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RESEARCH ARTICLE

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Characterizing historical transformation trajectories of the forest landscape in Rome's metropolitan area (Italy) for effective planning of sustainability goals

Francesco Solano[1] | Salvatore Praticò[2] | Gianluca Piovesan[1] | Alessandro Chiarucci[3] | Alessio Argentieri[4] | Giuseppe Modica[2]

[1]Department of Agriculture and Forest Sciences (DAFNE), University of Tuscia, Viterbo, Italy

[2]Dipartimento di Agraria, Università degli Studi Mediterranea di Reggio Calabria, Reggio Calabria, Italy

[3]Department of Biological, Geological and Environmental Sciences, University of Bologna, Bologna, Italy

[4]Department VI, Metropolitan City of Rome Capital, Rome, Italy

Correspondence
Salvatore Praticò, Dipartimento di Agraria, Università degli Studi Mediterranea di Reggio Calabria, Località Feo di Vito, I-89122 Reggio Calabria, Italy.
Email: salvatore.pratico@unirc.it

Abstract

With the aim at developing a landscape dynamics framework for environmental planning and management and testing the effectiveness of protected areas in achieving the 2030 Agenda of the United Nations sustainability goals, we characterized the historical transformation trajectories of forest area changes from 1936 to 2010 in the Metropolitan City of Rome Capital (Italy). Remote sensing-based products coupled with landscape pattern metrics and fragmentation analysis have been implemented, comparing different historical forest maps. The results show a remarkable forest area gain – from 17.6% to 25.5% – thanks to 68,299 ha of recently established forest. Statistical descriptors showed that the highest relative gain occurred in mountain zones, confirming a wide European forest recovery pattern in marginal areas from past deforestation and overexploitation. Deforestation mainly occurred in the flat and hilly areas where almost 26,000 ha of forests were lost since 1936. In summary, two main forest landscape dynamics were reconstructed: (I) the increase of forest cover fragmentation in the lowland areas; and (II) the rise in the forest area in the interior sectors of the mountain landscape, mainly within protected areas. Restoring the forest ecosystem's bioecological integrity has been highlighted as an urgent action for biodiversity conservation and carbon mitigation. In lowland areas, the study revealed the urgent need to establish new protected areas and rewilding spaces as landscape metrics are relatively below the sustainability targets for healthy forest ecosystems. The proposed framework can be used for testing the effectiveness of environmental planning and management in other forest landscapes to achieve the Agenda 2030 goals.

KEYWORDS

2030 Agenda of the United Nations, forest cover changes, forest fragmentation, global tree cover data (GTCD), landscape metrics

1 | INTRODUCTION

Nowadays, few terrestrial ecosystems have remained undisturbed by anthropic activities (Foley, 2005; García-Vega & Newbold, 2020). Therefore, many forest landscapes worldwide reflect ecological and socio-economic history (Caetano-Andrade et al., 2020; Curtis et al., 2018). In Europe, forests have been used for millennia by humans, who have transformed the species composition, structure and spatial patterns of the community (Munteanu et al., 2015), and consequently their natural disturbance regimes and functionality compared to natural ecosystems (Sommerfeld et al., 2018). In the Mediterranean biodiversity hotspot, the current structure and physiognomy of the remaining forests have been altered by recurring degradation and deforestation activities (e.g., Mensing et al., 2018) and tracking the progress in halting habitats and species loss through ecosystem restoration and conservation programmes is an urgent action (Watson et al., 2020). In recent times, most forests have been maintained and managed for their wood and non-wood products and for many other functions, such as slope stabilization, to prevent hydrogeological instability (Führer, 2000). Since the beginning of the last century, there has been a natural recovery of forests in many temperate regions worldwide as a consequence of the abandonment of traditional mountain agriculture, driven by socio-economic factors such as immigration in urban areas (Geri et al., 2010; Gibon et al., 2010; Nadal-Romero et al., 2016; Romero-Calcerrada & Perry, 2004; Sitzia et al., 2010; Tasser et al., 2007). In the same period, deforestation activities occurred for farming and urban sprawl in lowland environments, for which characterizing historical forest transformation trajectories is a fundamental step in environmental landscape planning.

It is essential to investigate the landscape changes in forest ecosystems to meet the goals of the 2030 Agenda of the United Nations (www.un.org/sustainabledevelopment/development-agenda) and improve effective planning strategies to increase their resilience (Turner, 2010).

In the global framework of biodiversity conservation and carbon stores, protected areas are recognized as the cornerstones of the global conservation strategy and can reduce forest loss compared to unprotected areas (Wolf et al., 2021). Protected areas can maintain higher biodiversity levels and carbon stocks than neighboring alternative land use areas (Coetzee et al., 2014) and must be seen as an irreplaceable tool to guarantee complex ecosystem functions (Coad et al., 2019). As recognized by the key multilateral environmental agreement aimed at slowing biodiversity decline (UN Agenda 2030, 2015; UN CBD, 2010), the expansion and effective management of protected areas is needed to mitigate the loss of biodiversity (Watson et al., 2014); thus, describing long-term regional changes in forest cover is critical for effective environmental management planning.

Understanding the dynamics of change and its impact on forest landscape functioning is crucial for biodiversity conservation (García-Vega & Newbold, 2020), and carbon mitigation strategies (Erb et al., 2018) and interesting solutions are being developed thanks to the integration of ecological history and remote sensing data. In this framework, landscape metrics and/or indices are often proposed and evaluated to assess landscape characteristics and to monitor changes in land use (Diaz-Varela et al., 2009; Geri et al., 2010; McGarigal, 2014; Modica et al., 2012; Uuemaa et al., 2009). The survival of threatened species also depends on the landscape dynamics and habitats' spatial configuration (Itani et al., 2020; Palmero-Iniesta et al., 2020; Rocha-Santos et al., 2020; Williams et al., 2020; Zhang, 2020), which change in quality, shape and position. Forest fragmentation can lead to the extinction of some species by isolating populations from each other and creating forest areas that are too small to be functional and maintain viable populations (Kettunen et al., 2007). Fragmentation can cause a change in ecological conditions with consequences on the abundance and distribution of species (May et al., 2019) due to the increase in forest edges and reduction in carbon storage capacity compared to a canopy-closed forest (Brinck et al., 2017).

In this regard, remote sensing data represent an alternative source for quantifying forest cover and its change over time (Lillesand et al., 2015; Taylor et al., 2020). Firstly, remote sensing products can cover large areas coherently, avoiding discontinuities due to administrative and national borders (Fagua et al., 2019; Hansen et al., 2013; Potapov et al., 2015). Second, long-term recording of satellite observations allows the quantification of forest cover trends over several decades (Cheng & Wang, 2019; Hermosilla et al., 2019; Hościło & Lewandowska, 2019; Qin et al., 2019; Vogeler et al., 2018). Besides, new research impulses have arisen, especially after the emergence of remote sensing applications based on cloud computing platforms (Gasparini et al., 2019; Potapov et al., 2012; Praticò et al., 2021).

This study presents a novel approach through the integrated use of historical forest cover data and remote sensing-based products to support environmental policies aimed at sustainable forest management, according to the development targets of the 2030 Agenda goals. The proposed framework is tested and applied in an important and representative Mediterranean environment, the Metropolitan City of Rome Capital (MCRC), in Italy. Here, different factors have influenced the natural and cultural landscape dynamics during the long history of landscape transformation. The reconstructed long-term forest cover changes, coupled with landscape pattern metrics and in-depth fragmentation analysis, were used to identify the primary forest landscape dynamics and their distribution according to an altitudinal gradient and concerning protected areas. Since we hypothesized that protected areas could guarantee greater integrity of forest ecosystems than non-protected areas, we derived an indirect indicator of forest functioning (Ćosović et al., 2020) based on remote sensing products such as the global tree cover data (GTCD) to describe their effectiveness as a tool in achieving the sustainability goals. In this context, our work suggests an innovative way to improve environmental knowledge to develop an effective landscape planning and management framework targeted to achieve the 2030 UN Agenda goals focused on restoring forest bioecological integrity.

2 | MATERIALS AND METHODS

Our proposed method can be summarized in the following main phases: (a) data acquisition and forest maps derivation; (b) altitudinal

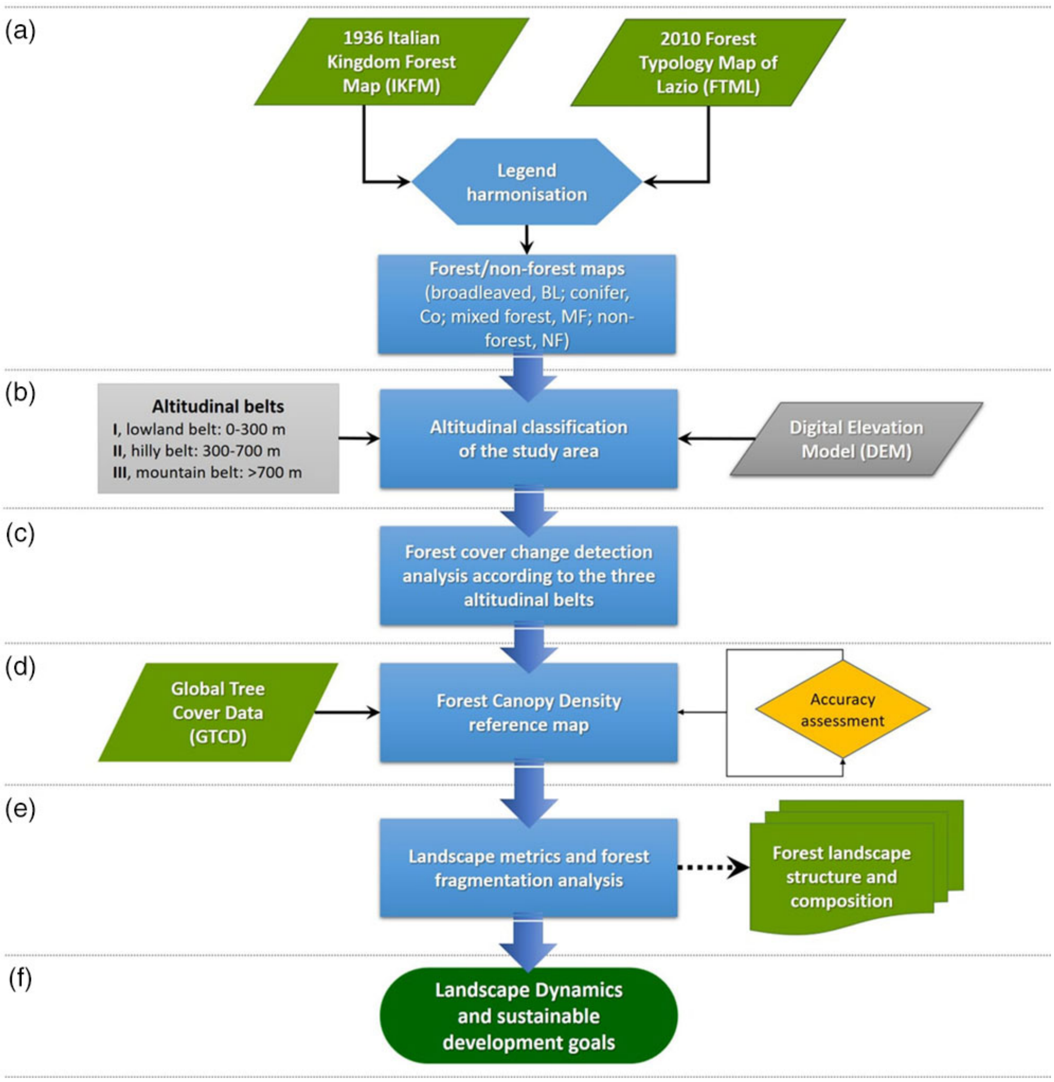

FIGURE 1 Workflow of the proposed method for developing an effective landscape planning and management framework targeted to achieve Sustainable Development Goals [Colour figure can be viewed at wileyonlinelibrary.com]

classification of the study area; (c) forest cover change detection analysis; (d) forest canopy density reference map; (e) landscape metrics and forest fragmentation analysis; and (f) landscape dynamics and sustainable development (Figure 1).

2.1 | Study area

The study area is the whole MCRC, covering 5363 km^2 in the Lazio region, Italy. It comprises the territory of Rome and 120 other municipalities, with more than 4.3 million inhabitants representing the largest metropolitan area in Italy. It is delimited to the west by the Tyrrhenian Sea and north to the southeast by mountains belonging to the central Italian Apennines (Figure 2a). A complex topography characterizes the MCRC with flat land, coastal and internal uplands, and mountain areas (up to 1854 m a.s.l. of Mount Autore) (Figure 2b). The mean annual temperature ranges from 13.1 to 15.2°C, with mean annual rainfall ranging from 700 to 1500 mm (meteorological stations are located at lowland and hilly sites; http://www.arsial.it/portalearsial/agrometeo/, accessed on 20 December 2020). Latest CORINE Land Cover data (Büttner et al., 2017) show that the area is mainly occupied by agricultural land (56%) and built-up areas (14%), while natural and semi-natural forests cover around 27%. Lowland forests are predominantly occupied by deciduous (*Quercus cerris* L., *Q. pubescens* Willd.) and evergreen (*Quercus ilex* L.) oak formations together with the hop hornbeam (*Ostrya carpinifolia* Scop.), whereas chestnut (*Castanea sativa* Mill.) and beech (*Fagus sylvatica* L.) dominate forests in the hills and mountains, respectively (Figure 2c).

2.2 | Data acquisition and forest maps derivation

To investigate the forest cover changes over time, we used the historical, geographical data of the 1936 Italian Kingdom Forest Map (IKFM)

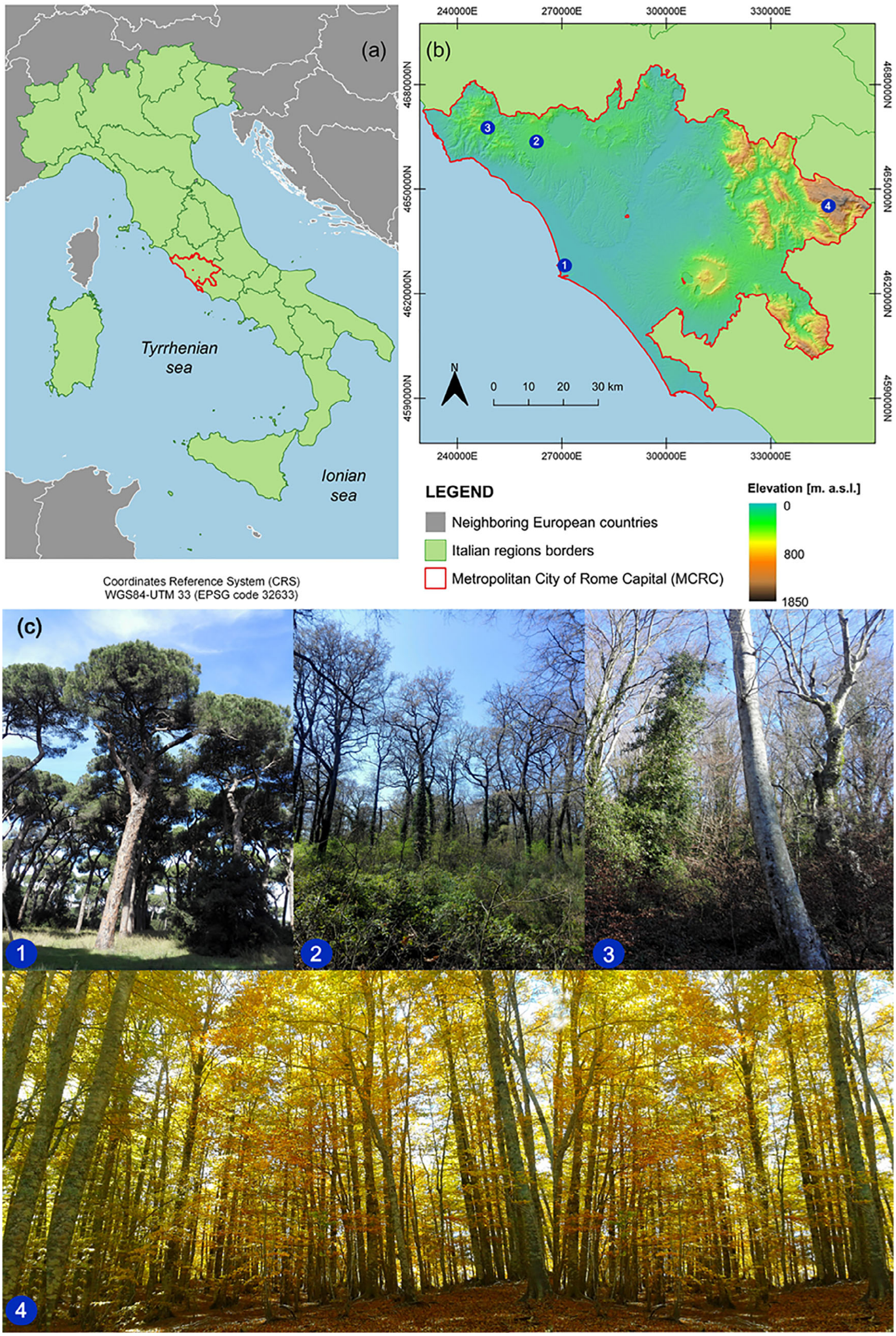

FIGURE 2 (a) study area location and (b) distribution of elevations over the Metropolitan City of Rome Capital (MCRC). Examples of high-forest types: 200 year- old umbrella pine stand along the coast (c1); mixed oak woods (c2) and old-growth mixed beech forest (c3) in the hilly belt; pure mountain beech forest (c4) [Colour figure can be viewed at wileyonlinelibrary.com]

and the forest typology map of the Lazio (FTML) region of 2010, allowing us to analyse a period of 74 years. The IKFM digital vector data were acquired from the dedicated WebGIS tool (http://carta1936.dicam.unitn.it/webgis/map1.php, accessed 20 December 2020). It represented the first homogenous map that reports Italian forests categorized under a recognizable scheme (Ferretti et al., 2018). The FTML was downloaded from the Lazio open data geoportal (http://dati.lazio.it/catalog/it/dataset/carta-forestale-su-base-tipologica-della-regione-lazio, accessed on 20 December 2020) in the digital vector format. It was obtained by exploring the fourth- and fifth-level CORINE Land Cover data of the Lazio Region Land Use Map (ARP, 2010). For all datasets, three general forest categories were extracted: broadleaved (BL), conifer (Co) and mixed forest (MF), adding a class of non-forest (NF) areas obtained by overlapping the two datasets with the boundary of the study area. To allow the extraction of these forest categories, we homogenized the legends from the two datasets. Since the 1936 dataset included a class labelled 'degraded forests', which was not in the 2010 dataset, it was decided to report an in-depth analysis separately from the other categories.

2.3 | Altitudinal classification of the study area

A digital elevation model (DEM) with a spatial resolution of 20 m × 20 m was used for dividing the study area into three main altitudinal zones. According to the mountain area definition of the Italian National Statistics Institute (ISTAT, 2007), we resampled the DEM in three altitudinal belts: (I) lowland belt, from 0 to 300 m. a.s.l.; (II) hilly belt, from 300 to 700 m a.s.l.; and III) mountain belt above 700 m a.s.l. For each forest dynamic (gain, loss and persistence), the values of topographical variables such as elevation and slope were extracted and compared in terms of differences by using univariate statistics and applying the Kruskal–Wallis nonparametric test (Kruskal & Wallis, 1952). Statistical analyses were performed with R statistical software (R Core Team, 2020).

2.4 | Forest cover change detection analysis

To detect the changes that occurred in the time interval investigated (1936–2010), we performed a change detection (Singh, 1989) followed by a post-classification comparison approach (Lu et al., 2004; Modica et al., 2017) for diachronic analysis. The two forest cover vector datasets (1936–2010) were overlaid in a GIS environment, obtaining unique vector data showing the forest categories' cover changes. We built a complete matrix of changes to quantify changes, reporting in rows the value of changes in the 1936 category and in columns the number of changes in the 2010 category. Finally, this dataset was overlaid on the resampled DEM to analyse the changes within different altitudinal belts and converted into a vector format. Then, another change matrix was implemented.

2.5 | Forest canopy density reference map

To reconstruct the forest canopy dynamics and qualify them from an ecological functional point of view, we used advanced remote sensing-based products that users can suitably customize to distinguish and identify the forest and NF components (Chiarucci & Piovesan, 2020). As the reference layer for forest cover status in 2010, we used the GTCD with a spatial resolution of 30 m × 30 m, (https://glad.umd.edu/dataset/global-2010-tree-cover-30-m, accessed on 27 January 2021). The GTCD dataset for the year 2010 (Hansen et al., 2013) is per-pixel estimates of percent maximum tree canopy cover, expressed as an integer value percentage (1%–100%). The dataset was first clipped using the study area boundary. Then, we defined the corresponding forest area using a threshold of percentage tree cover as an area that was larger than 0.49 ha and with a tree cover of more than 10%, consistent with the forest definition of the FAO (FRA, 2018) and resampled at the spatial resolution of 20 m × 20 m with class intervals every 10%. We performed an accuracy assessment to use the obtained map as a reference layer for forest canopy density. To produce sufficiently precise estimates of the classes' area, the sample size for each mapping class was chosen to ensure that the sample size was large enough (Global Forest Observations Initiative, 2013). Therefore, we calculated an adequate overall sample size for a stratified random sampling distributed among different strata (Cochran, 1977). First, we determined the number of sample units for the study area using the following Equation (1) (Olofsson et al., 2014)

$$n = \frac{\left(\sum W_i S_i\right)^2}{[S(\hat{o})]^2 + \left(\frac{1}{n}\right)\sum W_i S_i^2} \approx \left(\frac{\sum W_i S_i}{S(\hat{o})}\right)^2, \tag{1}$$

Where: n is the total sample size, W_i is the mapped proportion of the area of class i, and S_i is the standard deviation of class i (forest/non-forest). S_i was obtained according to the following formula (Equation (2))

$$S_i = \sqrt{U_i(1 - U_i)}, \tag{2}$$

Where: U_i is the expected user accuracy of class i. For both selected classes (forest/non-forest) we used 0.09 and 0.91 as mapped proportions of the forest class areas for the NF area. We also set an U_i of 0.9 and 0.8 for forest and non-forest classes, respectively. The overall sample size resulting from this calculation was 1528 sample points, and we applied stratified random sampling to allocate the samples to each stratum (altitudinal belt). As suggested by FAO (2016) and Congalton & Green (2019), we assigned a minimum size of 100 sample points to each altitudinal belt. We allocated the remaining number of samples proportionally, according to each stratum area (Table 1). Sample points were generated and randomly distributed in each altitudinal belt (Figure 3) using QGIS software (QGIS Development Team, 2020).

According to the FAO forest definition, we set, for each sample point, a square buffer zone of 70 m × 70 m (0.49 ha) with a systematic grid of 5 × 5 points and used them as ground truth references

TABLE 1 Number and allocation of the sample points in the three altitudinal belts

Altitudinal belt	Area (ha)	%	Sample points
(I) Lowland belt (0–300 m. a.s.l.)	376,007	70.1	1072
(II) Hilly belt (300–700 m. a.s.l.)	106,696	19.9	304
(III) Mountain belt (> 700 m. a.s.l.)	53,618	10.0	153
Total	536,3321	100	1528

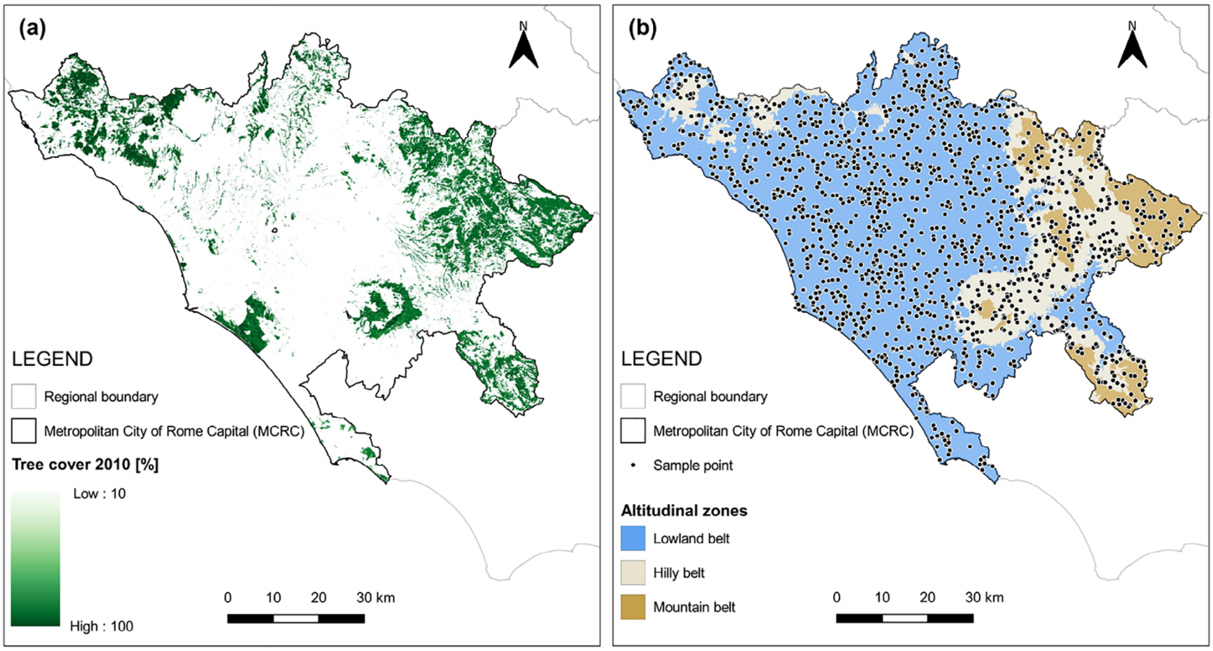

FIGURE 3 (a) the MCRC forest canopy density derived from the global 2010 tree cover data (Hansen et al., 2013) customized according to the FAO forest definition, (b) study area classification of the altitudinal belts showing sample point allocation used for the forest canopy density map classification accuracy (lowland belt = 0–300 m. a.s.l.; hilly belt = 300–700 m. a.s.l.; mountain belt ≥700 m. a.s.l.) [Colour figure can be viewed at wileyonlinelibrary.com]

(Figure 4). Within each plot, we identified forest or NF areas by counting the number of points covered by trees, based on a screen photointerpretation of Google Earth very high-resolution imagery for the year 2010 (Hansen et al., 2013; Lui & Coomes, 2015; Lwin et al., 2019; Potere, 2008; Tilahun, 2015). In each plot, when the tree crowns covered at least three points on the grid (3/25 = tree cover >10%), the sample was classified as forest, otherwise as non-forest. A confusion matrix (Congalton & Green, 2019; FAO, 2016) was then used to assess the accuracy of the forest canopy density map produced, using overall accuracy (OA), producer's accuracy (PA) and user's accuracy (UA), between the forest cover map and reference data. Once the canopy density reference map's accuracy was verified, the 2010 forest dataset (FTML) was used to extract the corresponding values, resulting in a reference forest canopy density map.

Furthermore, the forest canopy density reference map was used to analyse the canopy density percentage variations by distinguishing it by altitudinal belts and considering the forests within the protected areas (PrAs), that is, nature parks and Natura 2000 network areas, and non-protected (NP) wooded areas of the MCRC. The PrAs' official boundaries were downloaded from the WebGIS tool of the Lazio region (http://dati.lazio.it/catalog/it/dataset, accessed on 23 January 2021) in the vector format, suitably customized, and selected for the study area (Figure S1). Differences in canopy density values were tested applying the Kruskal–Wallis non-parametric test (Kruskal & Wallis, 1952) and the Mann–Whitney U test (Zar, 1996) as a post hoc pairwise comparison method after verifying the normality and homoscedasticity of the data with the Levene test (Levene, 1960) and Shapiro–Wilk test (Shapiro & Bradbury Wilk, 1965).

2.6 | Landscape metrics and forest fragmentation analysis

To quantify landscape changes closely linked to ecological processes, we analysed the forest landscape's structure and composition (McGarigal, 2014). To this end, metrics on size, shape and edge were used, selecting a few significant variables from the many available in the literature (Mcgarigal et al., 2002; Uuemaa et al., 2009). A set of seven metrics were calculated at class and landscape level: the number of patches (NP), mean patch size (MPS), edge density (ED), mean patch

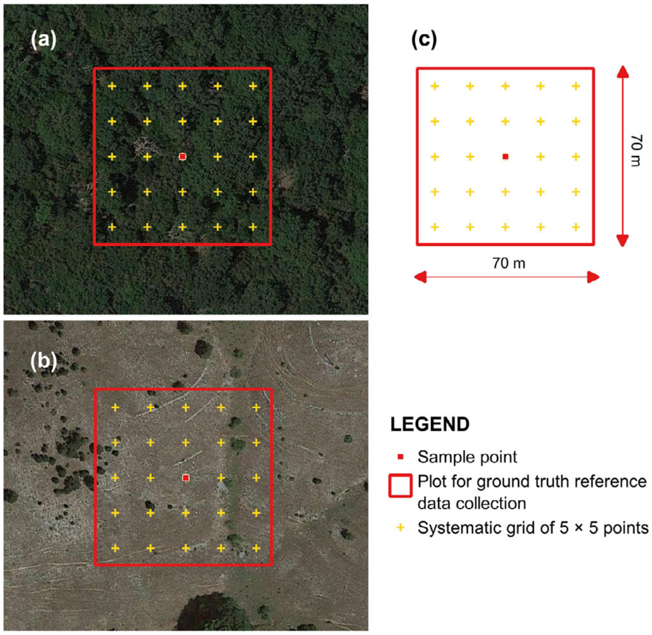

FIGURE 4 Sample point and the buffer zone of 0.49 ha generated in a GIS environment for ground truth reference data collection using Google Earth imagery. (a), An example of identifying forest area; (b), an example of identifying non-forest areas; (c), reference scheme of the reference plot and the systematic grid of 5 × 5 points [Colour figure can be viewed at wileyonlinelibrary.com]

edge (MPE), mean shape index (MSI), mean perimeter area ratio (MPAR) and mean fractal dimension (MFRACT). To calculate landscape metrics with the highest accuracy, referring to the input data, we used the vectorial data model and the plugin V-Late (vector-based landscape analysis tools extension) for ArcGIS (Lang & Tiede, 2003). Then, we computed the forest fragmentation using the raster-based forest fragmentation model of Riitters et al. (Riitters et al., 2000; Riitters et al., 2002). In this model, based on image convolution, the input raster must be binary (i.e., all cells are classified as forest = 1 or non forest = 0). Each forest cell is analyzed with the surrounding cells falling in a square mobile window centred on it. According to the six fragmentation classes, the analysed landscape is classified through the fragmentation index combining two different indicators: the density index (Pf) and the connectivity index (Pff). Pf represents the proportion (density) of forest pixels falling in the defined moving window. Pff is a measure of forest connectivity. It is obtained by dividing the number of forested pixel pairs in cardinal directions falling in the defined moving window by the total number of pixel pairs containing one or two forested pixels. The higher the value of Pff, the higher the connectivity value. Combining Pf and Pff maps according to the rules defined by Riitters et al. (2000), the following six categories of the forest fragmentation index (FFI) can be obtained: (1) interior (Pf = 1.0); (2) undetermined (density > 0.6 and density = connectivity); (3) perforated (density > 0.6 and density − connectivity > 0); (4) edge (Pf > 0.6 and density − connectivity < 0); (5) transitional (0.4 < density < 0.6); and (6) patch (density < 0.4). The cells that are classified as 'interior' are surrounded by forest cells. Therefore, they are not fragmented, that is, undisturbed. The other four categories exhibit some degree of fragmentation in a gradient from the interior to the perforated, edge, transitional, and patch fragmentation classes. The perforated category is dominated by relatively large and noncompact forest clusters alternating with 'holes' created by small patches of NF areas. In the case of the transitional category, forested pixels tend to be connected to other forested pixels but, at the same time, tend to be surrounded by other fragmentation categories (Fichera et al., 2015). The edge category concerns those landscape areas between compact forest clusters neighbouring to and compact NF clusters. Considering the scale dependence of spatial metrics and that low data resolution could lead to inaccurate landscape pattern analysis (Wickham & Riitters, 2019), as input data, we used a raster with 10 m × 10 m of geometrical resolution. Moreover, following Riitters et al. (2000, 2002) and other scholars (Kowe et al., 2020; Li et al., 2011), the square moving window was fixed to 5 × 5 pixels.

2.7 | Landscape dynamics and Sustainable Development Goals

This study's results were applied for addressing environmental management policies in favour of achieving the sustainable development goals of the 2030 Agenda for Sustainable Development of the United Nations (UN). In particular, we reconstructed the forest cover index (FCI) dynamics given the development target 15.1.1 (Forest area as a proportion of total land area) of the 2030 Agenda (https://unstats.un.org/sdgs/metadata/?Text&Goal=15&Target). The FCI was calculated as the relationship between the forest and the total study area, analysing the forest cover gain, loss, and persistence between 1936 and 2010. A set of forest landscape transformation indicators was used to evaluate the progress towards sustainable forest resources management (target 15.2.1). The net forest cover during the 74 years analysed was considered a legacy indicator for tracing sub-indicator 1 (Forest area annual net change rate). Data of forest canopy density was considered a proxy for describing the sub-indicator 2, 'Aboveground biomass stock in a forest'. By integrating the results of the FCI and forest change net rate and analysing their metrics within the protected areas of the MCRC, it was finally possible to evaluate their consistency and effectiveness in protected area management (sub-indicator 3, 'Proportion of forest area located within legally established protected areas'). While evaluating this indicator, nature parks and reserves were considered separately from Natura 2000 sites.

3 | RESULTS

3.1 | Forest land cover changes (1936–2010) in the MCRC

The forest cover increased from 94,624 ha in 1936 to 136,823 ha in 2010, representing a rise of FCI from 17.6% to 25.5% (Table 2). The general trend observed corresponded to an absolute increase of 44.6% (42,199 ha) in forest cover, 7.9% if referred to the whole study

TABLE 2 Contingency matrix showing the transition between different forest and non-forest land cover (values in ha) from 1936 to 2010 in the Metropolitan City of Rome Capital (MCRC) study area

	2010				
Forest/non-forest land cover	**Non-forest**	**Coniferous**	**Broadleaved**	**Mixed forest**	**Total**
1936					
Non-forest	**373,401**	2169	57,804	8325	441,700
Coniferous	744	**764**	109	8	1626
Broadleaved	4402	117	**22,403**	264	27,188
Mixed forest	20,953	1033	42,511	**1313**	65,811
Total	399,502	4084	122,828	9911	**536,325**

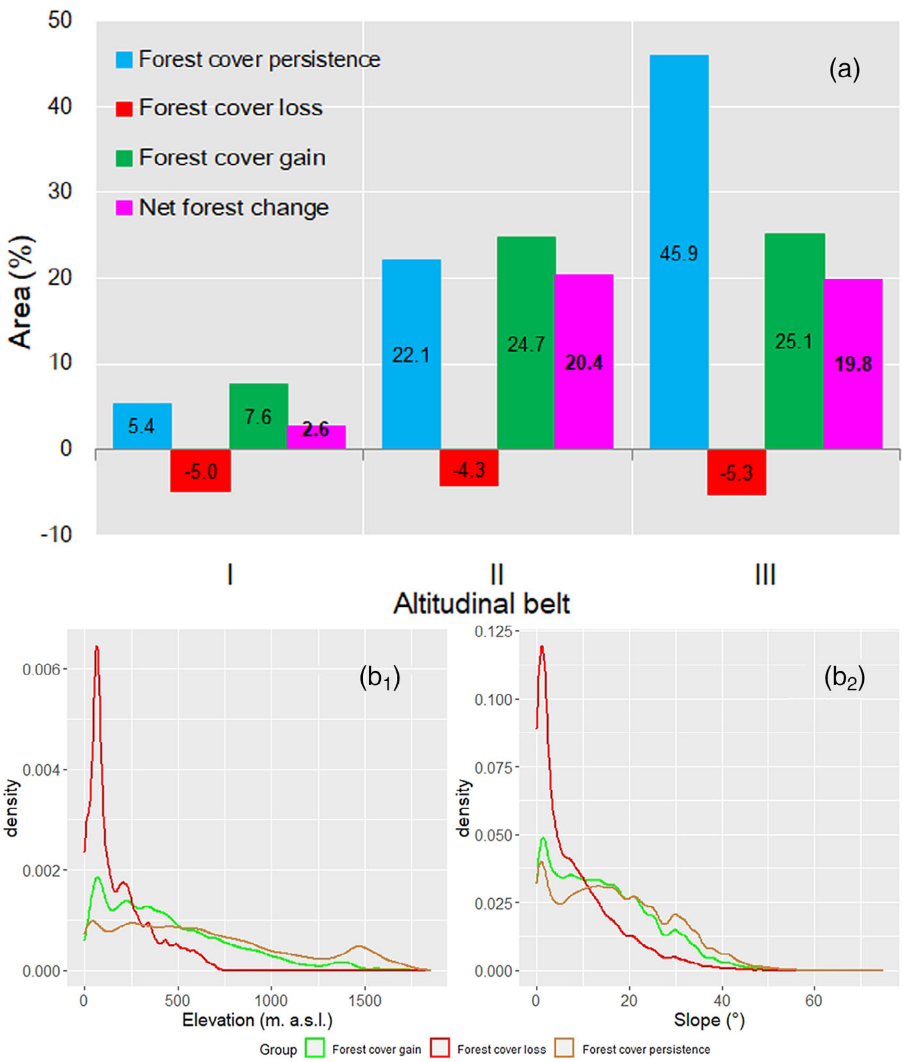

FIGURE 5 Percentage of forest cover gain, loss, persistence, and net cover change referring to the single altitudinal belt's (i.e., zones) total area, which occurred in the period between the years 1936 and 2010 (a); kernel density distribution plot of forest cover gain, loss, and persistence referring to differences in elevation (b_1) and slope (b_2). Data are reported according to the three defined altitudinal zones: (I) lowland belt, (II) hilly belt and (III) mountain belt [Colour figure can be viewed at wileyonlinelibrary.com]

area extension. Overall, there was a forest cover gain of 68,299 ha, against a cover loss of 26,100 ha. Forest cover persistence involved 68,524 ha of forest over the total forest area of the study area. The BL forest class recorded the largest areal increase, passing from 27,188 ha in 1936 to 122,828 ha in 2010 (gain of about 352%), followed by coniferous forest from 1626 ha to 4084 ha (+151%) (Table 2).

3.2 | Forest cover changes by topography

Forest area is unevenly distributed in the three altitudinal belts. In 2010, the FCI represented about 13% of belt I, 47% in belt II and 71% of the total land cover in belt III. The highest forest cover gain (new forests) occurred (25%) in hilly and mountain belts (Figure 5a). In comparison, the lowland belt showed the slowest net increase in the FCI

(3% instead of 20% in the other two belts). Forest persistence has a marked geographic distribution with a steep decreasing trend from mountain to lowland belt (Figure 5b).

As shown by the Kruskal-Wallis test (with $\alpha = 0.05$), the areas that experienced forest cover gain, loss or persistence dynamics displayed a significant difference concerning topographic factors (elevation and slope) (Table 3).

The dynamics of change within each altitudinal belt results in a general net increase (forest persistence plus forest cover gain) in the forest area. Indeed, the most considerable forest area loss – in terms of absolute value – is located at low altitudes, mainly in the lowlands and secondary, low hilly belts. In the mountain belt, BL forests were the most common category in 1936 (13,801 ha) and remained so even in 2010 with an increase in tree cover equal to 161% (36,576 ha in total) (Table S2). A similar cover gain occurred in the hilly belt, with +290% (from 11,842 ha in 1936 to 46,771 ha in 2010) and +150% in lowland areas (Table S2). A distinctive compositional dynamic occurred in the mountain belt because in 1936 there were no conifers in this belt. In the hilly and lowland belts, the increase of conifers was 221% and 76%, respectively (Table S2).

In 1936, there were about 3630 hectares of degraded forests, of which 1728 ha (48%) was in the mountain belt, 1068 ha (29%) in the hilly belt and the remaining 831 ha (23%) in the lowland belt (Figure 7). In 2010, most of the degraded forest in the mountain belt turned into BL forests (1173 ha), while 516 ha became deforested. A similar trend occurred in the hilly belt where 708 ha of 1068 ha became BL, and 333 ha became NF. The opposite trend was recorded in the lowland belt where about 76% of the degraded forests in 1936 (628 ha) were deforested, and only 22% (189 ha) turned into BL ones (Figure 6).

3.3 | Forest canopy density estimation according to the GTCD in 2010

The estimation of the forest canopy density reference map (Table S3) obtained an overall accuracy level of 99.01% for the altitudinal belt I,

TABLE 3 Univariate statistics summary regarding forest cover gain, loss, and persistence dynamic processes considering topographic factors such as elevation and slope

		Mean	SD	Min	Q1	Median	Q3	Max	Kruskal-Wallis test (χ^2)
Elevation (m)	Gain	403.75	314.50	0	164	319	575	1600	272.5*
	Loss	272.18	334.19	0	62	134	340	1850	
	Persistence	610.40	456.59	1	245	450	925	1840	
Slope (°)	Gain	13.67	10.04	0	5	12	20	65	234.2*
	Loss	8.14	8.31	0	2	5	12	75	
	Persistence	15.30	11.04	0	6	14	22	75	

Note: Kruskal-Wallis test (χ^2) with $\alpha = 0.05$
Abbreviations: Q1, first quantile; Q3, third quantile
*p-value < 0.05

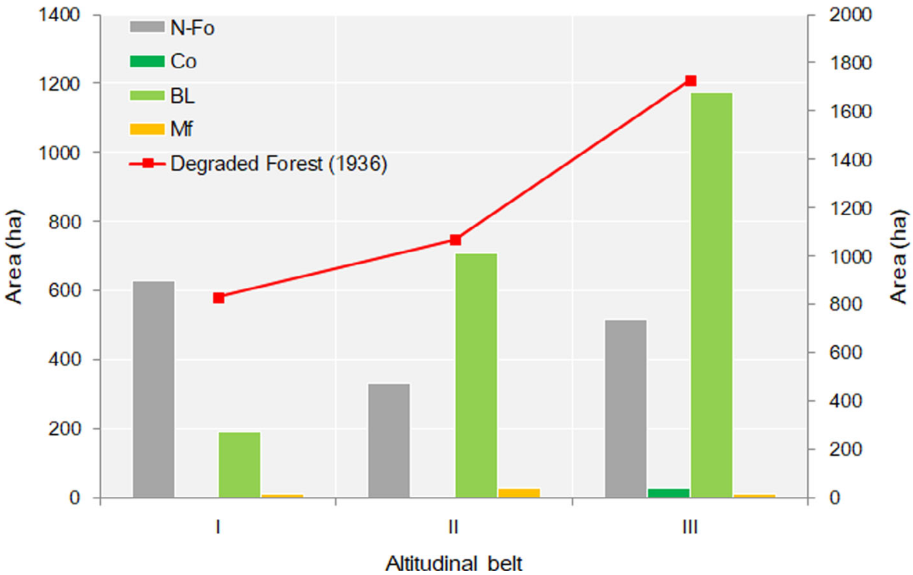

FIGURE 6 Extension of land cover changes in areas described as degraded forest in 1936. Data are presented according to the three altitudinal belts (I, lowland belt; II, hilly belt; III, mountain belt). Left y-axis label refers to the total area of the single forest or non-forest category; the right y-axis label refers to the total area of the 1936 degraded forest category [Colour figure can be viewed at wileyonlinelibrary.com]

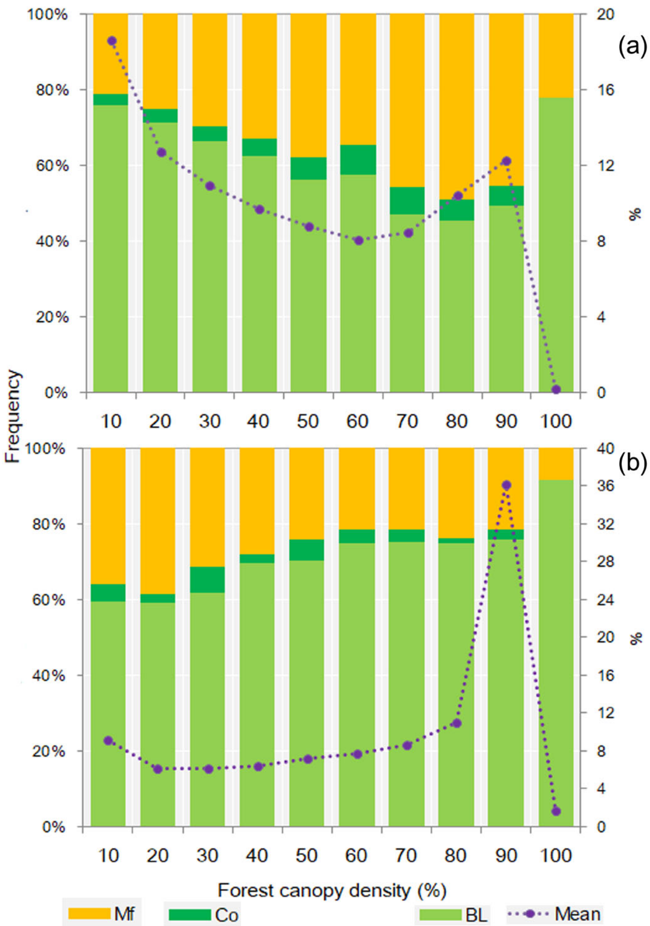

FIGURE 7 Forest canopy density percentage distribution: Forest cover gain (a) and forest cover persistence (b). The two categories' dynamics occurred between 1936–2010 in the MCRC study area. BL, broadleaved forest; Co, coniferous forest; Mf, mixed forest; and Mean, mean percentage cover value referred to the whole cover gain and persistence areas. Left y-axis label refers to the canopy density percentage frequency of a single forest category; the right y-axis label refers to the canopy density percentage frequency of all forest categories referring to the whole cover gain and persistence areas [Colour figure can be viewed at wileyonlinelibrary.com]

98.03% for the altitudinal belt II and 97.39% for the altitudinal belt III. The PA for the 'forest' classification varies with increasing altitude, from 98.95 to a value of 96.34. The UA reached the highest values in belts II and III (Table S3). The PA for the 'non-forest' classification achieved an overall value of 98% for all three altitudinal belts. In contrast, the UA decreases with altitude but still shows the classification process's reliability.

3.4 | Forest canopy density assessment

Forest canopy densities for areas that gained trees show that growth dynamics have led to forests' formation with an average canopy density value of 46% (for the whole study area) (Figure 7a). As the canopy density percentage's class increases, the forest extension decreases. The most widespread density percentage class in the cover gain area is 10%. Moving to canopy density up to a threshold value of 60%, the forests' frequency gradually decreases to only 8%. It then increases in frequency again for classes >70% of density values, with the latter class covering 12% of the MCRC. A canopy cover density ratio of 100% is present only on a tiny part of the study area (0.2%; ~ 14 ha). In forest grain areas, BL forest confirms a U shape distribution with a minimum of around 70%–80% of canopy density cover (Figure 7a). In 2010, no coniferous forest reached 100% canopy density (Figure 7a). The other MF category's frequency shows an increasing trend with increasing canopy density up to 80%, with a 133.33% increase in the distribution (from 21% to 49%) (Figure 7a).

Where persistence dynamics occurred (Figure 7b), the BL forests' frequency increases with canopy density. In contrast, the frequency of MF decreases. Moreover, in this case, coniferous forests do not reach a closed canopy structure (Figure 7b).

Considering the 2010 canopy density of forest cover gain areas within the altitudinal belts, low canopy densities (between 10% and 40%) are mainly distributed in the lowland belt (altitudinal zone I). Higher canopy density values are mainly distributed between the hilly belt and the mountain belt (zones II and III) (Figure S4).

The trend is confirmed even considering all MCRC (Figure 8), where the forests in the lowland belts, especially the coastal strip, have a lower canopy density than the forests of the mountain belt. Most deciduous and mixed deciduous forests are intensely coppiced, and these forest types occur in correspondence with sparsely, low- and medium- settled areas. These woodlands, therefore, maintain a lower density value than mountain forests that are managed following high forest systems. Moreover, a higher forest canopy density is a distinctive trait of protected areas (nature parks and Natura 2000 network areas) (Figure 8).

3.5 | Forest landscape dynamics

The number of patches shows the quantitative changes in forest cover both in the whole landscape and for different categories (Table 4; Table S5). In 1936, the forest area had minor fragmentation (Table 4) with respect to 2010 (Table S5). The general trend of the increase in the forest area is also linked to growth in the number of patches, as reflected in the MPS metric decrease, observed for all forest categories (Table S5). The MSI showed a general increase in size variability (Table 4) and individual categories (Table S5). The shape of the forests has also changed clearly, with an increase in the MPAR and MFRACT for all categories, showing an increase in the forest patch shapes' geometric complexity. The ED showed a different total margin between 1936 and 2010 (Table 4), with a relatively high increase for MFs. The MPE showed a considerable gain for BL forests and decreased for coniferous and MFs (Table S5).

Two different forest dynamics affected the landscape over this time period. On-the-one-hand, there was a slight increase in the interior areas (i.e., forest areas not affected by fragmentation). The dominant process was a significant rise in edge and patch categories that

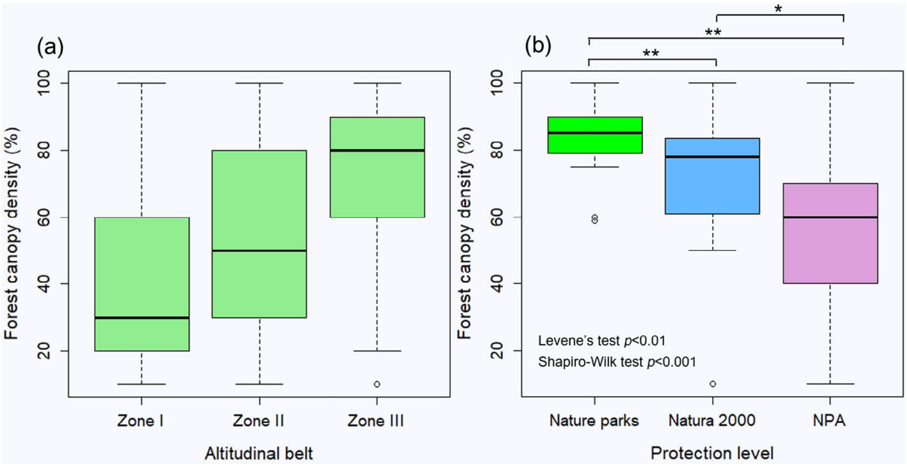

FIGURE 8 (a): Box plot of the forest canopy density percentage value in the three altitudinal zones (I, lowland belt; II, hilly belt; III, mountain belt) of the MCRC and (b) forest canopy density percentage value distribution of forests in nature parks, Natura 2000 network areas and non-protected areas (NPAs). There were statistically significant differences between forest canopy densities belonging to different protection levels as assessed using the Kruskal–Wallis test ($p < 0.001$). The Mann–Whitney U post hoc test showed that differences between nature parks, Natura 2000 and NPAs were significant (Mann–Whitney U test, * = $p < 0.01$; ** = $p < 0.001$) [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 4 Summary of landscape metrics analysis for the MCRC

Year	No. of patches (NP)	Mean patch size in ha (MPS)	Edge density in m ha^{-1} (ED)	Mean patch edge in m (MPE)	Mean shape index (MSI)	Mean perimeter-area ratio (MPAR)	Mean fractal dimension (MFRACT)
1936	1369	391.24	17.84	6979.77	1.612	0.018	1.286
2010	7391	72.47	64.99	4709.88	2.245	0.046	1.381

passed from 3.15% to 6.94% and from 2.40% to 6.42% of the total surface, respectively, causing an increase in the landscape fragmentation metrics (Table S6). While the transitional category characterizes most of the new forest areas of the 2010 landscape, the edge category affects most of the interior area in the 1936 landscape, highlighting a consistent forest fragmentation. In the central and northern part of the study area, the 2010 landscape is characterized by scattered and isolated forest patches (Figure 9). These dynamics are also shown by the MPS (Table 4), which significantly decreased in the four analysed landscape classes. On-the-other-hand, the form of patches in the 2010 landscape is more complex in all landscape classes, particularly for the BL forests (Table S5).

From 1936 to 2010, a loss of interior areas occurred in zone I, while an increase was recorded in the hilly and mountain belts (zones II and III) (Figure 10). An increase in forest fragmentation is associated with the loss of interior areas in the lowland belt, as shown by the rise in transitional and patch areas.

Major expansion (allocation) of interior areas is distributed in both protected and nonprotected areas in the altitudinal belt II and III while decreasing in the lowland areas (belt I) (Figure S7). Minor forest fragmentation in 1936 is reflected in edge, transitional, and patch area distribution over all altitudinal belts, inside and outside protected areas which are always lower than in 2010. Nevertheless, most of the increase in fragmentation has occurred in the mountain belt, according to a higher forest cover gain within protected areas such as natural parks (Figure S7).

4 | DISCUSSION

4.1 | Forest cover change distribution and fragmentation

The proposed integrated methodology has provided a landscape picture of forest cover and composition dynamics in the last 74 years in the metropolitan area of Rome. The identified changes provided some key drivers of the forest landscape transformation where forest cover gain and persistence dominated the reconstructed land use matrix. However, a general loss of forest area (deforestation) was seen from lowland to mountain environment. Nevertheless, forest loss was lower than the observed gain, generating a net increase in the forest area of around 8%, in line with the slow but stable trend of forest recovery observed in the Mediterranean area of Europe in the past 30 years (FAO & Plan Bleu, 2018). Our results are also consistent with other studies showing forest cover increase in this area (Biasi et al., 2015; Salvati et al., 2017). The depopulation of mountain villages (Falcucci et al., 2007) and the abandonment of agricultural activities in marginal areas are the leading causes of the expansion of forest ecosystems in particular in mountain areas (Geri et al., 2010; Salvati & Sabbi, 2011), also leading to transitions in regimes and values (Gulinck et al., 2018). Conifers and BL forests showed a general increase, with the latter expanding mainly in the mountain belt, confirming the trend observed for most of the Apennines (Malandra et al., 2018).

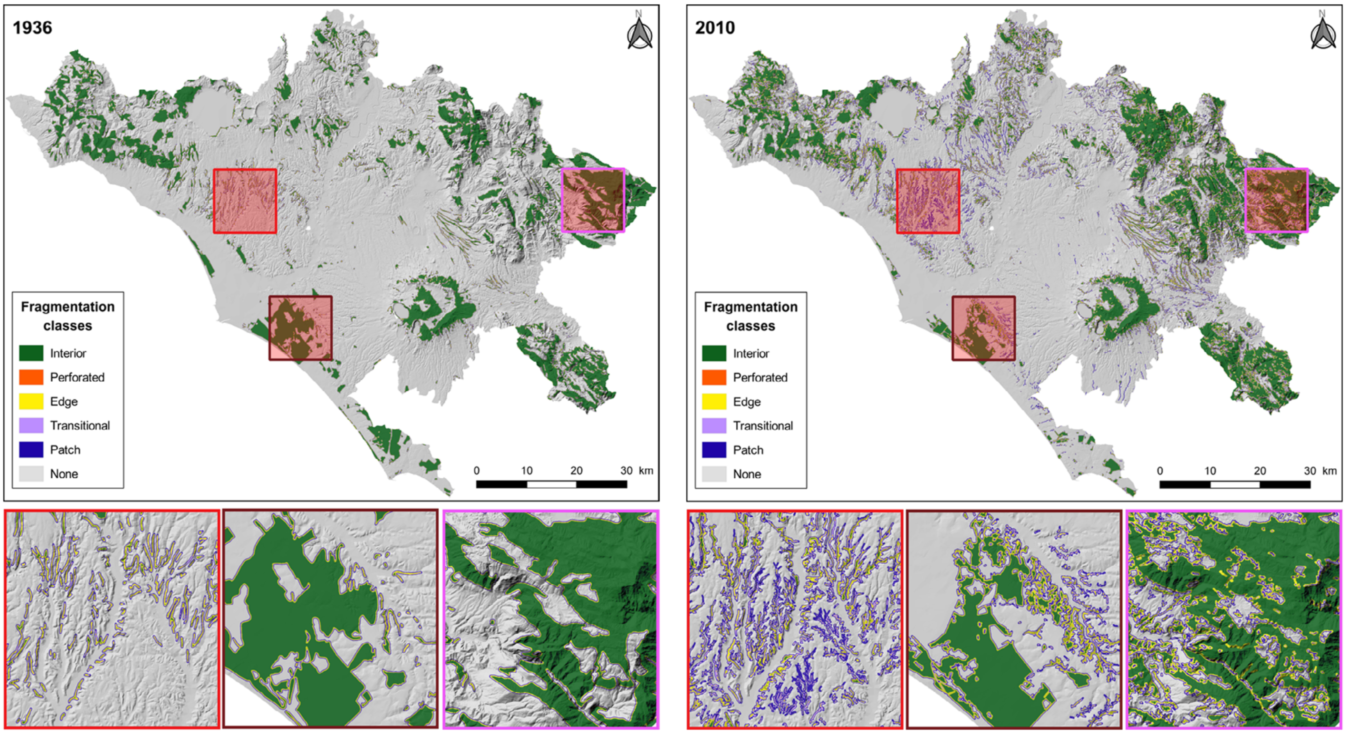

FIGURE 9 Map of forest fragmentation classes from the year 1936 (left) and 2010 (right) in the MCRC study area [Colour figure can be viewed at wileyonlinelibrary.com]

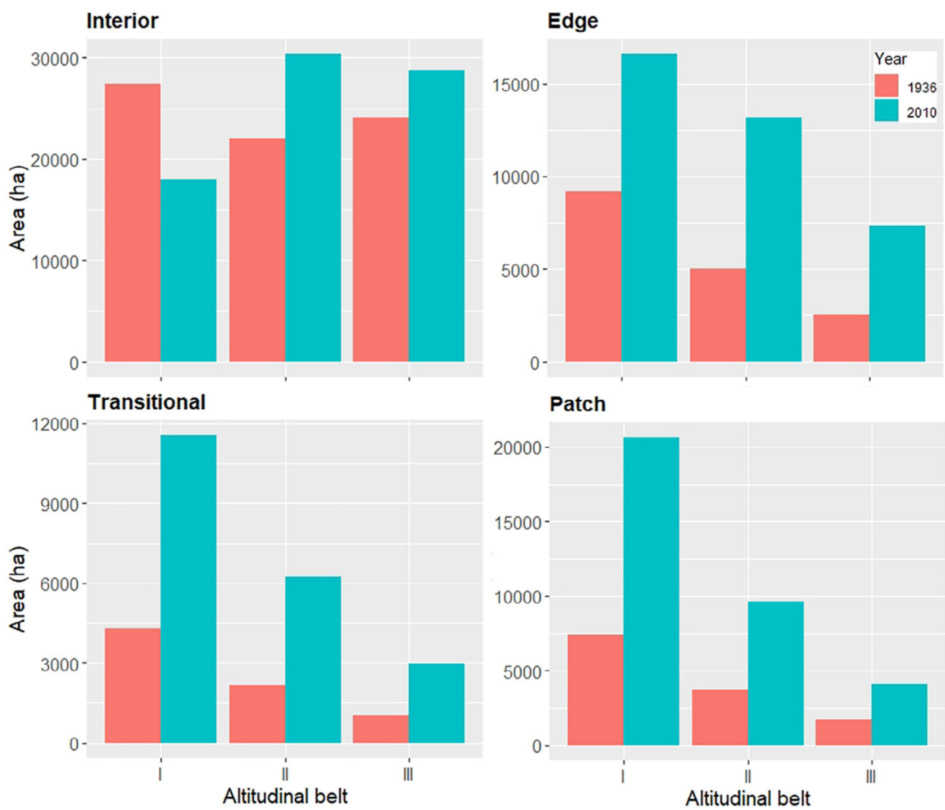

FIGURE 10 Forest fragmentation metrics changes and distribution by altitudinal belt for the MCRC study area [Colour figure can be viewed at wileyonlinelibrary.com]

Most of the relative forest cover increase, concerning every single belt, occurred at higher altitudes. (Geri et al., 2010) (Figure S8). Although the mountain belt represents only 10% of the metropolitan area, forests cover 71% of the zone, with the highest cover gain and persistence rate. This result confirms the rewilding trend that has characterized the Apennine landscape in the past 60 years. One of the main reasons is also to be found in the environmental management policies that have been adopted to promote the hydrogeological stability of the mountain territory. National laws enacted in 1923 (Royal Decree of 30 December 1923, n. 3267) and in 1952 (so-called 'Fanfani' law) for conserving and restoring forests are an example of this. These legislative measures, promoting silvicultural and reforestation activities, led to an increase in the FCI, thus anticipating the 2030 Agenda objectives. The increase of about 1100 hectares of coniferous forests (Figure S8) was due to such reforestation activities (Malandra et al., 2018) particularly with *Pinus nigra*, starting from the 1950s (De Sillo et al., 2012) that occurred on pastures or degraded forest landscapes.

The dominance of closed forests in the mountain landscape is also due to the progressive reduction of pastoral and harvesting activities, which, in turn, triggered the processes of secondary forest succession and recovery towards mature stages (De Sillo et al., 2012). However, while canopy recovery in forest ecosystems can be quite fast, the composition of recently established forests is characterized by many pioneer species of open habitats for which forest dynamics towards mature forest communities need more extended time periods (Amici et al., 2013). A noteworthy example found in the Simbruini mountains is the invasion by shrubs and trees of abandoned traditional terraces because they are no longer an economically sustainable cultivation technique.

In the last decades, forest restoration was principally due to a passive landscape rewilding due to the depopulation of mountain areas and ad hoc mountain management policy, mainly through the institution of protected areas. However, small patches of deforestation were detected up to the mountain belt, where new infrastructure and buildings were built primarily for tourist purposes of summer recreational activities and winter skiing (Figure S8).

A different forest dynamic occurred in the lowland belt. The actual FCI of 14% is well below the 40% of optimal human-modified landscapes for forest biodiversity conservation (Arroyo-Rodríguez et al., 2020). Here, the primary historical process is linked to new forest expansion in marginal areas and deforestation. There are two leading causes for the few forest persistent areas: deforestation for agricultural land reclamation (up to 1950s) and urban expansion (Salvati, 2013). In the flat areas around Rome's city area (campagna Romana), the forest and agricultural lands were the most exposed to increased human pressure driven by urban sprawl (Salvati et al., 2014). In some coastal and flat inland areas, beyond some examples of relict forests characterized by structural and compositional heterogeneity (Pratesi, 2015), woodlands have always been subjected to intensive forestry (e.g., coppices) for providing goods and extensive grazing by domestic animals. Nevertheless, umbrella pine (*Pinus pinea* L.) woods (Figure 2; Di Filippo et al., 2015) together with chestnut (*C. sativa*) stands play a fundamental role in shaping the coastal and hilly landscape and represent a historical heritage, which are destined to disappear without active forest management. Indeed, a lower FCI, together with lower canopy density, illustrates the lowland zones' poor conservation status regarding the interior areas. Higher FCI values found in the mountain belt suggest the progression towards the formation in mature closed forests, especially in protected areas, from where rewilding processes are underway due to the decrease of anthropogenic pressures (Dandy & Wynne-Jones, 2019). These two different forest dynamics are also evident concerning the degraded forests in 1936. Most of them recovered their canopy density in the mountain belt, while in the lowlands forest disappeared, was degraded increasing the high fragmentation pattern. These results point to the rewilding and gaining of forest cover in the mountain and hilly belts, denoting an effective environmental management for these interior areas, thus ensuring numerous ecosystem services. We showed that the increase in the FCI and canopy density percentage characterizes mountain ecosystems that have are located within the protected areas of the MCRC.

Canopy density monitoring and its continuity over time have proved to be a key action to measure forest's multifunctionality. Although the GTCD has a global reach, it has proved to be very reliable on a local scale. Visual interpretation of very high-resolution imagery, employed for data validation, confirms good results in deriving statistics on forest cover over large regions (Schepaschenko et al., 2019). As reported in the literature, photointerpretation can lead to an error that is less than 10% in estimating the extent of forest at a global scale (Bastin, Berrahmouni, et al., 2017; Bastin, Mollicone, et al., 2017; Schepaschenko et al., 2017). Using prior maps with satisfactory accuracy, integrating the accuracy of visual interpretation and performance of classification methods could be implemented in order to extend this approach to broader regions. In addition to the already known advantages of visual interpretation (Schepaschenko et al., 2019), further possibilities to improve forest observation will be given by the rising development of dedicated tools for visual interpretation providing very high-resolution (VHR) satellite imagery that can be viewed by users over many parts of the world (Lesiv et al., 2018). Canopy density is connected to biomass stocks; high stocking levels ensure water regulation, conservation of biodiversity, carbon sinks and the mitigation of climate change effects. For this reason, maintaining and implementing a continuous forest cover through the application of close to nature forestry will guarantee a better net value of timber, carbon sequestration, production of secondary products, scenic beauty and large numbers of habitat trees, compared to forests managed with higher impacting silvicultural models such as the even-aged coppice system (Peura et al., 2018). Forest canopy density can thus be considered as an indicator of harvesting pressure.

Besides, it is possible to highlight the urgent need for a new environmental policy and management of forest landscapes in the lowland belt to increase their cover as well as the level of naturalness. There is a need for an in-depth revision of planning and management strategies targeted to resolve issues related to anthropogenic pressure (Cosentino et al., 2018) and disturbances in the lowland belt. Reducing the forest's excessive exploitation, restoring forest cover and halting new infrastructure (urban expansion) are the main goals for achieving environmental sustainability. In future planning, other environmental man-induced disturbances should be addressed, such as preventing wildfires or the spread of exotic species that compromise forest ecosystems' functioning and reduce environmental sustainability.

4.2 | Protected areas as an effective tool towards Sustainable Development Goals

In this framework, we highlight the key role the protected areas have played in Rome's metropolitan area because of persisting forest ecosystems where the highest canopy density is guaranteed. The differences in tree cover density between forests within nonprotected and protected areas demonstrate how the latter provides considerable attention in managing the impact of forestry activities. This is due to conservation measures for effective nature protection. The establishment of a protected area network and management policies, with limited anthropogenic impact, have made it possible for forest ecosystems to follow more natural dynamics, at least in some well-defined zones, as in mountain landscapes.

However, the extension of interior areas is circumscribed to the mountain and hilly belt, while in the lowlands, human pressures have caused forest degradation and fragmentation. The restoration of the FCI to reach the 40% target and the delimitation of large forest blocks (10% of the whole landscape) are requisite for the conservation of forest interior species (Arroyo-Rodríguez et al., 2020). Indeed, the restoration of the forest interior area is an urgent task in lowlands. In the hilly belt, especially in Rome's suburban areas, numerous interior and transitional forests are mixed with agricultural areas, small urban settlements and seminatural elements. Here, environmental management for achieving the 2030 Agenda goals should be oriented to ensure the maintenance of a biodiversity-friendly forest landscape. Remarkably well-preserved interior areas surrounded by different-sized forest patches and a high-quality matrix with seminatural elements can play an important role in biodiversity conservation (Arroyo-Rodríguez et al., 2020).

Several studies confirm that a higher degree of forest cover contributes to mitigating heat waves within the ecosystems (von Arx et al., 2012, 2013). In contrast, the loss of cover leads to increased local heat, which aggravates the imbalance between the community's responses and climate change (Zellweger et al., 2020). The climatic processes' analyses are fundamental for understanding the relationship between land use, forest biodiversity and its functioning in this global change era. Moreover, a higher canopy density is connected to a greater mitigation capacity of surface runoff and reduced damage caused by floods during intense rainfall (EEA-European Environment Agency, 2015). Mature forests, ordinarily characterized by deeper soils, guarantee a better regulation of evapotranspiration phenomena, therefore positively affecting the ecosystem's hydrological balance. Continuous canopy coverage is also linked to a more significant presence and abundance of endangered species such as saproxylic insects (Hardersen et al., 2020; Rossi de Gasperis et al., 2016). For a sustainable future, we need a general and greater availability of mature and old-growth forest habitats for conserving endangered species dependent on ancient trees and deadwood (Peura et al., 2018).

The restoration of old-growth forests remains a relevant goal in these regions because conserving and restoring forest ecosystems with a high naturality level have a priority ranking in environmental planning for a sustainable future (Chiarucci & Piovesan, 2020). Protected areas can maintain higher biodiversity levels and carbon stocks than neighbouring alternative land use areas (Coetzee et al., 2014) and must be seen as an irreplaceable tool to guarantee complex ecosystem functions (Coad et al., 2019). As recognized by the key multilateral environmental agreement aimed at slowing biodiversity decline (UN Agenda 2030, 2015; UN CBD, 2010), the expansion and effective management of protected areas is needed to mitigate biodiversity loss (Watson et al., 2014).

The European Union (EU) is preparing a post-2020 global transformation framework centred on biodiversity and forest strategies (Visconti et al., 2019). It is driven by the ultimate ambition to ensure that by 2050 most ecosystems on the planet are restored and adequately protected. To this end, the new EU Biodiversity Strategy for 2030 is anticipating the forthcoming new targets of the Convention on Biological Diversity. The objective is to bring biodiversity in Europe on the road to recovery by 2030 as the hearth of a European Green Deal, in line with the 2030 Agenda for sustainable development and the Paris Agreement's objectives on climate change. Among the overall actions implemented in the European level strategy, protecting at least 30% of the Earth's surface through the increase of protected areas, including 10% of the strict nature reserves, is a priority goal. In this context, actions aimed at effectively managing all protected areas, starting from the Natura 2000 network, must be undertaken within the MCRC area. This area is located in the Mediterranean hotspot, where extensive ecosystem restoration is a priority action for conserving biodiversity and stabilizing the Earth's climate (Strassburg et al., 2020).

This research has highlighted many critical issues in protected area management. Above all, the need to restore connectivity and forest function in forests located in lowland areas, with the institution of new protected areas and corridors. Another key target will be the set aside of forests in strict nature reserves by identifying spaces to be left to rewilding processes to bring back functionality in forest ecosystems. This process could benefit from the fact that the lowland belt is characterized by fertile, deep soils and long vegetative seasons that guarantee a fast recovery of forest vegetation with a high carbon sink activity, in line with the IPCC strategy of carbon mitigation. A better protected areas strategy will bring direct benefits to the community living in the suburbs of a densely populated metropolitan area, particularly the health benefits associated with a forest's mitigating power during heat waves (Twohig-Bennett & Jones, 2018).

Starting from the methodology adopted in this research, further studies are needed for a distinction based on the bioecological diversity of ecosystems such as old-growth forest patches, rewilding forests (exploited forest landscapes undergoing long-term natural succession) and managed forests, as proposed by Chiarucci et al. (2020). Defining clear conservation objectives and measures and subjecting them to adequate monitoring is an immediate goal with respect to the 2030 Agenda. In this framework, our results will allow for effective landscape planning and management for biodiversity conservation to strengthen the current metropolitan ecological network (Modica et al., 2021).

5 | CONCLUSIONS

This research aimed at implementing a forest dynamic methodology through the integrated use of historical forest cover data and remote sensing-based products, providing operational indicators to effectively manage and restore the forest environments in the MCRC study area, according to the sustainable development targets of the 2030 Agenda goals. Our results have highlighted essential changes over the last 74 years, such as a global increase in the forest area and a net increase in the BL forest. However, the establishment of new forests is a distinctive trait of the mountain and hilly belts, with a trend in line with what has been observed in the rest of the Italian Apennine areas and other mountains of Europe due to land abandonment and specific management policies for mountain regions of Italy. On-the-other-hand, there was a significant loss of forest cover and interior areas in the lowland belts, especially along the coast and Rome's inner marginal areas, as the main consequence of urban sprawl and human pressure on natural ecosystems for agricultural land reclamation. In summary, two main dynamics have characterized the forest landscape: a widespread forest fragmentation located in the lowland and some locations in the hilly belt, and a slight increase in interior areas (not affected by fragmentation), especially in the mountain belt. By combining landscape metrics of land cover dynamics with canopy density values, we showed that the increase in the FCI and canopy density percentage characterizes mountain ecosystems that are located within the protected areas of the MCRC. Conversely, descending to the lowlands, this study raises a warning for all landscape indicators describing forest transformation in relation to sustainable development targets. In this belt, widespread human pressure on forest ecosystems is still causing loss of functionality (low canopy density), habitat degradation and fragmentation processes. In reviewing planning strategies, these different forest dynamics will need to be considered to better respond to future environmental sustainability challenges. The proposed approach, synthesizing different data inputs for dynamic landscape analysis and assessment in the Mediterranean environment, improves our environmental knowledge for the development of effective landscape planning and management, targeted to achieve the 2030 Agenda goals, the Convention on Biological Diversity and the IPCC strategy against climate change. Our findings could support the MCRC follow-up work in designing new protected areas and rewilding spaces in the lowland areas, where forests are far below the environmental sustainability targets. Moreover, these results integrated with updated data, provide useful geographical information base layers that will allow the Rome metropolitan area authority to calibrate an effective environmental planning and management strategy, for restoring forest functional integrity and naturalness. The proposed framework for characterizing historical transformation trajectories can also be used to test the effectiveness of environmental planning to achieve the 2030 Agenda goals in other forest landscapes.

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DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

ORCID

Francesco Solano https://orcid.org/0000-0002-2457-5517
Salvatore Praticò https://orcid.org/0000-0003-1684-178X
Gianluca Piovesan https://orcid.org/0000-0002-3214-0839
Alessandro Chiarucci https://orcid.org/0000-0003-1160-235X
Giuseppe Modica https://orcid.org/0000-0002-0388-0256

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