and western edges. The MODIS VCF derived forest density change product mostly expresses a slight decrease in these cities. In contrast, in the southeastern part of the country, the product shows mostly low to high density increases. The TCD derived forest density product shows a similar pattern, except that the area of density decrease is mostly confined to the city limits along the northwestern and southwestern edges of the map. All other areas mostly show a slight increase in density. The forest area change product shows a strong loss of forest area within almost all city boundaries, shifting to a strong increase in the central eastern part of the map.

Data availability

All corresponding data and the code used for data processing are published on our GitHub repository (https://github.com/blabohm/forest_dynamics).

We used Copernicus High Resolution Layer Tree Cover Density products for the years 2012 and 2018, available in the data browser of the Copernicus website (https://land.copernicus.eu/en/products/high-resolution-layer-tree-cover-density).

Limitations

The products presented in this paper are mainly based on Earth observation data, which usually have some methodological drawbacks.

Firstly, it is important to note that the TCD products are based on satellite data, which means that some data limitations apply. These include: a) reduced data availability due to frequent cloud cover, e.g. in Scandinavia or the French Overseas Territories; b) topographic over-correction on north- and northwest-facing slopes and certain reliefs; and c) multi-temporal co-registration errors that affect reliability in areas with high spatial heterogeneity, such as tree lines, alleys, small tree patches, urban tree cover, sparse canopies with light surfaces such as olive groves. It is clear that these limitations have a much greater impact in areas with sparse tree cover, such as southern Spain, Italy, Greece and parts of Portugal, Scandinavia and the Balkans. In addition, the release delay of HRL TCD products is typically around two years, making them of limited use for real-time change detection.

Second, the TCD products are based on partly different production methods, input data sources, and thus different resolutions, which somewhat limits their comparability over time (Copernicus user manuals). The only reasonable way to compare newer TCD products with the 2012 and 2015 time steps is to aggregate the newer products to 20 m, which reduces the accuracy. To ensure data quality and consistency, the presented products apply a 30 % threshold, following technical recommendations [22,24]. However, this excludes many potential areas of interest, especially in the higher resolution 2018 layer, such as individual trees or tree lines (see also [36]). For example, one of four 10 m raster cells may have > 90 % tree cover, but if the three surrounding cells have < 30 % cover, the raster cell is excluded.

Thirdly, it is important to note that the indicators used here are only proxies for forest extent, health and ecological value. As we have argued, canopy density is influenced by a wide range of factors. The final products on changes in forest extent and canopy density that we have presented here are a clear representation of the impact of the 2018 drought event. Therefore, by combining our results with other parameters (e.g. temperature, precipitation, drought indices), we can compare the impact of droughts on forest dynamics on a European scale. Furthermore, forest dynamics in this product cannot distinguish between natural and planted forests. In future research, we will overcome these shortcomings by distinguishing between forest dynamics in protected or managed areas and those in unprotected areas. In this way we expect to reduce the proportion of forest plantations in the protected area class and to obtain a cleaner picture or even a comparison of forest dynamics in natural and managed forest ecosystems.

Nevertheless, and as we have shown in the demonstration, our change products offer a simple and straightforward way to perform comparative spatial analysis at the European scale, with several advantages. Firstly, the products presented are based on Sentinel Earth Observation data, which will be continuously updated, thus providing a high resolution and high quality alternative to previously used data such as MODIS or Landsat based products. The method presented here allows for easy processing and production of the two forest dynamics indicators presented and thus supports the development of a robust European monitoring system, complementing other excellent products [9,12,13]. For example, Senf et al. (2021) found similar trends in forest mortality in Western and Northern Europe to those presented here, while Turubanova et al. (2023) confirmed our observations, particularly in the Baltic States, Eastern Europe and Fennoscandinavia [9,13]. To the best of our knowledge, no higher resolution data are currently available for the whole of Europe. As a consequence, the TCD data are much more precise in certain regions of Europe, as shown here, such as cities and, to some extent, urban-rural interfaces, making these products more relevant for planning practice or ecological assessment, e.g. ecotones.

Secondly, aggregating the products to 1 km^2 has several advantages. The amount of data can be easily handled by smaller machines and desktop GIS. This spatial resolution also represents a compromise between a European comparative perspective and a spatially dis-aggregated picture for urban or biodiversity assessments [37]. Most importantly, the 1 km^2 spatial resolution ensures consistency (e.g. based on the European INSPIRE regulation) and combination possibilities with other datasets. For example, the Global Human Settlement Layer (GHSL) Degree of Urbanization [38], which captures the full settlement hierarchy based on population density, contiguity and population size at 1 km^2 resolution, could easily be used to detect differences in dynamics related to human dominance of land use types.

Thirdly, the two indicators presented here, forest area and canopy density, are derived from the same data source and are harmonized and presented at the same resolution. This allows for easy combinations and broader conclusions beyond just forest area. The two indices do not always show converging trends, but rather diverging changes. The combination provides a comprehensive and compelling discussion of drivers and their impacts, ultimately leading to the combined observations of the two complementary indicators. By combining changes in forest area with changes in tree cover density as a novel proxy for forest health, we extend the idea of assessing forest dynamics beyond changes in forest area. This new approach allows us to show the spatial evolution of forests and trees in parallel with the detection of changes in their condition based on the same data source.

Ethics statements

We comply with the relevant ethical guidelines of MethodsX.

Credit author statement

Benjamin Labohm: Conceptualization, Software, Investigation, Validation, Visualization, Writing – Original Draft. **Manuel Wolff:** Conceptualization, Investigation, Writing – Original Draft. **Dagmar Haase:** Supervision, Writing-Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] State of Europe's Forests 2020 - FOREST EUROPE. For Eur - Minist Conf Prot For Eur 2020. https://foresteurope.org/state-europes-forests-2020/ (accessed June 20, 2024).
[2] I.D. Thompson (Ed.), Forest Resilience, Biodiversity, and Climate Change: a Synthesis of the Biodiversity/Resiliende/Stability Relationship in Forest Ecosystems, Secretariat of the Convention on Biological Diversity, Montreal, 2009.
[3] State of Europe's Forests 2015 - FOREST EUROPE. For Eur - Minist Conf Prot For Eur 2022. https://foresteurope.org/publications_type/state-of-europes-forests-2015/ (accessed June 20, 2024).
[4] FAO, The state of the world's forests 2018Forest Pathways to Sustainable Development, 2018.
[5] A.I. Marín, D. Abdul Malak, A. Bastrup-Birk, G. Chirici, A. Barbati, S. Kleeschulte, Mapping forest condition in Europe: methodological developments in support to forest biodiversity assessments, Ecol. Indic. 128 (2021) 107839, doi:10.1016/j.ecolind.2021.107839.
[6] F. Moreira, D. Ascoli, H. Safford, M.A. Adams, J.M. Moreno, J.M.C. Pereira, et al., Wildfire management in Mediterranean-type regions: paradigm change needed, Environ. Res. Lett. 15 (2020) 011001, doi:10.1088/1748-9326/ab541e.
[7] M. Schelhaas, G. Nabuurs, A. Schuck, Natural disturbances in the European forests in the 19th and 20th centuries, Glob. Change Biol. 9 (2003) 1620–1633, doi:10.1046/j.1365-2486.2003.00684.x.
[8] C. Senf, R. Seidl, Post-disturbance canopy recovery and the resilience of Europe's forests, Glob. Ecol. Biogeogr. 31 (2022) 25–36, doi:10.1111/geb.13406.
[9] C. Senf, R. Seidl, Mapping the forest disturbance regimes of Europe, Nat. Sustain. 4 (2020) 63–70, doi:10.1038/s41893-020-00609-y.
[10] S. Trumbore, P. Brando, H. Hartmann, Forest health and global change, Science 349 (2015) 814–818, doi:10.1126/science.aac6759.
[11] K. Albrich, W. Rammer, M.G. Turner, Z. Ratajczak, K.H. Braziunas, W.D. Hansen, et al., Simulating forest resilience: a review, Glob. Ecol. Biogeogr. 29 (2020) 2082–2096, doi:10.1111/geb.13197.
[12] J. Lecina-Diaz, C. Senf, M. Grünig, R. Seidl, Ecosystem services at risk from disturbance in Europe's forests, Glob. Change Biol. 30 (2024) e17242, doi:10.1111/gcb.17242.
[13] S. Turubanova, P. Potapov, M.C. Hansen, X. Li, A. Tyukavina, A.H. Pickens, et al., Tree canopy extent and height change in Europe, 2001–2021, quantified using Landsat data archive, Remote Sens. Environ. 298 (2023) 113797, doi:10.1016/j.rse.2023.113797.
[14] M. Patacca, M. Lindner, M.E. Lucas-Borja, T. Cordonnier, G. Fidej, B. Gardiner, et al., Significant increase in natural disturbance impacts on European forests since 1950, Glob. Change Biol. 29 (2023) 1359–1376, doi:10.1111/gcb.16531.
[15] P. Ruiz-Benito, G. Vacchiano, E.R. Lines, C.P.O. Reyer, S. Ratcliffe, X. Morin, et al., Available and missing data to model impact of climate change on European forests, Ecol. Model 416 (2020) 108870, doi:10.1016/j.ecolmodel.2019.108870.
[16] FAOGlobal Forest Resources Assessment 2020, 2020.
[17] DiMiceli C., Sohlberg R., Townshend J. MODIS/Terra Vegetation Continuous Fields Yearly L3 Global 250m SIN Grid V061 2022. https://doi.org/10.5067/MODIS/MOD44B.061.
[18] ESA. WorldCover | WORLDCOVER n.d. https://esa-worldcover.org/en (accessed June 20, 2024).
[19] M.C. Hansen, P.V. Potapov, R. Moore, M. Hancher, S.A. Turubanova, A. Tyukavina, et al., High-resolution global maps of 21st-century forest cover change, Science 342 (2013) 850–853, doi:10.1126/science.1244693.
[20] J. Townshend, M. Hansen, M. Carroll, C. DiMiceli, R. Sohlberg, C. Huang, MODIS Collection 6.1 (C61) VCF Product User Guide, 2019.
[21] GLADDataset|GLAD, 2024 https://glad.umd.edu/dataset accessed June 20, 2024.
[22] EEACopernicus Land Monitoring Service – High Resolution Layer Forest Product Specifications, 2021 https://land.copernicus.eu/en/technical-library/hrl-forest-2012-2015/@@download/file accessed June 19, 2024.
[23] C. Senf, D. Pflugmacher, Y. Zhiqiang, J. Sebald, J. Knorn, M. Neumann, et al., Canopy mortality has doubled in Europe's temperate forests over the last three decades, Nat. Commun. 9 (2018) 4978, doi:10.1038/s41467-018-07539-6.
[24] EEACopernicus Land Monitoring Service High Resolution land cover characteristics Tree-cover/forest and change 2015-2018, 2017 https://land.copernicus.eu/en/technical-library/hrl-forest-2018/@@download/file accessed June 19, 2024.
[25] Delwart S. ESA Standard Document 2015.
[26] R. Seidler, Patterns of Biodiversity Change in Anthropogenically Altered Forests ☆, Ref. Module Life Sci, Elsevier, 2017, doi:10.1016/B978-0-12-809633-8.02186-5.
[27] R. Coville, T. Endreny, D.J. Nowak, Modeling the Impact of Urban Trees on Hydrology, in: D.F. Levia, D.E. Carlyle-Moses, S. Iida, B. Michalzik, K. Nanko, A. Tischer (Eds.), For.-Water Interact., vol. 240, Springer International Publishing, Cham, 2020, pp. 459–487, doi:10.1007/978-3-030-26086-6_19.
[28] D.J. Nowak, E.J. Greenfield, The increase of impervious cover and decrease of tree cover within urban areas globally (2012–2017), Urban. For. Urban. Green. 49 (2020) 126638, doi:10.1016/j.ufug.2020.126638.
[29] A. Rikimaru, P. Roy, S. Miyatake, Tropical forest cover density mapping, Trop. Ecol. (2002).
[30] M.B. Chandrashekhar, S. Saran, P.L.N. Raju, P.S. Roy, Forest canopy density stratification: how relevant is biophysical spectral response modelling approach? Geocarto. Int. 20 (2005) 15–21, doi:10.1080/10106040508542332.
[31] M. Sahana, H. Sajjad, R. Ahmed, Assessing spatio-temporal health of forest cover using forest canopy density model and forest fragmentation approach in Sundarban reserve forest, India, Model Earth Syst. Environ. 1 (2015) 49, doi:10.1007/s40808-015-0043-0.

[32] EEAEEA Reference Grid For Europe (1km), May 2011, EEA Geospatial Data Cat, 2013 https://sdi.eea.europa.eu/catalogue/geoss/api/records/d9d4684e-0a8d-496c-8be8-110f4b9465f6 accessed June 20, 2024.
[33] R Core TeamR: A language and Environment For Statistical, 2022.
[34] R Core TeamR: A Language and Environment for Statistical Computing, 2023.
[35] H.R. Terra: Spatial data analysis n.d.
[36] T. Grupp, P. Mishra, M. Reynaert, A.A. Van Benthem, An Evaluation of protected area policies in the European Union, SSRN Electron. J. (2023), doi:10.2139/ssrn.4665580.
[37] Y. Dou, F. Cosentino, Z. Malek, L. Maiorano, W. Thuiller, P.H. Verburg, A new European land systems representation accounting for landscape characteristics, Landsc. Ecol. 36 (2021) 2215–2234, doi:10.1007/s10980-021-01227-5.
[38] Corbane C., Politis P. GHS-composite-S2 R2020A - Sentinel-2 global pixel based image composite from L1C data for the period 2017-2018 2020. https://doi.org/10.2905/0BD1DFAB-E311-4046-8911-C54A8750DF79.