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Assessing the spatial coherence of forest cover indicators from different data sources: A contribution to sustainable development reporting

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ABSTRACT

The accuracy of forest area estimates has improved over time as a result of field/cadastral surveys, enhanced remote sensing techniques, and the effectiveness of algorithms for automatical recognition of land cover types. However, forest statistics seem to be less accurate in disaggregated spatial domains such as small administrative units. To evaluate the contribution of different data sources to small-area forest cover estimation in Europe, we compared seven indicators with different spatial coverage and resolution. The analysis considered multiple information sources from innovative initiatives, such as the Copernicus Land monitoring scheme, and traditional (national) surveys. More specifically, the study examined the spatial coherence of these indicators at the municipal scale in Italy to achieve two objectives: (i) assessing the overall precision of forest cover rates and (ii) identifying spatial variations in forest cover rates associated with the technical characteristics of each data source. A spatial econometric approach was used to identify the sources of spatial divergence in forest cover rates and determine the data providers best suited to meet the information requirements of environmental reporting at the desired spatial scale. The results reveal that the selected indicators show varying degrees of internal coherence, with some indices displaying strong correlations and others delineating heterogeneous spatial patterns. Our study highlights the importance of choosing the right information source assessing forest area at the municipal level and provides a valuable approach quantifying the coherence and reliability of environmental indicators in monitoring key aspects of sustainable development.

1. Introduction

Quantifying the extent of forest cover – and its change over time – at continental, national, and local scales is critical in sustainability science because of the primary services provided by forests to ecosystems and human well-being (Becagli et al., 2016). Due to the benefits associated with forests, investigating their state and changes is crucial in order to highlight inequalities in the spatial distribution of natural resources (Zambon et al., 2017). The accuracy of detecting small-scale forest changes has increased over time as a result of more precise field and cadastral surveys, improved remote sensing techniques, and the continued development of new algorithms for automatic recognition of land cover types (Cavalli et al., 2023). The launch of global and European programmes providing refined satellite data (De Fioravante et al.,

Abbreviations: CLC, Corine Land Cover; EEA, European Environment Agency; FAO, Food and Agriculture Organization of the United Nations; GWR, Geographically Weighted Regression; ISPRA, Italian Institute for Environmental Protection and Research; LCCS, Land Cover Classification System; MERIS, Medium Resolution Imaging Spectrometer; MMU, Minimum Mapping Unit; PCA, Principal Component Analysis; OLS, Ordinary Least Square; SPOT, Satellite Pour l'Observation de la Terre; MODIS, Moderate Resolution Imaging Spectroradiometer; ESA, European Space Agency; CCI, Climate Change Initiative; JRC, Joint Research Centre; EC, European Commission; CLM, Copernicus Land Monitoring initiative.

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2021a, 2021b; Cecili et al., 2023) has finally granted the high-resolution data sources needed to run innovative procedures and algorithms (e.g. Francini et al., 2023). The availability of open-source land cover data obtained from global (or regional) earth observation programs allows a comprehensive analysis of the spatial distribution of forest resources with a relatively high (spatial and temporal) resolution (Ferretti and Chiarucci, 2003). One program that assures a continuous land cover monitoring in Europe is the Copernicus Land Monitoring initiative managed by the European Environment Agency (EEA) and the Joint Research Centre (JRC) of the European Commission (EC). This initiative has released high spatial resolution data for all land cover and use changes in Europe, as well as ancillary biophysical variables (Francini and Chirici, 2022). The Corine Land Cover (CLC) initiative, one of the program's datasets, has been providing regular land cover data at a relatively detailed spatial scale since the early-1990s (D'Amico et al., 2021).

Furthermore, there are other initiatives contributing to land cover monitoring in Europe. For instance, the European Space Agency (ESA) has developed land cover maps covering different epochs using data from Envisat and Sentinel-2 satellites (ESA, 2017). Such programs offer key information for land cover monitoring, enabling scholars, policy-makers, and environmentalists, to monitor changes in forest area over time (Bonfiglio et al., 2002). This aspect became more and more important for science because of the growing demand for accurate (geo-spatial and diachronic) data informing policy strategies (Vizzarri et al., 2015), the definition of which is often complicated due to inherent monitoring constraints (Salvati et al., 2016). However, although the accuracy of forest cover estimation has increased significantly over time, uncertainty in forest cover statistics is still high (Seebach et al., 2011), at least at detailed spatial domains (e.g. small administrative units). As a matter of fact, the multiple (field and remote) data sources made recently available from innovative initiatives and more traditional (national) surveys have given room to very different figures of forest cover rates at both regional and local levels (e.g. Schuck et al., 2003).

Forest cover is a key variable in sustainable development reporting (Ferretti and Chiarucci, 2003; Seebach et al., 2011; Bontemps et al., 2022). More specifically, it represents the base of various indicators that quantify planning targets and policy advancements (i) directly related with two Sustainable Development Goals (SDG13: 'Climate Action'; SDG15: 'Life on Land') or (ii) indirectly related with other goals such as 'Responsible Consumption and Production' (SDG12), 'Sustainable Cities and Communities' (SDG11), as well as 'Affordable and Clean Energy' (SDG7). Being only partially reduced in the presence of more precise and reliable information sources (Ferrara et al., 2016), spatial uncertainty in forest cover rates justifies a comprehensive assessment of the contribution of different data sources to environmental reporting (Salvati and Carlucci, 2014), trying to delineate their strengths and weaknesses in a comparative perspective (Corona, 2018).

Based on these assumptions, our study compares the spatial outcomes of a panel of forest cover indicators derived from seven data sources with different geographical coverage and resolution in Italy, with the aim at assessing their spatial coherence and reliability at a fine-grained scale (e.g. municipalities). Spatial econometric techniques (both global and local: Salvati et al., 2018) were used to test the internal coherence in the combined use of forest cover rates derived from different data sources and the potential role of information redundancy when using local administrative units as the elementary spatial domain for environmental reporting (Sallustio et al., 2016). Thanks to its flexibility, this operational framework can be generalized to different socioeconomic contexts and ecological processes (Loepfe et al., 2012), facilitating the development of coherent indicator dashboards to monitor socio-environmental dynamics and inform forest policies.

2. Methodology

2.1. Study area

Italy is a Mediterranean country extending 301.330 km^2 of land classified into three elevation zones (35 % mountains, 42 % uplands, 23 % lowlands). Although regional variations exist, the country has a temperate climate with dry summers (Salvati et al., 2008). Forests extend across both hilly and flat areas (Biasi et al., 2015a), while the densest coverage is found in the Alpine mountain range, which runs through the north of the country, and the Apennines, from Central to Southern Italy (Smiraglia et al., 2015). Alpine forests are basically dominated by conifers, such as firs, larches, and pines (Congedo et al., 2016). Coniferous forests are also found in the Apennines, together with mixed and deciduous forests, which include oaks, beech, chestnut, and hornbeam (Vizzarri et al., 2015). The Po Valley, the largest lowland in Northern Italy, has mainly agricultural areas with poplar plantations and some oak and riparial residual forests. The two major islands also have distinctive forest ecosystems (Ferretti et al., 2014). Mediterranean scrub, which includes mastic, arbutus, and myrtle, among others, constitutes the majority of Sardinian woods (Barbati et al., 2007). Sicily in turn has a characteristic Mediterranean vegetation, with carobs, holm oaks, aleppo pines, and wild olives dominating the rural landscape (Bajocco et al., 2015). It is worth noting that air temperature, elevation, and geographical features of various places affect the types of forests all over Italy (Avitabile and Camia, 2018). This landscape diversity translates into a wide range of plant species and habitats in the Italian forest environment (Biasi et al., 2015b), which adds to the country's biodiversity, probably the largest in Europe (Barbati et al., 2018).

2.2. Forest cover indicators

The present study examined the spatial distribution of seven forest cover indicators (COR3, COR4, CBB, HRL, COPG, ESA, FAO), each produced from a different data source (i.e. land cover map) dated 2018, as follows:

(i) COR3: a pan-European CLC map with a standard (third-level) nomenclature (a total of 44 classes) derived from Copernicus Land initiative;
(ii) COR4: a national CLC map with an enhanced (forth-level) nomenclature (92 classes, with a focus on natural areas) produced by ISPRA;
(iii) CBB: a CLC Backbone raster map disseminated by EEA;
(iv) HRL: a Copernicus High Resolution Layer of forest cover and density, a raster file with 10 m cell resolution;
(v) COPG: Copernicus Global Land Cover, a raster dataset with a specific nomenclature and a spatial resolution of 10 m;
(vi) ESA Land Cover Map, a raster dataset with a specific nomenclature (22 classes) and a spatial resolution of nearly 300 m;
(vii) FAO Land Cover Map, a raster dataset with a specific nomenclature (10 classes) and a spatial resolution of 250 m.

These sources provide freely accessible and fully geo-referenced data (Barbati et al., 2014) with different spatial resolutions and heterogeneous definitions of 'forest area' (Quaranta et al., 2023). Additionally, these sources provide a representative overview of forest monitoring tools (i.e. geo-spatial databases) currently available at both global, continental and national scale in Europe (Ferrara et al., 2016). The target indicators (i.e. forest cover rates) were made available at the spatial scale adopted in this study (7904 municipalities) as the percent share of forests in total municipal area (Salvati et al., 2018). Forest cover rates were derived from a 'tabulate area' procedure run in ArcGis (release 10, ESRI, Redwoods, CA) on a shapefile of municipal boundaries provided by the Italian National Institute of Statistics (Istat), using the forest definition adopted in each map. The technical details of each map (i - vii) are given here below.

2.2.1. Corine land cover (COR3)

CLC is a comprehensive dataset disseminated by Copernicus Land Monitoring Service, under the coordination of EEA, providing valuable information on land cover and land-use patterns across Europe. The national teams of participating nations, which include EEA members and collaborating countries, undertook the classification of satellite imagery to build the CLC datasets. The dataset leverages imagery from a multitude of high-resolution optical satellites, including – but not limited to – Sentinel-2 from the Copernicus program, and Landsat. These satellite sources collectively contribute to the generation of the CLC dataset. Subsequently, these datasets are amalgamated into a coherent and seamless map of Europe's land cover and land use status, using standardized methodologies and terminology (Bajocco et al., 2012). The CLC dataset for the year 2018 is classified into five thematic classes (artificial surfaces, agricultural areas, forest and semi-natural areas, wetlands, and water bodies). Within these main categories, a hierarchical three-level nomenclature includes a total of 44 classes (Costa et al., 2018). This intricate classification system ensures a granular and detailed representation of different land cover and land-use patterns across the continent. Three out of 44 classes (Broad-leaved forest, 311; Coniferous forest, 312; Mixed forest, 313) were adopted to calculate the COR3 indicator. It is worth noting that the Minumum Mapping Unit within the CLC dataset is defined at 25 ha (Gschwantner et al., 2022). This criterion underlines the commitment to precision and accuracy maintained by the Copernicus Land Monitoring Service in its endeavor to provide comprehensive and scientifically valuable information regarding land cover and land use dynamics in Europe (Copernicus Land Monitoring Service, 2021a).

2.2.2. IV level Corine land cover (COR4)

The COR4 index derives from an extensive, fourth-level classification survey carried out by ISPRA, starting from the third-level classification of the CLC map (see above). This classification involves photointerpretation and provides data for various reference years including 2018. It also includes additional specifications regarding forest cover classes (Pekkarinen et al., 2009). Fourteen classes (Broad-leaved forest, 3111–3117; Coniferous forest, 3121–3125; Mixed forest, 3131–3132) depicting different forest types characteristic of Italy out of 67 land-use classes were here considered.

2.2.3. Corine land cover Backbone (CBB)

The CLC database includes high-resolution maps, offering insights into both land cover and land cover changes (Parviainen and Frank, 2003). The CLC + Backbone represents a key component, providing comprehensive European land cover information in the form of a wall-to-wall geometric vector reference layer with essential thematic content and a 10-meter spatial resolution raster product referred to the year 2018. As a complement of the backbone layer, the CLC + Core, a database/web application, uses innovative data fusion techniques to enable the creation of customized products at 100-meter spatial resolution. This integrated CLC + system extends and enhances the existing range of technical solutions that may address the evolving requirements for land cover and land use assessment and reporting (Copernicus Land Monitoring Service, 2022). When calculating the CBB indicator, three forest types (Woody needle leaved trees, Woody Broadleaved deciduous trees, and Woody Broadleaved evergreen trees) out of 11 discrete classes were here considered.

2.2.4. Copernicus high resolution layers (HRLs)

Copernicus High Resolution Layers provide details on tree cover density with high spatial precision for various reference years, including 2018. These data are available in various resolutions, including disaggregated 10-meter and standard 100-meter layers. Reference datasets, intermediary layers, and expert-level products are made accessible from Copernicus Land Monitoring Service (2021a).

2.2.5. Copernicus global land cover (COPG)

Undergoing regular updates, the Copernicus Global Land Cover Map is a dynamic dataset constructed using geographical data and satellite imagery that offers comprehensive information on land cover types of the Earth's surface (Copernicus Land Monitoring Service, 2021b). Core information was derived from several satellite missions, including the Sentinel-2 mission, the Landsat program with data from satellites like Landsat 8 and Landsat 7, capturing multispectral imagery, and other Earth Observation Satellites such as SPOT and MODIS. The map creation process involves various steps, including data collection, preprocessing, image categorization, validation, post-processing, and map development (D'Agata et al., 2023). For the calculation of the COPG indicator, ten classes of forest density, expressed as a percentage of cover per pixel (from 1 % to 10 % to 91 %-100 %), were here considered.

2.2.6. European Space Agency Climate change initiative (ESA-CCI)

The ESA-CCI Land Cover Map is a project designed to provide a global land cover product tailored to meet the requirements of the Global Climate Observing System (GCOS) and the broader climate change research community. This map provides a representation of the physical materials on the Earth's surface, including elements such as grass, asphalt, trees, bare ground, and water. The project explores the use of ESA Synthetic Aperture Radar (SAR) sensors to address specific challenges related to land cover assessment. The imagery come from Envisat's MERIS instrument, which boasts a spatial resolution of 300 m, as well as Sentinel-2, with the potential to provide a global land cover map with a 10-meter resolution. Map classification refers to the LCCS developed by FAO (2014). The ESA-CCI database offers an unprecedented time series of global land cover data spanning from 1992 to 2020. This dataset was compiled through the reprocessing and interpretation of data from five distinct satellite missions (ESA, 2017). Eleven forest types were here considered in the calculation of the ESA indicator, as follows: tree cover, broadleaved, evergreen, closed to open (>15 % coverage), code 50; tree cover, broadleaved, deciduous, closed to open (>15 %), code 60; tree cover, broadleaved, deciduous, closed (>40 %); 62: Tree cover, broadleaved, deciduous, open (15–40 %), code 61; tree cover, needleleaved, evergreen, closed to open (>15 %), code 70; tree cover, needleleaved, evergreen, closed (>40 %), code 71; tree cover, needleleaved, evergreen, open (15–40 %), code 72; tree cover, needleleaved, deciduous, closed to open (>15 %), code 80; tree cover, needleleaved, deciduous, closed (>40 %), code 81; tree cover, needleleaved, deciduous, open (15–40 %), code 82; tree cover, mixed leaf type (broadleaved and needleleaved), code 90.

2.2.7. Global land cover SHARE (FAO)

The Global Land Cover (GLC-SHARE) database was developed by Land and Water Division of FAO. It comprises eleven thematic land cover layers with a spatial resolution of 30 arcseconds (equivalent to 1 km^2). In order to provide a comprehensive global view of land cover types, this database integrates the high-resolution 'best available' information on national, regional, and sub-national land cover. GLC-SHARE data is available in GeoTIFF format and follows the LCCS standards. This resource can be freely accessed through the FAO Geonetwork site (FAO, 2014). In the calculation of FAO indicator, ten layers (with different forest densities) of the general class named 'tree covered area' were here jointly considered.

2.3. Statistical analysis

A statistical framework based on spatial econometrics was used to assess the coherence of the seven forest cover indicators (COR3, COR4, CBB, HRL, COPG, ESA, FAO) at the municipal scale in Italy (Salvati and Carlucci, 2014). The following statistics were considered: (a) the average value of forest cover and its variability on a national scale; (b) the internal coherence of (local) forest cover values, considering the global correlation between pairs of indicators; (c) the external coherence of (local) forest cover values, considering the global (linear or non-linear) relationship between pairs of indicators; and (d) the spatial coherence of (local) forest cover values, considering the spatial relationship between pairs of indicators (Quaranta et al., 2023).

This approach was operationalized through six (sequential) steps: (i) descriptive statistics were calculated for each indicator to analyze the spatial distribution of forest cover rates across Italian municipalities; (ii) parametric and non-parametric (pair-wise) correlations were performed to examine the internal (absolute and relative) coherence between the statistical distributions of forest cover indicators; (iii) global regression models were used to test the external coherence across the entire spectrum of forest cover rates; (iv) quantile regression was used to evaluate the precision of each indicator at five levels of forest cover; (v) local regression models were applied to identify spatial discrepancies when comparing the seven indicators pair-wise, and, finally, (vi) a multivariate analysis was performed to discover the latent relationship between the indicators, considering them jointly (Salvati et al., 2018).

2.3.1. Descriptive statistics

In the first step, 8 descriptive statistics were calculated: mean, median, mean-to-median ratio, coefficient of variation, normalized range (max-to-min/mean), quantilic range [($perc_{75th}$-to-$perc_{25th}$)/median], skewness, and kurtosis. This analysis identifies the most significant characteristics of the statistical distribution of each indicator (COR3, COR4, CBB, HRL, COPG, ESA, FAO). These metrics offer a consistent evaluation of (i) central tendency, (ii) variability, and (iii) distribution shape for the indicators in question at municipal level, outlining the overall coherence (or discrepancies) in the assessment of forest cover rate at national scale.

2.3.2. Correlation analysis

To assess the internal coherence of each forest cover indicator at the municipal scale (n = 7904), 21 pairwise correlations were run testing the following associations: COR3 *vs* COR4, COR3 *vs* CBB, COR3 *vs* HRL, COR3 *vs* COPG, COR3 *vs* ESA, COR3 *vs* FAO, COR4 *vs* CBB, COR4 *vs* HRL, COR4 *vs* COPG, COR4 *vs* ESA, COR4 *vs* FAO, CBB *vs* HRL, CBB *vs* COPG, CBB *vs* ESA, CBB *vs* FAO, HRL *vs* COPG, HRL *vs* ESA, HRL *vs* FAO, COPG *vs* ESA, COPG *vs* FAO, ESA *vs* FAO. We assumed a strong (linear or non-linear) relationship as a proof of internal coherence between the statistical distribution of these indicators. Two correlation coefficients were used, both parametric (Pearson) and non-parametric (Spearman), verifying the internal coherence of the absolute scores (cardinal measures) determined using Pearson coefficients, and the relative scores (ordinal measures) determined using Spearman coefficients. Significant correlations were assessed at $p < 0.05$ after Bonferroni's correction for multiple comparisons. If the Spearman coefficient exceeds the corresponding Pearson coefficient, it means that ordinal measurements between specific sets of indicators show greater coherence than cardinal measures, in turn suggesting the existence of a non-linear relationship between variables (Salvati et al., 2018).

2.3.3. Ordinary least square (OLS) regression models

OLS (pair-wise) regression models were used to test the external coherence of forest cover rates assuming a one-to-one linear relationship between each pair of indicators, for the all the pair-wise comparisons reported above. The analysis initially identified linear (or more complex) relationships between indicators, including second-order (quadratic) and third-order (cubic) trends. Key metrics such as adjusted-R^2 values, regression coefficients, as well as the relative errors were considered. Additionally, to check for heteroscedasticity and the existence of autocorrelation in the residuals of each tested model, the Breusch-Pagan and Durbin-Watson tests were used, respectively. The Akaike's Information Criterion was considered when examining quadratic and cubic relationships.

2.3.4. Quantile regression models

To further explore the external coherence, i.e. the relationship between indicators at specific *loci* of the statistical distribution, quantile regressions were performed for the 21 pair-wise comparisons described above, considering five different percentiles (10th, 25th, 50th, 75th, 90th). Regression results include estimates of slope coefficients and the associated significance levels testing the null hypothesis of non-significant regression coefficients *via* Student t statistics at $p < 0.001$. Slope and intercept similarities between models were also evaluated to ascertain a consistent behavior of forest cover indicators at different distributional *loci* as a result of internal and external coherence, regardless of the amount of forest area in each municipality.

2.3.5. Local regression models

A refined investigation of the spatial coherence (i.e. regional variability and local heterogeneity) of forest cover indicators was obtained running Geographically Weighted Regressions (GWRs) that consider the spatial pattern at the base of the relationship between each couple of variables (Ali et al., 2007). For each of the 21 pair-wise comparisons discussed above, GWRs were used to estimate local regression models that account for spatial dependency and heterogeneity (Brunsdon et al., 2002). A GWR specification for a given location, denoted as s = 1 to n, is:

$$Y(s) = X(s)B(s) + e(s) \quad (1)$$

where Y(s) and X(s) represent the dependent variable and the predictor measured at location s, respectively, B(s) denotes the column vector of regression coefficients at location s, and e(s) stands for the random error at location s. Weighted least squares were used to estimate the regression parameters at each location, making them spatially explicit as a function of s (Anselin, 2001). In particular, when using GWR, potential limitations associated with inferential conclusions arising from a small sample of data should be considered (Zambon et al., 2017). However, such limitations were not encountered in the context of this study. The results of the models include (i) a global measure of goodness-of-fit (adjusted R^2), which was compared with the same index obtained from the respective OLS regression, and (ii) local coefficients (R^2, intercept, slope, standard residuals) illustrated through maps. GWRs verified the spatial coherence of forest indicators and shed light on the role of regional variability and local heterogeneity when testing various sources of land cover information.

2.3.6. Multivariate analysis

PCA, a statistical technique that reduces dimensionality and identifies latent patterns in complex datasets (D'Agata et al., 2023), was finally used with the aim at summarizing the econometric results illustrated above. More specifically, the PCA validated the different dimensions of coherence (see above) of the municipal ranking generated from each indicator by a matrix with 7 columns (corresponding to the forest cover indicators) and 7904 rows (representing the Italian municipalities). Identification of the most relevant components was achieved by keeping those with eigenvalues greater than 1. The most relevant results of this analysis were visualized using a biplot, which established associations between the component loadings (i.e. the correlations between input variables and the principal components) and scores (i.e. the correlations between geographical units and the principal components).

3. Results

3.1. Descriptive statistics

The statistical distribution of the seven indicators shows notable heterogeneity (Table 1). A descriptive analysis of the spatial series of forest cover indicators at the municipal level in Italy reveals the existence of three groups of indicators with comparable averages (SM.

Table 1
Descriptive statistics of the spatial distribution of seven indicators of forest cover in Italy, municipal scale (n = 7904 units), see the methodological section for abbreviations.

Metric	COR3	COR4	CBB	HRL	COPG	ESA	FAO
Mean	0.26	0.26	0.41	0.30	0.32	0.27	0.32
Median	0.19	0.19	0.40	0.28	0.28	0.17	0.26
Mean/median	1.39	1.39	1.01	1.06	1.13	1.61	1.23
Coefficient of variation	97.6	98.6	66.3	70.6	65.0	105.9	88.5
Normalized range	3.80	3.81	2.40	2.92	2.89	3.64	3.11
Quantile range	2.37	2.42	1.22	1.35	1.25	2.87	1.99
Skewness	0.66	0.66	0.13	0.26	0.46	0.78	0.47
Kurtosis	−2155	−2148	−1720	−1810	−2010	−2274	−1856

Figure 1). One group includes COR3, COR4, and ESA, with mean values between 0.26 and 0.27 (i.e. forests cover, on average, 26 %-27 % of the municipal area). Another group consists of HRL, COPG, and FAO, with average values between 0.30 and 0.32. Both of these groups differ from the average value of CBB (0.41); Similar median values may confirm this general pattern. The lack of stability across indicators is evident in the coefficient of variationof the forest cover rate across Italian municipalities, varying from 65 % (COPG) to 106 % (ESA). COR3, COR4 and ESA display the highest spatial variability, followed by FAO. The ratio between the mean and median values ranges from 1.01 to 1.61, revealing a moderate asymmetry in the statistical distribution of the seven indicators. The normalized range [(max–min)/mean] varies between 2.4 and 3.8, revealing latent differences in frequency distributions; the quantile range [(p_{75}-p_{25})/median] ranges between 1.2 and 2.9. Skewness varies significantly across indicators, ranging between 0.13 and 0.78; kurtosis takes on relatively high values and is almost homogeneous in all statistical distributions.

3.2. Correlation analysis

A total of 21 comparisons were performed to assess the level of pairwise association between forest cover indicators in Italian municipalities (Table 2). Correlation coefficients derived from these pair-wise comparisons reveal consistently strong, positive correlations that are highly significant, spanning into a range of values between 0.88 and 1. Despite a substantial (cross-sectional) heterogeneity due to the large sample size investigated (n = 7904 units), these values outline the internal coherence of the seven forest indicators. Although there are cases where the Spearman coefficient slightly exceeds the Pearson coefficient, both coefficients consistently show similar values, confirming the appropriateness of using linear correlations instead of more complex approaches (e.g. polynomial trends). These results highlight that the indicators' ranking maintains a high level of consistency, even if minor (absolute) disparities exist between geographical units.

Table 2
Pair-wise correlation analysis (moment-product linear parametric Pearson coefficient, r; non-linear non-parametric co-graduation Spearman rank coefficient, r_s) of seven indicators of forest cover in Italy, municipal scale (n = 7904 units); bold indicates coefficients > |0.95| reflecting a satisfactory (spatial) coherence between indicators; italics indicate coefficients > |0.90| reflecting a sufficient (spatial) coherence between indicators (see the methodological section for abbreviations).

Indicators	COR3	COR4	CBB	HRL	COPG	ESA
Pearson coefficient						
COR4	**0.998**					
CBB	0.880	0.881				
HRL	*0.916*	*0.916*	**0.974**			
COPG	*0.942*	*0.943*	*0.929*	**0.958**		
ESA	*0.936*	*0.936*	0.860	0.900	*0.934*	
FAO	**0.970**	**0.969**	0.886	*0.916*	*0.943*	*0.927*
Spearman coefficient						
COR4	**0.994**					
CBB	0.880	0.885				
HRL	*0.914*	*0.918*	**0.977**			
COPG	*0.926*	*0.930*	*0.933*	**0.958**		
ESA	*0.922*	*0.919*	0.860	0.900	*0.920*	
FAO	**0.970**	**0.967**	0.880	*0.913*	*0.928*	*0.922*

3.3. Ordinary least Square regression models

Comparing the adjusted-R^2 values measuring the goodness-of-fit between the cubic, quadratic, and linear specifications, consensus emerges on the performance of these three models across all pairwise comparisons (SM.Table 1). These results suggest that the linear specification stands out as the most reliable and (statistically) parsimonious option, with adjusted-R^2 values ranging between 0.739 and 0.997. In any pairwise comparison, the incremental improvement in R^2 due to the increasing degree of the fitted (polynomial) equation remains relatively small. Conversely, regression slopes and intercepts show a slightly greater variability, with values ranging between 0.716 and 1.308 and between −0.096 and 0.166, respectively. The Durbin-Watson statistic was always close to 2, reflecting a negligible serial autocorrelation. The most coherent results were achieved for COR3, COR4, ESA, and FAO indicators (adjusted R^2 exceeding 0.9 and regression coefficients (slope and intercept) approaching 1 and 0, respectively, thus reflecting a one-to-one linear relationship).

3.4. Quantile regression models

Table 3 shows the results of quantile regressions (10th, 50th, and 90th percentile) adopting a linear specification for each of the 21 pairwise comparisons reported in SM.Table 2. Quantiles were used to delineate specific *loci* of the statistical distribution of the seven indicators, that correspond to higher levels of the forest cover rate. In particular, the pseudo-R^2 coefficient shows a slight decline from the first to the fourth percentile, indicative of more heterogeneous indicator values at higher levels of forest cover, as reflected in the corresponding increase of the intercept coefficients. As expected, this decline was more evident for indicators derived from high-resolution layers (CBB, HRL, COPG) than for those derived from low-resolution layers (COR3, COR4, ESA, FAO).

3.5. Local regression models

Table 4 provides the results of GWRs testing the spatial congruence of the adopted indicators. Local regressions consistently demonstrate higher goodness-of-fit than the corresponding OLS regressions for all pairwise comparisons. In particular, the global R^2 of GWR models typically approached 0.9, despite a considerable heterogeneity because of the large sample size. GWRs allow visualization of local estimates for goodness-of-fit and regression parameters through maps (SM.Figure 2 and 3). The increase in R^2 varies from 0.6 % (COR4 *vs* FAO) to 12.8 % (CBB *vs* ESA), and is higher for indicators derived from high-resolution layers than those derived from low-resolution layers. These results indirectly demonstrate a greater spatial coherence (i.e. less local heterogeneity) of indicators derived from low-resolution map sources.

Table 3
Results of quantile regression models comparing pair-wise the spatial outcomes of seven indicators of forest cover in Italy (n = 7904 units) by specification and estimation criterion; all models are significant at $p < 0.0001$; "P-R^2" indicates Pseudo-R^2 (see the methodological section for abbreviations).

Pairwise Comparison	Quantile-10th			Quantile-50th			Quantile-90th		
	P-R^2	Intercept (*err*)	P-R^2	P-R^2	P-R^2	Slope (*err*)	P-R^2	Intercept (*err*)	Slope (*err*)
COR3 *vs* COR4	0.988	−0.001(*0.000*)	0.978	0.978	0.978	1.000(*0.000*)	0.976	0.000(*0.000*)	1.000(*0.000*)
COR3 *vs* CBB	0.749	−0.047(*0.003*)	0.853	0.853	0.853	0.856(*0.005*)	0.552	−0.059(*0.001*)	0.856(*0.005*)
COR3 *vs* HRL	0.784	−0.090(*0.001*)	0.858	0.858	0.858	1.106(*0.006*)	0.612	−0.050(*0.001*)	1.106(*0.006*)
COR3 *vs* COPG	0.830	−0.163(*0.002*)	0.852	0.852	0.852	1.167(*0.006*)	0.655	−0.106(*0.002*)	1.167(*0.006*)
COR3 *vs* ESA	0.848	−0.011(*0.001*)	0.820	0.820	0.820	0.887(*0.004*)	0.667	0.006(*0.001*)	0.887(*0.004*)
COR3 *vs* FAO	0.874	−0.042(*0.001*)	0.915	0.915	0.915	0.862(*0.003*)	0.778	−0.004(*0.001*)	0.862(*0.003*)
COR4 *vs* CBB	0.751	−0.049(*0.003*)	0.853	0.853	0.853	0.863(*0.005*)	0.554	−0.062(*0.001*)	0.863(*0.005*)
COR4 *vs* HRL	0.785	−0.091(*0.002*)	0.858	0.858	0.858	1.114(*0.006*)	0.615	−0.054(*0.001*)	1.114(*0.006*)
COR4 *vs* COPG	0.831	−0.163(*0.001*)	0.852	0.852	0.852	1.176(*0.005*)	0.659	−0.110(*0.002*)	1.176(*0.005*)
COR4 *vs* ESA	0.846	−0.015(*0.001*)	0.819	0.819	0.819	0.894(*0.004*)	0.668	0.002(*0.001*)	0.894(*0.004*)
COR4 *vs* FAO	0.871	−0.049(*0.001*)	0.915	0.915	0.915	0.865(*0.003*)	0.774	−0.005(*0.001*)	0.865(*0.003*)
CBB *vs* HRL	0.918	0.001(*0.000*)	0.855	0.855	0.855	1.271(*0.003*)	0.783	0.014(*0.001*)	1.271(*0.003*)
CBB *vs* COPG	0.852	−0.084(*0.002*)	0.756	0.756	0.756	1.239(*0.005*)	0.597	−0.008(*0.002*)	1.239(*0.005*)
CBB *vs* ESA	0.802	0.025(*0.001*)	0.701	0.701	0.701	0.827(*0.006*)	0.393	0.155(*0.004*)	0.827(*0.006*)
CBB *vs* FAO	0.841	0.015(*0.001*)	0.697	0.697	0.697	0.920(*0.004*)	0.536	0.079(*0.002*)	0.920(*0.004*)
HRL *vs* COPG	0.875	−0.072(*0.002*)	0.822	0.822	0.822	0.985(*0.003*)	0.693	−0.022(*0.001*)	0.985(*0.003*)
HRL *vs* ESA	0.820	0.014(*0.001*)	0.756	0.756	0.756	0.684(*0.005*)	0.482	0.100(*0.002*)	0.684(*0.005*)
HRL *vs* FAO	0.841	0.007(*0.001*)	0.754	0.754	0.754	0.739(*0.003*)	0.586	0.048(*0.001*)	0.739(*0.003*)
COPG *vs* ESA	0.838	0.049(*0.001*)	0.813	0.813	0.813	0.683(*0.004*)	0.599	0.126(*0.002*)	0.683(*0.004*)
COPG *vs* FAO	0.843	0.034(*0.001*)	0.825	0.825	0.825	0.706(*0.003*)	0.650	0.091(*0.001*)	0.706(*0.003*)
ESA *vs* FAO	0.830	−0.075(*0.001*)	0.836	0.836	0.836	0.923(*0.006*)	0.642	−0.011(*0.001*)	0.923(*0.006*)

Table 4
Global results of Geographically Weighted Regressions (GWR) comparing pair-wise the spatial outcomes of seven indicators of forest cover in Italy (n = 7904 units) with the results of Ordinary Least Square (OLS) regressions (see SM. Table 1); "AIC" indicates the Akaike Information Criterion; "(Δ)R^2" indicates the absolute ratio between GWR and OLS R^2; see the methodological section for abbreviations.

Model/ Estimate	Distance Band (km)	AICc	Global R^2 (GWR)	(Δ)R^2 (GWR/ OLS)
COR3 *vs* COR4	227.1	−43995	0.997	1.001
COR3 *vs* CBB	224.3	−13615	0.843	1.087
COR3 *vs* HRL	224.3	−15286	0.873	1.040
COR3 *vs* COPG	224.4	−16768	0.894	1.007
COR3 *vs* ESA	224.4	−16265	0.888	1.012
COR3 *vs* FAO	224.5	−22136	0.947	1.006
COR4 *vs* CBB	224.3	−13553	0.843	1.086
COR4 *vs* HRL	224.3	−15203	0.873	1.039
COR4 *vs* COPG	224.4	−16734	0.895	1.007
COR4 *vs* ESA	224.4	−16137	0.887	1.014
COR4 *vs* FAO	224.5	−21801	0.945	1.006
CBB *vs* HRL	224.3	−24485	0.964	1.016
CBB *vs* COPG	224.3	−18440	0.922	1.067
CBB *vs* ESA	224.3	−12430	0.834	1.128
CBB *vs* FAO	224.3	−13455	0.854	1.089
HRL *vs* COPG	224.2	−25213	0.947	1.031
HRL *vs* ESA	224.3	−17739	0.862	1.066
HRL *vs* FAO	224.3	−18192	0.870	1.036
COPG *vs* ESA	224.4	−19911	0.891	1.021
COPG *vs* FAO	224.4	−20437	0.898	1.010
ESA *vs* FAO	224.4	−13350	0.873	1.015

3.6. Principal Component analysis

Table 5 shows the results of the PCA, which summarizes the characteristics of the seven indicators used in this study to identify latent patterns and, possibly, the underlying contextual factors. By decomposing a matrix of pairwise linear correlations for the seven indicators, PCA extracted the first two components that explain together 97 % of the total variance. The indicators considered show a homogeneous correlation with Component 1 (93.8 %), with positive loadings between 0.38 and 0.43. In contrast, Component 2 shows variable loadings across indicators (ranging between −0.30 and 0.73). The biplot illustrating the relationships between the input variables (SM.Figure 4), reveals two distinct groups of indicators in different quadrants. In line with the results illustrated above, the first group includes CBB, HRL, and COPG, although their patterns within the quadrant are not completely aligned – an indirect evidence of their marked heterogeneity. Meanwhile, the remaining indicators in the fourth quadrant (COR3, COR4, ESA, FAO) show strong similarity.

Table 5
Results of a Principal Component Analysis (loadings and the proportion of extracted variance by axis) of seven indicators of forest cover in Italy (n = 7904 units).

Variable	Axis 1	Axis 2
COR3	0.38	−0.28
COR4	0.39	−0.27
CBB	0.39	0.73
HRL	0.31	0.40
COPG	0.30	0.11
ESA	0.43	−0.30
FAO	0.42	−0.23
Explained variance (%)	*93.8*	*3.3*

4. Discussion

Current research addresses the urgent need to quantify forest cover and monitor its changes, evaluating the coherence of indicators derived from various geo-spatial data sources and their redundancy when applied to local administrative units (Barbati et al., 2007; Avitabile and Camia, 2018; Bontemps et al., 2022). Quantitative techniques derived from sequential econometric methods can be used to assess the reliability of a panel of forest cover indicators grounded on a multidimensional notion of coherence (Lorenz and Fischer, 2013). The proposed framework – which includes various techniques such as correlation analysis, regression models and principal component analysis - has demonstrated its flexibility to different environmental conditions and socioeconomic contexts (Salvati et al., 2018). Furthermore, it assessed the precision of a wide range of indicators that quantify a target phenomenon from multiple data sources (Quaranta et al., 2023).

The data collected reveal a recurring challenge in the various phases of the statistical analysis process (Francini and Chirici, 2022). The correlation analysis and the PCA performed on the values of forest cover rate at the municipal scale identified two groups of indicators in a non-trivial way: (i) a set of internally consistent indicators derived from the CLC map (COR3, COR4) or based on ESA and FAO maps, and (ii) a more heterogeneous set of indicators derived from adaptations (or thematic refinements) of CLC products (i.e. CBB and HRL) and Copernicus (COPG) global map. CBB, HRL and CBB reveal peculiar characteristics and incoherencies, with the CBB showing more divergent values from the others. This led to inconsistent descriptive statistics (Quaranta et al., 2023), with lowest coefficient of variation, normalized range, quantile range and skewness and highest kurtosis (Bajocco et al., 2012). In the PCA, the CBB values were significantly different from the others, being associated only with Component 2 and showing a high explanatory power, probably due to the intrinsic heterogeneity of this indicator (Keenan et al., 2015).

The regression results confirm the linear relationship among forest cover indicators and the similarity of forest cover figures derived from medium-low resolution maps (CLC3, CLC4, ESA, FAO), regardless of the definition of 'forest area' adopted (e.g. Ferrara et al., 2016). Descriptive statistics from these data sources have comparable mean values (and similar median values and coefficients of variation) at the country scale (Vega et al., 2021). Quantile regressions confirm the external coherence of such figures at multiple *loci* of the statistical distribution of CLC3, CLC4, ESA, and FAO. Finally, local regressions document the greater spatial coherence of the forest cover values derived from medium-low resolution maps compared with those derived from high-resolution maps (Vizzarri et al., 2015), showing an evident local heterogeneity which is hardly interpretable (Nesha et al., 2021).

In this regard, the results of the statistical analysis suggest that there is currently no sufficient map capable of offering statistically homogenous forest cover values by municipality in Italy, and that it is not irrelevant or arbitrary whether one or the other forest map is used for assessing forest area in small administrative units, e.g. for environmental reporting and/or accounting for sustainable development (Ferretti and Chiarucci, 2003). Consequently, the development of a single recognized and shared georeferenced tool is crucial on a national scale (Corona, 2018). Precisely for this purpose, the General Directorate of Mountain Economy and Forestry of the Italian Ministry of Agriculture, food and forest sovereignty, has launched a new program for the creation of a national forest map with high geometric resolution (D'Amico et al., 2023).

The selection of reference sources for the assessment of forest area at a spatially detailed administrative scale should be carried out carefully to ensure distinct information (Cavalli et al., 2023). The clustering of the indicators here considered is linked to aspects such as spatial resolution, the detail of semantic classes, the geometric properties of objects, and the various phases of producing maps from different satellite observations (Costa et al., 2018). These aspects allow a meaningful evaluation of a panel of indicators to calibrate forest management strategies at local and national levels, going beyond the definition of 'forest' adopted in each source map (e.g. Camarretta et al., 2018).

The empirical results of this study also highlight that there is no one-size-fits-all map for the assessment of forest cover in the European context (Seebach et al., 2011). Indeed, low-resolution and high-resolution map sources have offered two contrasting views of forest cover in Italy (e.g. Smiraglia et al., 2015). This finding is in line with earlier research that has noted the challenges of reconciling divergent values of forest cover (Salvati et al., 2016). The insights gained from this research resonate beyond the boundaries of the study area and have broader implications for sustainability monitoring, environmental reporting, and forest conservation and valorization efforts worldwide (Tomppo et al., 2008). Therefore, this study reinforces the call for continued efforts to improve the accuracy of forest cover monitoring and to consider the intrinsic characteristics and limitations of different data sources (e.g. Ferretti et al., 2014). More specifically, results of spatially explicit econometric designs analysing individual indicators or composite indexes derived from different data sources – both official statistics and other public-domain references – may contribute significantly to theory and practice of environmental assessment by improving monitoring tools and instruments in a context of increased digital information, both proximal and remote (De Fioravante et al., 2021a, 2021b).

A deeper integration of proximal and remote sources at the European scale will surely contribute to the effective enrichment of official statistics in the field of forestry (Keenan et al., 2015). Additionally, a comparative analysis of systematic and non-systematic errors in both proximal and remote surveys and how they may affect official statistic estimates at various temporal and spatial scales seems particularly appropriate in a context of growing demand of geo-spatial information for environmental reporting (Quaranta et al., 2023). Future research should finally assure a better integration between total (e.g. census) and partial (e.g. sampling) data sources, giving more value respectively to the wide information stock offered by (Eurostat homogenized) agricultural censuses at the country scale and LUCAS (Land Use and Coverage Area frame Survey) sampling at the continental level in Europe (e.g. Bajocco et al., 2012). While being largely informative for forest reporting, maps and geo-spatial databased from LUCAS monitoring system (e.g. Smiraglia et al., 2015), the relatively small sampling size of this reference allows the provision of official statistics at very aggregated spatial domains, basically geographical macro-regions (NUTS-1 level) and administrative regions (NUTS-2 level). Small-area estimation of LUCAS statistics based on additional information stemming from population and agricultural censuses, business and land registers, or similar public sources (Ferrara et al., 2016), seems to be an appropriate topic for future studies.

The indirect approach here used to analyse the coherence of a dashboard of forest cover indicators promises broader applicability to other variables that measure complex environmental processes and socioeconomic phenomena (Cavalli et al., 2022). This approach, rooted in geographical information systems and exploratory data analysis, will benefit from the growing availability of digital geo-referenced data and technological advancements (Congedo et al., 2016). Furthermore, there is the possibility to expand this approach by exploring time-series datasets, allowing comparisons across different indicators for all municipalities at various time points (Borrelli et al., 2014). Analyzing the informativeness of a group of variables within a dashboard of indicators is a promising avenue for future research that requires more investigation and practical testing based on advanced statistical approaches.

5. Conclusions

Environmental and forest policies, as well as their implementation within operative management processes, should be evidence-based (Corona, 2018). However, earlier studies have documented how an accurate quantification of forest cover rates at a fine-grained scale, such as municipal units, poses substantial challenges (Nesha et al., 2021). Our study contributes to the body of knowledge by highlighting the operational complexity associated with selecting data sources and subsequently assessing forest cover figures, particularly in small administrative units (Sallustio et al., 2016). The variations observed between different forest cover indicators derived from various sources stress the need for meticulous consideration when choosing data for administrative-scale assessment (Pekkarinen et al., 2009); even seemingly similar definitions of forests can produce significantly different results due to mapping features, influencing statistical results and, consequently, policy recommendations (Parviainen and Frank, 2003). For large-scale monitoring programs that rely on indicator dashboards, it is imperative to not only ensure internal and external coherence, statistical reliability and redundancy, but also to quantify the informative power of the individual components and the stability of results to any change in the composing dimensions, basically time and space. The proposed approach could improve the effectiveness of such monitoring programs in guiding environmental planning and policy decisions in different contexts.

CRediT authorship contribution statement

Alessia D'Agata: Formal analysis. **Pavel Cudlin:** Conceptualization, Investigation, Project administration, Resources, Supervision. **Ioannis Vardopoulos:** Data curation, Validation, Visualization, Writing – review & editing. **Giuseppe Schinaia:** Data curation, Formal analysis, Software, Writing – review & editing. **Piermaria Corona:** Conceptualization, Resources, Software, Writing – review & editing. **Luca Salvati:** Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft.

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.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.111498.

References

Ali, K., Partridge, M.D., Olfert, M.R., 2007. Can geographically weighted regressions improve regional analysis and policy making? Int. Reg. Sci. Rev. 30 (3), 300–329.
Anselin, L., 2001. Spatial effects in econometric practice in environmental and resource economics. Am. J. Agric. Econ. 83 (3), 705–710.
Avitabile, V., Camia, A., 2018. An assessment of forest biomass maps in Europe using harmonized national statistics and inventory plots. For. Ecol. Manage. 409, 489–498.
Bajocco, S., De Angelis, A., Salvati, L., 2012. A satellite-based green index as a proxy for vegetation cover quality in a Mediterranean region. Ecol. Ind. 23, 578–587.
Bajocco, S., Dragoz, E., Gitas, I., Smiraglia, D., Salvati, L., Ricotta, C. (2015). Mapping forest fuels through vegetation phenology: The role of coarse-resolution satellite time-series. PloS One 10(3), e0119811.
Barbati, A., Corona, P., Marchetti, M., 2007. A forest typology for monitoring sustainable forest management: the case of European forest types. Plant Biosystems 141 (1), 93–103.
Barbati, A., Marchetti, M., Chirici, G., Corona, P., 2014. European Forest Types and Forest Europe SFM indicators: Tools for monitoring progress on forest biodiversity conservation. For. Ecol. Manage. 321, 145–157.
Becagli, C., Bertini, G., Di Salvatore, U., Fabbio, G., Fabrizio, F., Salvati, L., 2016. Monitoring managed forest structure at the compartment-level under different silvicultural heritages: an exploratory data analysis in Italy. J. Sustain. For. 35 (3), 234–250.
Biasi, R., Brunori, E., Smiraglia, D., Salvati, L., 2015a. Linking traditional tree-crop landscapes and agro-biodiversity in Central Italy using a database of typical and traditional products: A multiple risk assessment through a data mining analysis. Biodivers. Conserv. 24, 3009–3031.
Biasi, R., Colantoni, A., Ferrara, C., Ranalli, F., Salvati, L., 2015b. In-between sprawl and fires: Long-term forest expansion and settlement dynamics at the wildland–urban interface in Rome, Italy. Int J Sust Dev World 22 (6), 467–475.
Bonfiglio, A., Cuomo, V., Lanfredi, M., Macchiato, M., 2002. Interfacing NOAA/ANHRR NDVI and soil truth maps for monitoring vegetation phenology at a local scale in a heterogeneous landscape of Southern Italy. Int. J. Remote Sens. 23 (20), 4181–4195.
Bontemps, J.D., Bouriaud, O., Vega, C., Bouriaud, L., 2022. Offering the appetite for the monitoring of European forests a diversified diet. Ann. For. Sci. 79 (1), 1–9.
Borrelli, P., Modugno, S., Panagos, P., Marchetti, M., Schütt, B., Montanarella, L., 2014. Detection of harvested forest areas in Italy using Landsat imagery. Appl. Geogr. 48, 102–111.
Brunsdon, C., Fotheringham, A.S., Charlton, M., 2002. Geographically weighted summary statistics—a framework for localised exploratory data analysis. Comput. Environ. Urban Syst. 26 (6), 501–524.
Camarretta, N., Puletti, N., Chiavetta, U., Corona, P., 2018. Quantitative changes of forest landscapes over the last century across Italy. Plant Biosystems 152 (5), 1011–1019.
Cavalli, A., Francini, S., Cecili, G., Cocozza, C., Congedo, L., Falanga, V., Spadoni, G., Maesano, M., Munafò, M., Chirici, G., Scarascia Mugnozza, G. (2022). Afforestation monitoring through automatic analysis of 36-years Landsat Best Available Composites. IForest-Biogeosciences and Forestry, 15(4), 220–228.https://doi.org/10.3832/ifor4043-015.
Cavalli, A., Francini, S., McRoberts, R.E., Falanga, V., Congedo, L., De Fioravante, P., Maesano, M., Munafò, M., Chirici, G., Scarascia Mugnozza, G., 2023. Estimating Afforestation Area Using Landsat Time Series and Photointerpreted Datasets. Remote Sens. (Basel) 15 (4), 923.
Cecili, G., De Fioravante, P., Dichicco, P., Congedo, L., Marchetti, M., Munafò, M., 2023. Land Cover Mapping with Convolutional Neural Networks Using Sentinel-2 Images: Case Study of Rome. Land 12 (4), 879.
Congedo, L., Sallustio, L., Munafò, M., Ottaviano, M., Tonti, D., Marchetti, M., 2016. Copernicus high-resolution layers for land cover classification in Italy. J. Maps 12 (5), 1195–1205.
Copernicus Land Monitoring Service (2021b). HRL Forest 2018 Product User Manual. Available at: https://land.copernicus.eu/user-corner/technical-library/forest-2018-user-manual.pdf (accessed October 2023).
Copernicus Land Monitoring Service (2021a). CORINE Land Cover Product User Manual (Version 1.0). Available at: https://land.copernicus.eu/user-corner/technical-library/clc-product-user-manual.pdf (accessed October 2023).
Copernicus Land Monitoring Service (2022). CLC+ Backbone Product Specification and User Manual: Raster Product. Available at: https://land.copernicus.eu/user-corner/technical-library/clc-bb_user_manual_ras.pdf (accessed October 2023).
Corona, P., 2018. Communicating facts, findings and thinking to support evidence-based strategies and decisions. Annals of Silvicultural Research 42, 1–2.
Costa, H., Almeida, D., Vala, F., Marcelino, F., Caetano, M., 2018. Land cover mapping from remotely sensed and auxiliary data for harmonized official statistics. ISPRS Int. J. Geo Inf. 7 (4), 157.
D'Agata, A., Ponza, D., Strolu, F.A., Vardopoulos, I., Rontos, K., Escrivà, F., Chelli, F., Alaimo, L.S., Salvati, L., Nickayin, S.S., 2023. Toward sustainable development trajectories? Estimating urban footprints from high-resolution copernicus layers in Athens. Greece. Land 12 (8), 1490.
D'Amico, G., Vangi, E., Francini, S., Giannetti, F., Nicolaci, A., Travaglini, D., Chirici, G., 2021. Are we ready for a National Forest Information System? State of the art of forest maps and airborne laser scanning data availability in Italy. iForest-Biogeosciences and Forestry 14 (2), 144.
D'Amico, G., Chirici, G., Corona, P., Romano, R., Di Domenico, G., Giannetti, F., Mattioli, W., 2023. Differenze locali e prospettive globali per le foreste italiane: la definizione di bosco nel prossimo Sistema Informativo Forestale Nazionale. L'italia Forestale e Montana 78, 15–29.
De Fioravante, P., Luti, T., Cavalli, A., Giuliani, C., Dichicco, P., Marchetti, M., Chirici, G., Congedo, L., Munafò, M., 2021a. Multispectral Sentinel-2 and SAR Sentinel-1 Integration for Automatic Land Cover Classification. Land 10 (6), 611. https://doi.org/10.3390/land10060611.
De Fioravante, P., Strollo, A., Assennato, F., Marinosci, I., Congedo, L., Munafò, M., 2021b. High Resolution Land Cover Integrating Copernicus Products: A 2012–2020 Map of Italy. Land 11 (1), 35.
ESA, European Space Agency (2017). Land Cover CCI Product User Guide Version 2. Tech. Rep., 2017. Available at: maps.elie.ucl.ac.be/CCI/viewer/download/ESACCI-LC-Ph2-PUGv2_2.0.pdf (accessed October 2023).
FAO, Food and Agriculture Organization (2014). Global Land Cover SHARE (GLC-SHARE) database Beta-Release Version 1.0. Available at: https://www.fao.org/uploads/media/glc-share-doc.pdf (accessed October 2023).
Ferrara, A., Kelly, C., Wilson, G.A., Nolè, A., Mancino, G., Bajocco, S., Salvati, L., 2016. Shaping the role of 'fast' and 'slow' drivers of change in forest-shrubland socio-ecological systems. J. Environ. Manage. 169, 155–166.
Ferretti, M., Chiarucci, A., 2003. Design concepts adopted in long-term forest monitoring programs in Europe—problems for the future? Sci. Total Environ. 310 (1–3), 171–178.
Ferretti, M., Marchetto, A., Arisci, S., Bussotti, F., Calderisi, M., Carnicelli, S., Cecchini, G., Fabbio, G., Bertini, G., Matteucci, G., de Cinti, B., Salvati, L., Pompei, E., 2014. On the tracks of Nitrogen deposition effects on temperate forests at their southern European range–an observational study from Italy. Glob. Chang. Biol. 20 (11), 3423–3438.
Francini, S., Cavalli, A., D'Amico, G., McRoberts, R.E., Maesano, M., Munafò, M., Scarascia Mugnozza, G., Chirici, G., 2023. Reusing Remote Sensing-Based Validation Data: Comparing Direct and Indirect Approaches for Afforestation Monitoring. Remote Sens. (Basel) 15 (6), 1638.
Francini, S., Chirici, G., 2022. A Sentinel-2 derived dataset of forest disturbances occurred in Italy between 2017 and 2020. Data Brief 42, 108297.
Gschwantner, T., Alberdi, I., Bauwens, S., Bender, S., Borota, D., Bosela, M., Tomter, S. M., 2022. Growing stock monitoring by European National Forest Inventories: Historical origins, current methods and harmonisation. For. Ecol. Manage. 505, 119868.
Keenan, R.J., Reams, G.A., Achard, F., de Freitas, J.V., Grainger, A., Lindquist, E., 2015. Dynamics of global forest area: Results from the FAO Global Forest Resources Assessment 2015. For. Ecol. Manage. 352, 9–20.
Loepfe, L., Lloret, F., Román-Cuesta, R.M., 2012. Comparison of burnt area estimates derived from satellite products and national statistics in Europe. Int. J. Remote Sens. 33 (12), 3653–3671.
Lorenz, M., Fischer, R., 2013. Pan-European forest monitoring: an overview. Dev. Environ. Sci. 12, 19–32.
Nesha, M.K., Herold, M., De Sy, V., Duchelle, A.E., Martius, C., Branthomme, A., Pekkarinen, A., 2021. An assessment of data sources, data quality and changes in national forest monitoring capacities in the Global Forest Resources Assessment 2005–2020. Environ. Res. Lett. 16 (5), 054029.

Parviainen, J., Frank, G., 2003. Protected forests in Europe approaches-harmonising the definitions for international comparison and forest policy making. J. Environ. Manage. 67 (1), 27–36.

Pekkarinen, A., Reithmaier, L., Strobl, P., 2009. Pan-European forest/non-forest mapping with Landsat ETM+ and CORINE Land Cover 2000 data. ISPRS J. Photogramm. Remote Sens. 64 (2), 171–183.

Quaranta, G., Salvia, R., Cudlin, P., Salvati, L., 2023. Evaluating the spatial coherence of composite indexes of land degradation at small administrative units. Environ. Impact Assess. Rev. 103, 107226.

Sallustio, L., Munafò, M., Riitano, N., Lasserre, B., Fattorini, L., Marchetti, M., 2016. Integration of land use and land cover inventories for landscape management and planning in Italy. Environ. Monit. Assess. 188, 1–20.

Salvati, L., Carlucci, M., 2014. A composite index of sustainable development at the local scale: Italy as a case study. Ecol. Ind. 43, 162–171.

Salvati, L., Petitta, M., Ceccarelli, T., Perini, L., Di Battista, F., Scarascia, M.E.V., 2008. Italy's renewable water resources as estimated on the basis of the monthly water balance. Irrig. Drain. 57 (5), 507–515.

Salvati, L., Zitti, M., Perini, L., 2016. Fifty years on: long-term patterns of land sensitivity to desertification in Italy. Land Degrad. Dev. 27 (2), 97–107.

Salvati, L., Ferrara, A., Chelli, F., 2018. Long-term growth and metropolitan spatial structures: An analysis of factors influencing urban patch size under different economic cycles. Geografisk Tidsskrift (danish Journal of Geography) 118 (1), 56–71.

Schuck, A., Päivinen, R., Häme, T., Van Brusselen, J., Kennedy, P., Folving, S., 2003. Compilation of a European forest map from Portugal to the Ural mountains based on earth observation data and forest statistics. Forest Policy Econ. 5 (2), 187–202.

Seebach, L.M., Strobl, P., San Miguel-Ayanz, J., Gallego, J., Bastrup-Birk, A., 2011. Comparative analysis of harmonized forest area estimates for European countries. Forestry 84 (3), 285–299.

Smiraglia, D., Ceccarelli, T., Bajocco, S., Perini, L., Salvati, L., 2015. Unraveling landscape complexity: land use/land cover changes and landscape pattern dynamics (1954–2008) in contrasting peri-urban and agro-forest regions of northern Italy. Environ. Manag. 56, 916–932.

Tomppo, E., Olsson, H., Ståhl, G., Nilsson, M., Hagner, O., Katila, M., 2008. Combining national forest inventory field plots and remote sensing data for forest databases. Remote Sens. Environ. 112 (5), 1982–1999.

Vega, C., Renaud, J.P., Sagar, A., Bouriaud, O., 2021. A new small area estimation algorithm to balance between statistical precision and scale. Int. J. Appl. Earth Obs. Geoinf. 97, 102303.

Vizzarri, M., Chiavetta, U., Chirici, G., Garfì, V., Bastrup-Birk, A., Marchetti, M., 2015. Comparing Multisource Harmonized Forest Types Mapping: a Case Study from Central Italy. i-Forest 8 (1), 59–66.

Zambon, I., Colantoni, A., Carlucci, M., Morrow, N., Sateriano, A., Salvati, L., 2017. Land quality, sustainable development and environmental degradation in agricultural districts: A computational approach based on entropy indexes. Environ. Impact Assess. Rev. 64, 37–46.