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Landscape Characteristics in Relation to Ecosystem Services Supply: The Case of a Mediterranean Forest on the Island of Cyprus

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Abstract: The Mediterranean area is one of the most significantly altered biodiversity hotspots on the Earth's surface; it has been intensively affected by anthropogenic activity for millennia, forming complex socioecological systems. In parallel, the long history of natural ecological processes and the deep interlinking with human populations led to landscape patterns, such as spatial heterogeneity, that facilitate the provision of essential ecosystem services (ESs). As such, a comprehensive understanding of the underlying factors that influence the supply of ESs is of paramount importance for effective forest management policies that ensure both ecological integrity and human welfare. This study aimed at identifying local specific interactions across three different spatial scales between landscape metrics and ESs using global and geographical random forest models. The findings showed that dense forest cover may have a positive effect on the supply of ESs, such as climate regulation and timber provision. Although landscape heterogeneity is considered among the main facilitators of ecosystem multifunctionality, this did not fully apply for the Marathasa region, as forest homogeneity seems to be linked with provision of multiple services. By assessing under which landscape conditions and characteristics forest ESs thrive, local stakeholders and managers can support effective forest management to ensure the co-occurrence of ESs and societal wellbeing.

Keywords: ecosystem services; landscape structure; random forest (RF); geographical random forest (GRF); Mediterranean forest; Marathasa; Cyprus

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1. Introduction

The composition and structure of landscapes have been shown to have a significant impact on ecological processes and the multifunctionality of ecosystems [1]. The specific characteristics of a given landscape are mainly formed by anthropogenic activities (such as deforestation, urbanisation, agriculture, tourism, and mining) along with climatic conditions, geomorphological characteristics, and natural and human disasters. The Mediterranean region, where human–nature interactions have been ongoing for millennia, is characterized by highly heterogeneous vegetation, habitat types, and landscapes, resulting in rich biodiversity and a vast supply of ecosystem services (ESs) [2–5]. Mediterranean forests are an example of dynamic ecosystems with a variety of ESs to human society [6,7]. However, increasing environmental changes and alterations in the intensity of human activities have led to two main patterns. The first pattern has resulted from increased human pressures, leading to landscape diversification and the creation of isolated patches that function as biodiversity islets and support important ESs [8]. The second pattern has arisen from the abandonment of agricultural and pastoral activities, resulting in the gradual homogenization of forests and often in a negative impact on biodiversity and several ESs [9–11].

Landscape structure has extensively been used to assess the integrity of ecosystems (especially regarding their capacity to maintain biodiversity) and to study the influence of humans in its transition processes [12]. In parallel, several studies have investigated the relationships between the configuration of a landscape and the supply of essential ESs [5,13–16]. Considering the dependency between Ess and a landscape's composition and structure, Termorshuizen and Opdam (2009) [17] introduced the concept of "landscape services (LSs)", describing them as "the range of functions that are or can be retrieved by a landscape and be valued by humans for economic, sociocultural, and ecological reasons". Although the concepts of LSs and Ess overlap, the difference between these is that for the former, the supply of ESs is linked to the landscape's patterns and its social dimension; while for the latter, the supply of ESs is based solely on ecosystems and their spatial configuration [18–20]. Given that the spatial characteristics and patterns of a landscape are considered among the main principles for the provision of ESs, the identification and understanding of how specific landscape features act in favour of ES supply is of primary importance [21,22]. Furthermore, the quantification of a landscape's structure delivers crucial knowledge about the impacts of landscape feature on ecological processes, and for this reason, it can be used as a tool to systematically monitor the effects of landscape changes on ecosystems [23].

Landscape metrics are the means used for quantifying the spatial configuration of a given landscape, and they are usually employed to assess the impact of landscape structure on ecological functionality and biodiversity [12,24]. The ease of obtaining landscape metrics over large geographical regions and their rapid calculation feasibility compared to data- and time-intensive models, such as species distribution models, field data assessments, and/or other modeling procedures, has led to their widespread use [25,26]. By using a land use/cover map, landscapes can be analyzed at three levels (namely, patch, class, and landscape level) allowing for the characterization of patch size, shape, and/or the connectivity land use/cover classes, and the diversity of an entire landscape [27,28]. It is well documented that in order to completely comprehend a landscape's structure it is necessary to estimate and evaluate a set of multiple landscape metrics, as each metric studies a unique characteristic of the landscape. However, in most cases, landscape metrics are highly correlated, leading to the misinterpretation of findings, hindering their use in multivariate statistical analyses [26,29]. To address these issues and select a representative set of metrics, many statistical and theoretical frameworks have been developed. Such frameworks are based on expert knowledge and literature review [4,30–32], principal component analysis and factor analysis [29,33,34], regression models [35], and, more recently, on machine learning (ML) algorithms that are used in ecological applications [5,36].

Machine learning algorithms have become one of the main tools used in Earth and life sciences, such as remote sensing [37], GIS and environmental spatial analysis [38,39], ESs [40,41], and ecology [42,43]. Compared to traditional statistical techniques, ML has several advantages, such as accurate predictive and classification capabilities, increased ability to manage complex relationships (non-linear), and the capability to automate tasks [44]. There are two types of ML approaches, namely, supervised and the unsupervised algorithms; and multiple methods/algorithms, such as tree-based methods, neural networks, support vector machines, genetic algorithm, fuzzy inference systems, and Bayesian methods [41,45]. The most frequently used ML method in ecological applications is random forest (RF) due to its versatility and high accuracy in responding to different research questions [36]. Among the advantages of RF are included the internal self-testing procedures, the high predictive accuracy, and the ability to estimate the importance of each input variable [46]. However, despite the important advantages of all ML algorithms, in most cases, the spatial aspect of the data cannot be used in the model calibration procedure. Considering the spatial heterogeneity of ecological datasets, the use of "global" algorithms/techniques limits the identification of spatially varying relationships within the study area. To address this issue, geographical weighted regression (GWR) was developed by Fotheringham et al. [47], which is based on the traditional regression technique. Georganos et al. [48] and Georganos and Kalogirou [49] have introduced the geographical random forest (GRF) approach, which is based on GWR principals and is increasingly used in various scientific fields, including epidemiology [50], socioeconomic studies [48], natural disasters [51], forestry [52], and agriculture [53], where in all cases GRF outperformed RF.

The recent advances in remote sensing data and methods allow the thematically and spatially accurate mapping of land uses and habitats across various spatial scales. This, in turn, allows the analysis of landscape structure and composition in a quantitative manner using landscape metrics. However, the relationship between landscape structure and composition and the supply of ecosystem services in forest dominated landscapes is poorly understood. This study implements a spatially explicit approach using random forest and geographical random forest algorithms to assess ES supply in relation to landscape metrics across three spatial scales. The aim of the study is to investigate the validity of using landscape spatial characteristics as indicators of ES supply. The specific objectives of the study are (a) to generate a thematically and spatially accurate land use/cover map of the area using readily available remote sensing data and well documented methods; (b) to assess the performance of two modeling approaches for identifying relationships between landscape spatial characteristics and supply of ES; and (c) to identify the spatial characteristics that appear to be most highly related to the supply of ES. The results of the study are expected to provide a useful tool for the monitoring of ES supply and valuable information regarding the specific landscape characteristics that can support ecosystem multifunctionality by enabling co-occurrence of multiple ES.

2. Materials and Methods

2.1. Study Area

Marathasa is a geographical area of the mountainous mass of the Troodos Mountain range and occupies an area of ~208 Km^2; that is, 2.2% of the total area of Cyprus (data source: https://www.data.gov.cy/, accessed on 1 January 2023). The largest part of the Marathasa area is covered by state forests, while the geological structure of the area is that of the Troodos ophiolite (igneous rocks which make up the oceanic crust). The landscape's morphology is characterized by a mountainous topography with high and variable mountain peaks, often over 1000 m in altitude (altitude range: 163 m to 1932 m). The Marathasa region is particularly characterized by gorges, which have resulted from the changes of the sea surface and those of the sea and the renewal of the rivers and the marine terraces. The landscape contributed to the shape of a dense network of river systems which are often of a dendritic pattern and which maintain their flow over a long period [54]. The natural ecosystems have evolved through both environmental conditions and human impact. The presence of human communities in Marathasa is observed as early as the 6th–9th century (647–965 AD), where several small settlements (5–10 houses) were established on the mountains of Marathasa when the inhabitants of the coastal areas sought safer places in the mainland [55]. During the past two centuries, the region of Marathasa has been defined by the administrative boundaries of 14 communities (villages). The northern and western communities showed a population increase over time in relation to the communities of southern Marathasa [55]. The region's professional activity has been directly linked to the primary sector of economy, namely, agricultural activities and timber sale [54]. However, since 1980, urbanization contributed to the population reduction in the area (inhabitants in 1982: 4341; inhabitants in 2011: 1523). Data from CORINE Land Cover (CLC) inventory in 2018 show that most of the land is occupied by forests (Figure 1).

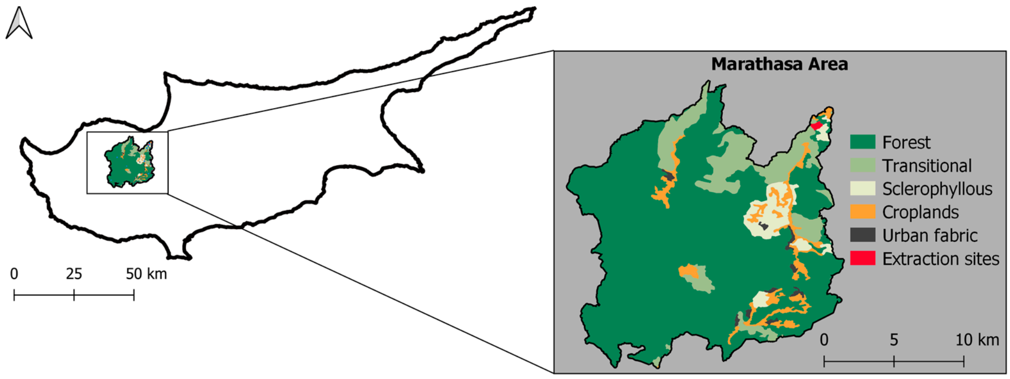

Figure 1. Map of the study area and the main LULC classes according to CORINE.

2.2. Mapping Land Cover and Ecosystem Services Supply

The land use/cover (LULC) dataset was produced using a pre-processed Level 1 Landsat 8 OLI image acquired in 2021 and an object-oriented classification scheme (OBIA) developed and evaluated by Kefalas et al. [56]. The applied OBIA scheme is stepwise, and it is based solely on crisp or fuzzy rules that use vegetation indices (Table A1). Through this procedure, the study area was divided into seven LULC classes (three density-based vegetation classes, open/rocky areas, croplands, settlements, and inland water). The accuracy assessment was based on the use of ground-truth data, verified in situ, and the estimation of statistical measures such as Kappa index (K) and overall accuracy (OA).

Based on data availability and the merit for estimating ESs to achieve effective forest management on the study area, four ESs were selected and mapped covering all ES categories (following the Common International Classification of Ecosystem Services (CICES)) [57]. Specifically, one ES refers to the Provisioning ES section, two in the Regulating and Maintenance section, and one in the Cultural section (Table 1).

Table 1. The estimated ecosystem services and their indicators/proxies.

ES Section	Ecosystem Service	Indicator/Proxy	Data Source
Provisioning	Materials from timber (MT)	Presence of forest and agroforest land	1
Regulating and Maintenance	Climate regulation (CR)	Below and above ground carbon storage	1 & 2
	Erosion protection (EP)	Soil erosion prevention	1, 3, 4, & 5
Cultural	Recreation (RC)	Recreation potential	1, 3, 6, 7

Data sources code: (1) Land Cover data; (2) Carbon Dioxide Information Analysis Centre (15 December 2022) [58]; (3) ASTER Digital Elevation Model (DEM) (15 December 2022) [59]; (4) Soil erodibility index (K-factor) (15 December 2022) [60]; (5) Rainfall erosivity index (R-factor) (15 December 2022) [60]; (6) Hiking trails (available in: https://www.prettymap.gr/troodos/geotourism/el.html (10 December 2022); https://www.data.gov.cy/ (accessed on 12 January 2023); mapping by the project WaterWays); (7) Sites with touristic and/or cultural merit (mapping by the WaterWays project).

Provisioning ESs are all nutritional, material, and energetic outputs that are derived from a living ecosystem [57]. Materials from timber (MT) represent the products from trees harvested from natural forests and plantations [61], and to map this service, the presence of forest and agroforest land was considered.

Regulating and maintenance ESs are defined as the way in which local ecosystems control the biotic and abiotic features of the environment in order to enhance human well-being [57,61]. The Intergovernmental Panel on Climate Change (IPCC) reported that transitions and processes in a given landscape, such as LULC changes, soil degradation, and deforestation, play a crucial role in the emissions of greenhouse gases [62]. Natural ecosystems, and especially forests, regulate climatic conditions through several processes including carbon sequestration, moisture production, and temperature control [63]. The Climate regulation (CR) service was mapped considering the carbon pool table derived from the INVEST Carbon Storage and Sequestration model. This model combines the amount of carbon stored in four carbon pools (aboveground biomass, belowground biomass, soil organic matter, and dead organic matter) based on LULC. Erosion prevention (EP) represents the capacity of ecosystems to prevent erosion, and was calculated using the soil erosion prevention framework based on the RUSLE equation [64]:

$$Es = Y - \beta e,\ \{Y = R \times LS \times K, \beta e = Y \times a\},$$

where Es represents the actual ES provision (tons of soil not eroded), Y represents the structural impact, βe represents the mitigated impact (where $a = C$ and $e_s = 1 - a$), R represents the rainfall erosivity factor, LS represents the topographic factor, K represents the soil erodibility factors, and C represents the vegetation cover factor.

The non-material services offered from ecosystems that affect the physical and mental state of people are defined as cultural services. To estimate and map the potential of the Marathasa forest to offer recreational activities (RC), a multicriterial model was developed considering two main factors: (a) the biophysical factor; and (b) the cultural factor. The biophysical factor was a combination of four indicators that characterize ecosystems in terms of natural attractiveness; these indicators were the Normalized Difference Vegetation Index (estimated from Landsat 8 OLI image), the Shannon's Landscape Diversity Index (estimated using the LULC thematic map), and the Geodiversity index [65]. The cultural factor was defined by the presence of hiking trails and sites with touristic and/or cultural merit (such as camping sites, churches, old bridges, and water mills) as those indicators were either point or line features, while a kernel density tool was used to create a continuous raster layer.

To estimate and map the total ES supply, each ES map was standardized to a scale between 0 and 1, based on the minimum and maximum values (higher values corresponded to a greater magnitude of ES) and combined.

2.3. Landscape Characteristics That Contribute to ES Supply

This study identified the landscape characteristics that are related to ES supply across three scales. The unit of analysis was based on hexagonal grids of three sizes, with apothem of 50, 250, and 500 m. For each hexagonal grid, a set of 17 landscape metrics were estimated at class and landscape level (56 metrices in total). The selected metrics refer to the area, the core area, and the edges of a given landscape and class (Total Area (TA), Total Core Area (TCA), Total Edge (TE), Edge Density (ED), Largest Patch Index (LPI)), the shape of a landscape (Landscape Shape Index (LSI)), the aggregation of landscape and classes (Patch Density (PD), Cohesion, Division, Effective Mesh Size (MESH), and Contagion), and the landscape diversity (Patch Richness (PR), Patch Richness Density (PRD), Relative Patch Richness (RPR), Shannon's Diversity Index (SHDI), and Simpson's Diversity Index (SIDI)).

The identification of landscape metrics related to ESs was based on global and local random forest (RF) algorithms. Landscape metrics were used as explanatory variables. while the total ES supply formed the response variables (Figure A1). Random forest is a non-parametric machine learning approach which is used for classification and regression purposes. It is suitable when the relationship among variables is non-linear and when multicollinearity is evident [66–68]. The first step when employing an RF model is the creation of a training set, on which the model development is based, and a test set, which is used to validate the initial model. In the case of Marathasa forest, we created the training dataset from 70% of randomly selected samples of the initial dataset. The remaining 30%, namely, the out-of-bag (OOB) set, is excluded from the model training and is used to estimate the RF's model efficiency [69]. The total number of randomly selected samples used for training and testing vary according to the spatial scale, and they were 36,817 in the apothem of 50 m, 1586 in the apothem of 250 m, and 428 in the apothem of 500 m. The second step is to parameterize the RF model by setting the appropriate (1) number of randomly selected predictors at each tree (mtry); (2) the minimum number of records contained in a leaf (nodesize); and (3) the number of trees (ntrees). The optimal number for mtry was estimated using the function "rf.mtry.optim" given from the spatialML

R package [49], while the node size was set to 1, as suggested by Breiman (2001) and Lorilla et al. (2020) [5,66]. Regarding the ntrees parameter, different values were tested, and the ones with the highest accuracy were selected as more appropriate for their use in the RF model (Table A3). The third step was the implementation of the RF model. In the case of a regression, the main outputs are the variables' importance and error rate that are estimated by the OOB method [50].

Despite the advantages of RF models, the spatial heterogeneity of the data cannot be assessed and validated. To address this issue, Georganos et al. [48] extended the "traditional" RF model by developing the geographical random forest (GRF), which is a disaggregation containing several local sub-models. The fundamental principles of GRF are same to the ones of geographical weighed regression (GWR) [47], where the model is calibrated locally rather than globally. Thus, using a GRF model, for each spatial unit i, an RF local model is estimated, taking into consideration an n number of neighbour observations. Each local model has its own performance, predictive power, and variables importance. A simplistic GRF equation is [48] as follows:

$$Y_i = a(u_i, v_i)x_i + e, i = 1 : n,$$

where Y_i is the value of the dependent variable for the ith observation, $a(u_i, v_i)x$ is the prediction of an RF model calibrated on location i, (u_i, v_i) are the coordinates, and e is an error term.

Similar to GWR, important factors in a GRF are the "kernel" or "neighbourhood" (the area that the local model considers in calibration) and the "bandwidth" (the maximum distance away from the RF location) [48,49]. There are two types of kernels (a) the "fixed kernel" and (b) the "adaptive kernel", where in the former, the neighbourhood is defined by a circle; while in the latter, as the number of nearest neighbours that are to be included in the modeling procedure [70]. The size of the bandwidth also plays a significant role in the modeling procedure as it determines the distance limit at which observations are considered to fall in the sub-model. If the bandwidth is large, then local models would be turned into a global model as all observations are used. In contrast, if the bandwidth is small, the independent variables are less biased [71]. In this study, we used adaptive kernel with the appropriate bandwidth size estimated using an automated function offered in spatialML R package [72], which re-testes various bandwidth sizes to obtain the highest R^2 value for the local model. The performance of both global and local RF models was assessed by estimating the coefficient of determination R^2 and the mean square error. The modeling procedures were implemented using the open-source R version 4.2.2, R Studio version 2022.12.0, and the R packages: rgdal [73], spatialML [72], cli [74], and caret [75].

It is worth noting that GRF produces a map for each independent variable, presenting the local importance to the dependent variable. To present the direction of the relationship between ESs supply and LM, the local bivariate relationship mapping procedure was used, considering the total ES supply and the two most important LMs for each scale of analysis. The output of this procedure is a map presenting six classes: (a) not significant; (b) positive linear; (c) negative linear; (d) concave; (e) convex; and (f) undefined complex.

3. Results

3.1. Distribution of LULC and ES Supply

After applying the OBIA classification scheme in Marathasa forest, the overall accuracy assessment and the Kappa statistics index were 91% and 0.89, respectively (Table A2). The LULC class with the highest thematic and spatial accuracy was the open and rocky areas (producer accuracy: 0.97) followed by high-density natural vegetation (producer accuracy 0.91) (Table A2). The accuracy of LULC classes varied between 0.80 in the agricultural areas and 0.97 for open/rocky areas (Table A2). The dominant LULC class was the medium-density natural vegetation covering more than 40% of the study area (Table 2). Areas covered by high- or low-density vegetation were less intense, as in both cases they extended approximately at the 25% of Marathasa (Table 2). High- and medium-density natural vegetation mainly occupied the central part of the area, while small stands of dense vegetation were located in the northwest part of the Marathasa (Figure 2). Open and rocky areas are distributed mainly in northern and eastern parts, covering 1200 ha (~5% of the area), while the agricultural areas, shaping four agricultural zones (three on the east and one on the west), covered almost 1640 ha (little more than 5% of the area) (Table 2 and Figure 2).

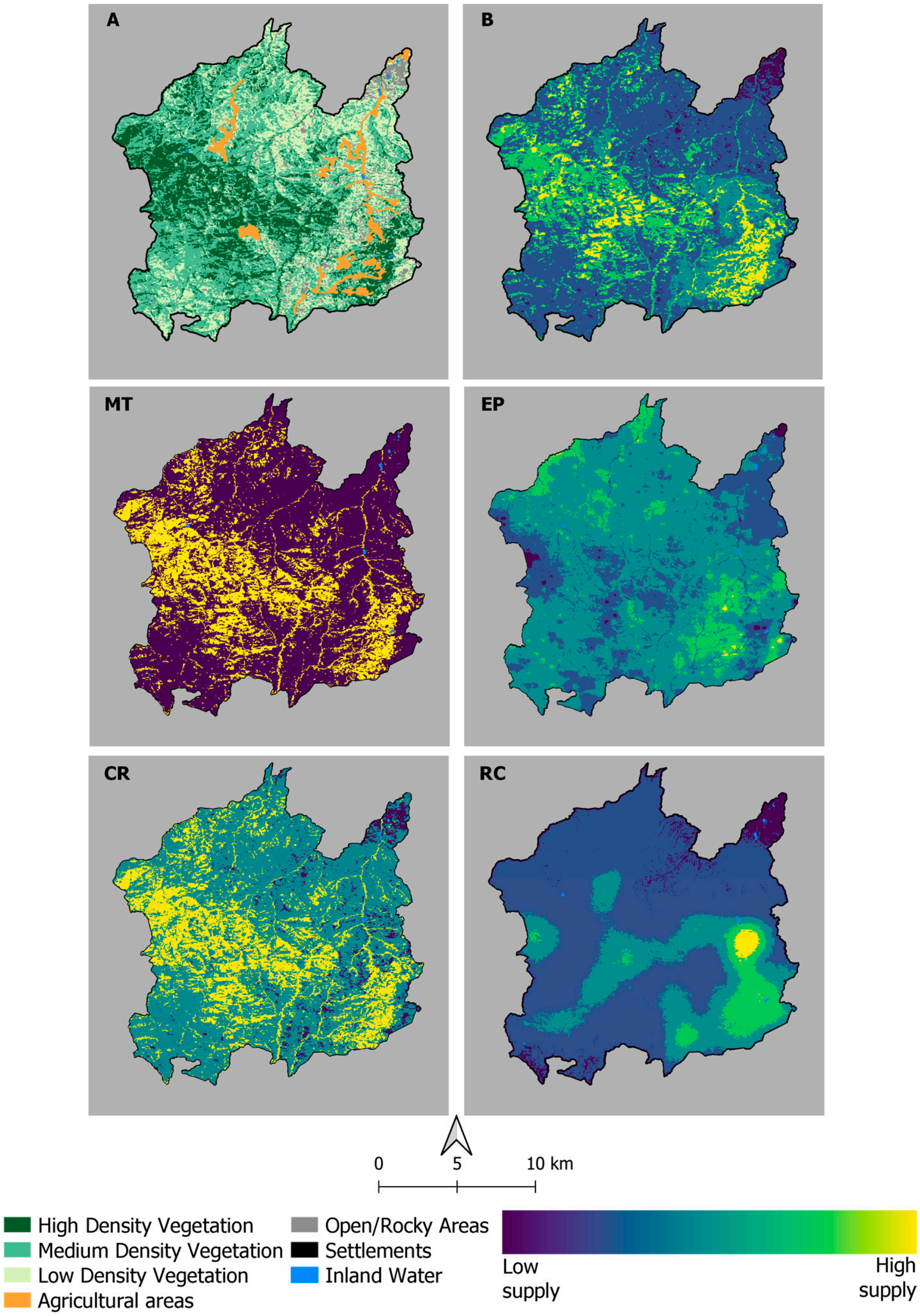

Figure 2. Distribution of (**A**) land use/cover and (**B**) total ecosystem services supply and the individual ESs (MT: Material from Timber; CR: Climate Regulation; EP: Erosion Prevention; RC: Recreation Potential).

Table 2. Part A: extend of LULC; Part B: the mean value of ESs supply.

Part A			Part B	
LULC	**Area (ha)**	**%**	**ES**	**Mean Value**
HDNV	7571.91	24.22	MT	0.48
MDNV	12,973.78	41.50	EP	0.55
LDNV	7824.86	25.03	CR	0.63
OR	1252.06	4.01	RC	0.28
AA	1639.63	5.24		
TOTAL	31,262.23			

HDNV: High Density Natural Vegetation; MDNV: Medium Density Natural Vegetation; LDNV: Low Density Natural Vegetation; OR: Open and Rocky areas; AA: Agricultural Area; MT: Material from Timber; EP: Erosion Prevention; CR: Climate Regulation; RC: Recreation Potential.

The total ES supply exhibited lower values in the northern part of the study area, which is occupied mainly by low-density vegetation, while at the central forested part, the mean total value showed higher ES supply (Figure 2). Due to the forest's nature to support ecological functions, ESs presented high mean value (Table 2). Depending on the relation between individual ESs and forest cover, ESs presented two different spatial distribution patterns. The first relates to the "materials from timber" and "climate regulation" services, where the distribution of their higher values was aligned with the distribution of the high-density natural vegetation (Figure 2); the second spatial pattern is linked to "erosion prevention" and "recreation potential" services. In the case of "erosion prevention", higher supply was located in the eastern and in the northwest parts of the study area (Figure 2); those areas are not only characterized by forest cover but also by a smooth surface relief. Regarding the service of "recreation potential", higher values were observed in the eastern part of the Marathasa forest, where sites with touristic and/or cultural merit were located (Figure 2).

3.2. Contributing Landscape Characteristics to ES Supply

Global and geographical random forest was used to identify the specific landscape characteristics that are correlated to the total supply of ES. Both global and local RF models for the total ES supply had excellent performance, as indicated by the R^2 measures, which were close to 90% across all scales (Table 3). Specifically, for the global and local RF models for the 250 m and 500 m apothem grids, R^2 exceeded 87%, while in the case of the 50 m apothem, R^2 values were slightly lower, reaching 86.64% and 87.63% for the global and local models, respectively (Table 3). The pseudo-local coefficient of determination showed different patterns among the spatial scales (Figure 3). Specifically, at the 50 m scale, the performance of GRF was excellent in the majority of the area (pseudo-R^2 > 80%), while in areas occupied by sparse vegetation or characterized as open/rocks, the performance was poor (pseudo-R^2 < 40%). This pattern was also evident at the 500 m scale, where better performance was found in areas occupied by dense forests. Finally, at the 250 m scale, higher performance was observed in areas primarily covered by medium and low-density vegetation, while in areas occupied by forest, the performance was moderate (40% < pseudo-R^2 < 60%) (Figure 3).

Figure 4 shows the ranking of the ten most important landscape metrics (LMs). Across all three scales of analysis, the majority of the most important LM variables were related to the high-density vegetation class. These metrics mainly express aggregation (estimated through the Effective Mesh Size, Largest Patch Index, Cohesion, and Division) and configuration (estimated through the Total Core Area and Edge Density). Exceptions to this pattern were the metrics Contagion, Proximity, and Simpson's Diversity Index calculated at the landscape level, and the metrics of Edge Density and Cohesion calculated for the medium-density natural vegetation class. The former metrics express the landscape's aggregation and were found to be important in the case of 250 m, while the latter metrics express the class aggregation and configuration and were found to be important in the case of 500 m.

Table 3. Performance of global and local random forest models on the different scales of analysis.

	RF Model Mean Total ES Supply R^2 (OOB) MSE	 R^2 (Not OOB) MSE	GRF Model Mean Total ES Supply R^2 (OOB) MSE	 R^2 (Not OOB) MSE
50 m	86.64% 0.01	93.45 0.01	87.63% 0.01	98.71 0.00
250 m	87.45% 0.02	95.78% 0.0.	87.84% 0.01	98.85% 0.00
500 m	87.64% 0.02	97.56% 0.01	88.98% 0.01	99.58% 0.00

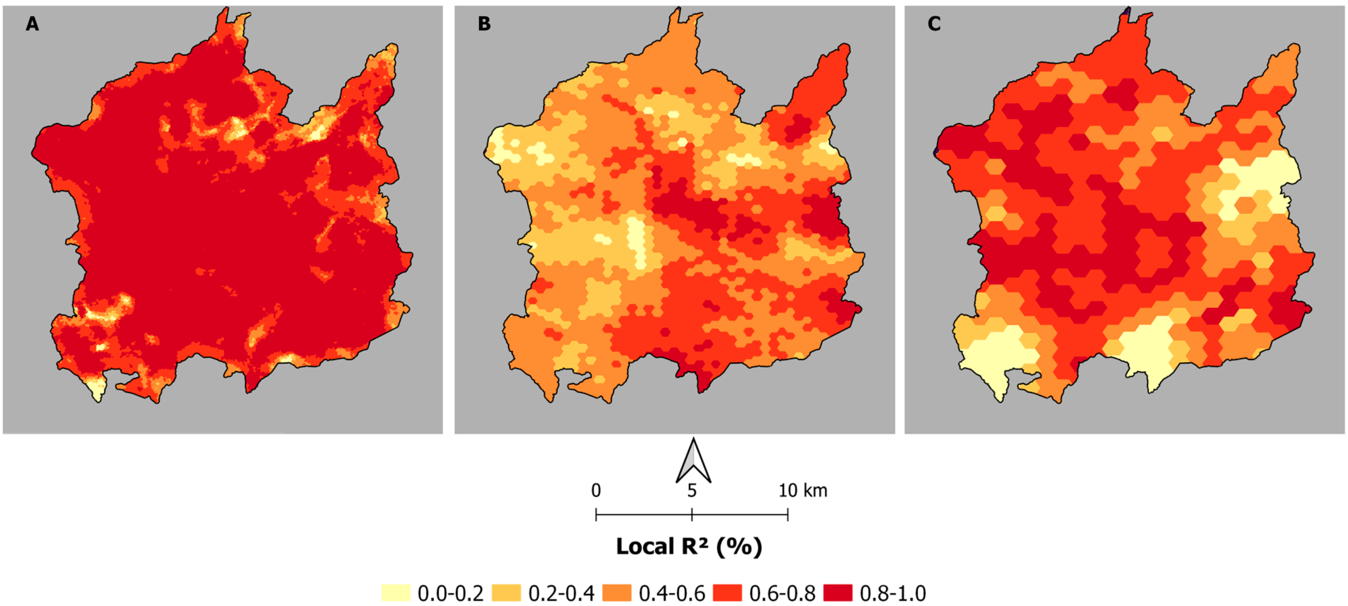

Figure 3. Pseudo-local coefficient of determination of GRF: (**A**): 50 m; (**B**): 250 m; and (**C**): 500 m apothem.

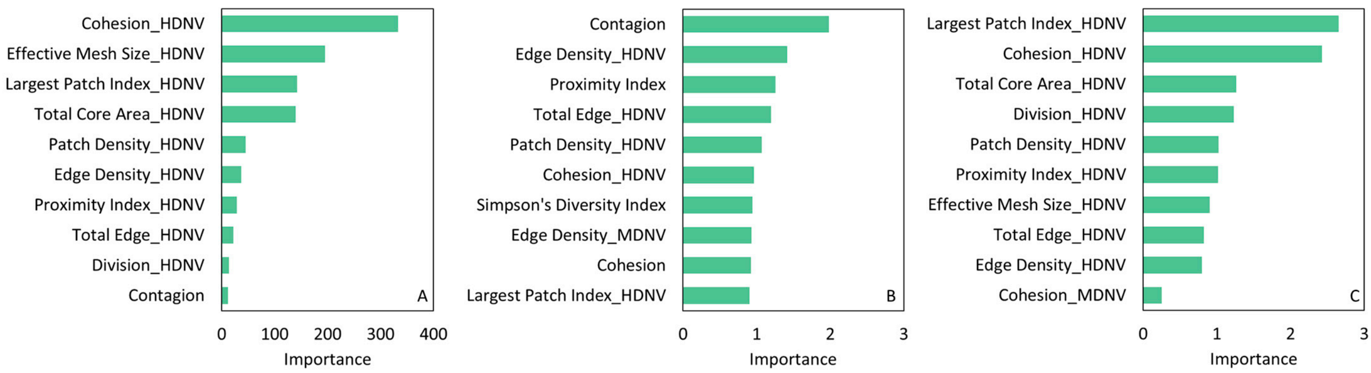

Figure 4. Ten most important variables for mean total ES supply per each scale of analysis: (**A**): 50 m; (**B**): 250 m; and (**C**): 500 m apothem.

To further analyze the spatial distribution of local variable importance, the magnitude (Figure 5 and Table A4) and direction (Figure 6) were mapped for the two most important landscape metrics (LMs) at each scale of analysis. At the 500 m scale, the Largest Patch

Index and Cohesion LMs for the HDNV class were found to be highly important and positively related in two main parts of the Marathasa forest, which were characterized by high-density vegetation. At the 250 m scale, the LM contagion, which expresses landscape aggregation, was found to be highly important mainly in the central part of the study area, characterized by high landscape heterogeneity. However, in the central part of the forest, the relationship was negative, while in areas around the main forest body, the relationship was significant but complex (neither positive nor negative). Finally, at the 50 m scale, one can identify specific places where the importance of LMs was high. The importance of individual and smaller forest stands can be recognized, considering the relatively higher values of importance of LMs in areas where high-density natural vegetation was not in excess (Figures 2 and 5). In parallel, the direction of the relationships was positive (linear positive or convex) in the MESH index, indicating that extended forest stands favourably affect ES supply. The Cohesion Index for the 50 m scale was positively related in areas mainly characterized by high-density natural vegetation, while in areas where medium- or low-density vegetation was the primary land cover type, the relationship was negative (linear negative or concave) (Figures 5 and 6).

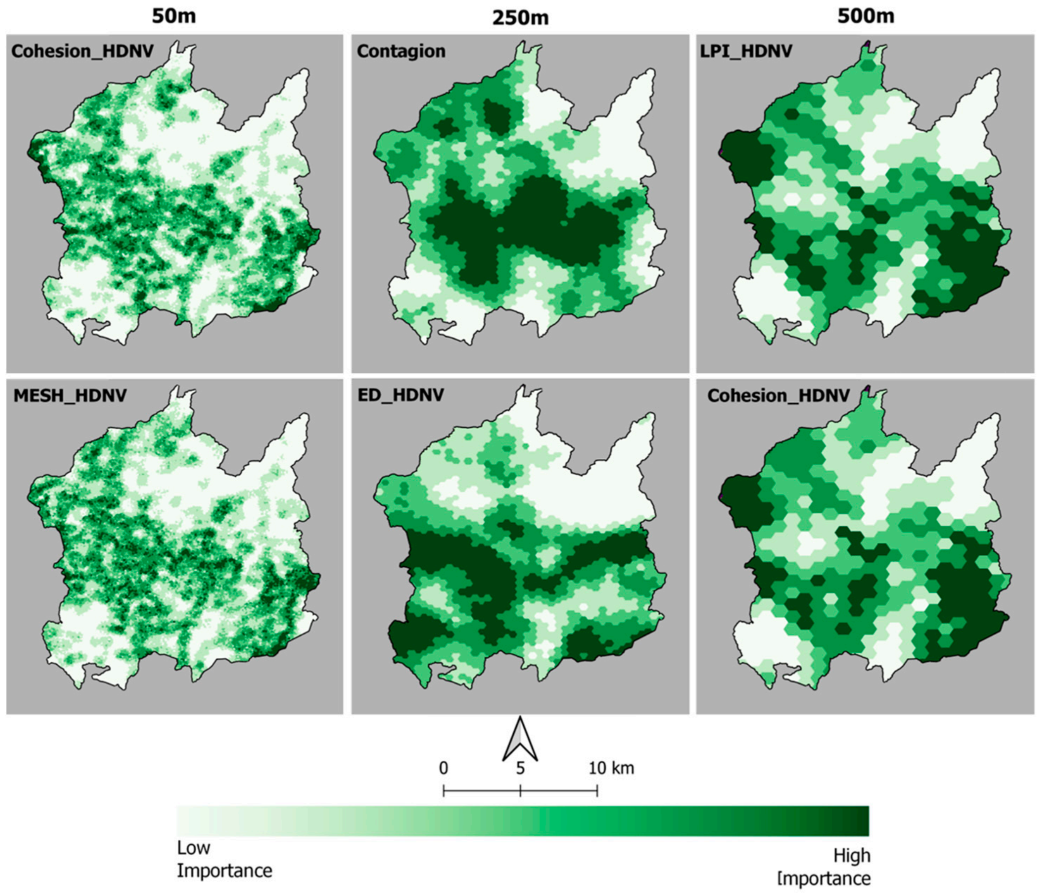

Figure 5. Maps of the two most important landscape metrics for mean total ES supply per each scale of analysis.

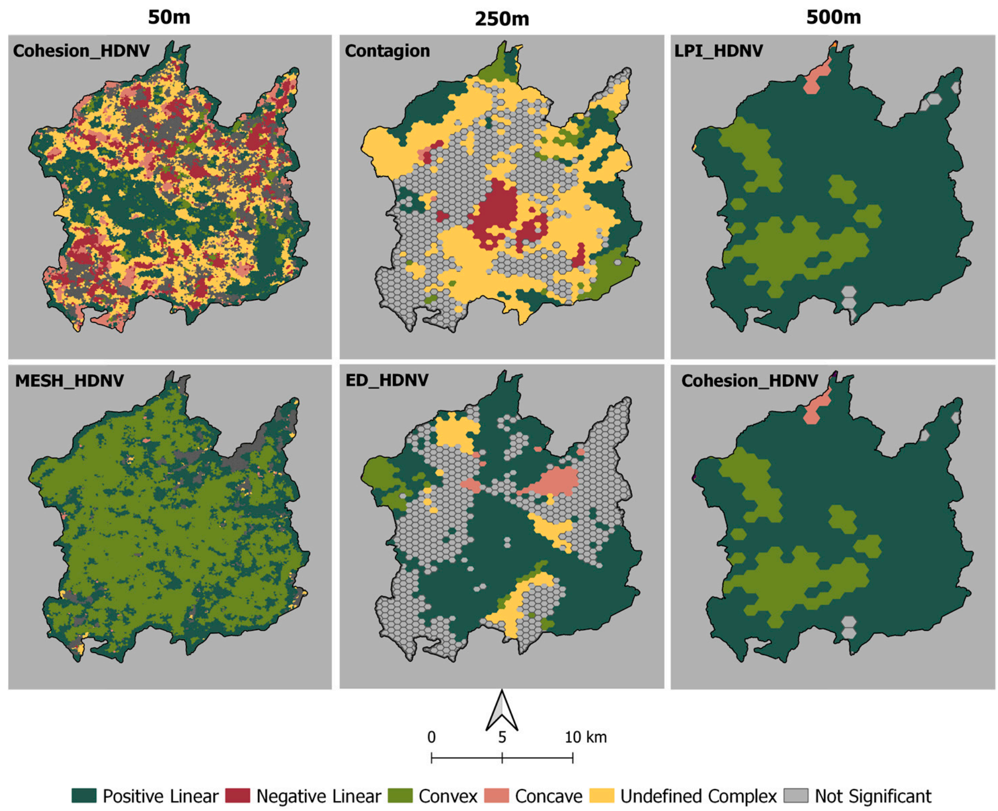

Figure 6. Local bivariate relationships among the two most important landscape metrices and the mean total ES supply per each scale of analysis.

4. Discussion

Forests in the Mediterranean basin have been characterized as a biodiversity and ecosystem services (ESs) hotspot primarily due to the complex and heterogeneous landscapes shaped by long-term interactions among human activities, natural environment, and climatic conditions [2,76]. As the material and non-material products derived from forests are strongly linked to human well-being, mapping the provision of essential services, as well as examining the conditions under which these ESs thrive, provides essential knowledge towards effective forest management policies that secure both ecological integrity and human welfare [77]. From this perspective, several studies on Mediterranean forests have shown that previous or existing forest management policies have played a significant role in the provision of ES, especially supporting various ecological processes [6,8].

The analysis of the landscape's composition and structure provides information required for developing conservation measures and sustainable management strategies for natural ecosystems [78], as well as data that can be used to further develop products indicating the status, the processes, and the functioning of an area. For this reason, a state-of-the-art object-oriented image (OBIA) classification procedure was applied providing land use/cover data with high thematic and spatial accuracy, similar to products produced via OBIA for other Mediterranean landscapes [57,79]. It is worth noting that in areas where landscape is characterized by high complexity, OBIA outperforms traditional pixel-based classification procedures [77], while in parallel, it can be used as a tool for systematic monitoring [11]. The composition of Marathasa's landscape is characterized mainly by medium density vegetation, i.e., shrubs and maquis; followed by low density vegetation, i.e., phryganic vegetation and natural grasses; and finally, by high density vegetation i.e., dense stands of maquis and pines. Considering the dynamics of Mediterranean forest [4,11,79], and especially the dynamics and status of Cypriot forests [80–84], this composition seems to be the result of the progressive evaluation of the more degraded ecosystems transitioning gradually from sparse vegetation to more dense forest stands through secondary ecological succession. In parallel, in the western part of the study area, where dense forest stands mainly occur, several management actions have been applied aiming to conserve the narrowly-distributed Cedar forest (*Cedrus brevifolia)*. The implemented measures consisted of silvicultural interventions (i.e., forest thinning and natural and artificial plantations) shaping a dense and heterogenous forest landscape [81].

The Marathasa region was found to provide essential forest-related ESs that are strongly linked to both physical characteristics and the presence of anthropogenic activities and cultural elements. Overall, areas occupied by high-density vegetation provide multiple ES, while areas characterized by low-density vegetation or open rocks have lower supply values. The individual ESs presented two different patterns regarding their spatial distribution. The services of "materials from timber" and "climate regulation" tend to co-occur across the study area and reach their highest supply in areas where dense forest is dominant. This pattern is rather expected, given the crucial role of forests as carbon sinks with significant impact in mitigating the effects of climate change [76,81,84] and the importance of forested areas in providing materials to local communities. The second spatial pattern referred to the services of "soil erosion prevention" and "recreation potential"; these did not strictly follow the distribution of high-density forest, as both services were mapped following multicriteria modeling procedures which take into consideration various geospatial data [64,65]. In the case of EP, as expected, higher values were not only observed in forested areas but also in areas where the surface relief is smooth, which is in line with other studies that examined erosion risk and control at various scales [9,65,82]. Similarly, the RC supply had greater values in areas covered by high-density vegetation as a result of the higher weight value given to the degree of the biophysical factor. At the same time, the RC value is higher in areas in which sites with tourist and cultural merit are present, and, as indicated by De Valck et al. [85], mixed landscapes that include forest, farmlands, infrastructure, and cultural elements are assessed positively by visitors [85].

As previously mentioned, examining the conditions under which ESs are maximized offers fundamental knowledge to support effective forest management and planning. One way to estimate and assess the status, dynamics, and shaping factors of a given landscape is through landscape metrics [12], which were employed in this study as explanatory variables of ES supply. The implementation of the cutting-edge machine learning algorithms of random forests and geographical random forests at three different spatial scales proved effective in identifying the spatial and thematic parameters that lead to increased provision of significant ES. Overall, both RF and GRF showed excellent performance in all scales, with GRF outperforming the aspatial RF, as has been observed in other cases where both spatial and aspatial RF models have been used [48–50]. However, the main advantage of GRF models is not their performance (predictive or explanatory) but their ability to produce maps presenting a possible spatial interaction among explanatory and response variables [48]. Regardless of the scale of analysis, the outputs from the modeling procedure showed that the configuration and aggregation of dense vegetation positively influence the supply of ESs, which aligns with the findings of a previous study demonstrating that regulating and recreational services are significantly and positively affected by homogenous forests [5]. Although the aforementioned results are in contrast with the main ESs concept which states that areas with diverse landscapes supply a high number of ESs [86], in the current study, the mapped ESs are strongly linked to forest cover. This result indicates that landscape diversity alone does not necessarily lead to the supply of multiple ESs, and that the dominant vegetation that characterizes a given landscape plays a fundamental role in the provision of ESs [5,87].

The holistic framework used here offers a comprehensive understanding of how the composition and structure of a given landscape contribute to the supply of ES. Since landscapes are mainly influenced by the presence or absence of humans, considering landscape structure in the ES context offers useful insights towards understanding the complex relationship between humans and nature. Additionally, contemporary mapping and modeling procedures can assist spatial planners, conservationists, and decision makers in developing and applying strategies, actions, and measures that consider both the global and local characteristics of an area, thereby ensuring effective management.

Limitations of the Study

Due to the complexity of Mediterranean forest landscapes, revealing the interlinkages between ecosystem services and landscape characteristics is not a straightforward task. Here, we attempted to assess these relationships by combining the conceptual framework of ecosystem and landscape services and a cutting-edge methodological approach. However, there are some limitations and improvements that should be considered when interpreting the findings of such approaches.

In terms of the use of random forest, such models can be prone to overfitting if the number of trees is too large or if the model is overly complex. This can result in an underestimation or overestimation of the relationship between landscape metrics and ecosystem services, leading to the generalization of the results. While random forest models can provide variable importance measures, the interpretation of these measures for landscape metrics may be challenging as their complex interactions with ESs may not be clearly evident through variable importance rankings. Finally, the accuracy and availability of data used to derive landscape metrics and measure ESs can significantly impact the results. Incomplete or biased data may introduce errors and uncertainties in the model, affecting the reliability of the relationship assessment.

In regard to the ESs studied in Marathasa forest, future research should consider multiple ESs to provide more insights into landscape multifunctionality and the relevant underlying processes. Our study, due to the limited available data, focused on four forest-related ESs and did not consider other important ESs, such as food provision, which could be related to the agricultural regions distributed across the studied region. Furthermore, the relationships between ESs and landscape metrices were assessed for a single year, which restricted the extraction of knowledge on the dynamic nature of Mediterranean forest landscapes.

5. Conclusions

The spatial arrangement and configuration of different land-cover types within a landscape can influence the provision and distribution of ES. By using global and geographically weighted random forest models, this study aimed to assess the provision of ESs in relation to the composition and structure of a forest-dominated landscape.

Prior to the mapping of ES, an object-based image classification was applied to identify the LULC evident in the study area. More than 90% of the landscape was occupied by natural vegetation with medium density vegetation (shrubs and maquis) covering approximately 41% of the total area, followed by low (phryganic vegetation) and high-density vegetation (dense stands of maquis and pines) reaching ~25% and ~24%, respectively. This composition of land cover classes resulted from the succession of vegetation where ecological processes and management interventions facilitated the transition from sparse vegetation to more dense forest stands.

The holistic approach applied in this study offers improves our understanding of how the composition and structure of a given landscape contribute to the supply of ESs. The existence of high-density forests, although it may reduce landscape heterogeneity, leads at the same time to the maximization of ESs related to climate regulation and provision to local communities. Future research should focus on providing an overview of Ess not studied here for a comprehensive understanding of how a landscape's composition can influence the multifunctionality of forests and the human population that depends on healthy ecosystems.

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Appendix A

Table A1. Vegetation indices used in LULC mapping.

Vegetation Index	Formula
Normalized Differencing Vegetation Index (NDVI)	$NDMI = \frac{NIR-RED}{NIR+RED}$
Modified Soil-Adjusted Vegetation Index (EVI)	$MSAVI = \frac{2\rho_{NIR}+1-\sqrt{(2\rho_{NIR}+1)^2-8(\rho_{NIR}-\rho_{RED})}}{2}$
Normalized Differencing Moisture Index (NDMI)	$NDMI = \frac{NIR-SWIR1}{NIR+SWIR1}$

Where: *NIR*: Near-infrared band; *RED*: Red band; and *SWIR1*: Short-wave infrared band.

Table A2. Accuracy assessment.

	HDNV	MDNV	LDNV	OR	AA	Total	UA
HDNV	32	3	0	0	0	35	0.91
MDNV	3	31	1	0	1	36	0.86
LDNV	0	1	31	1	4	33	0.94
OR	0	0	2	34	2	36	0.94
AA	0	1	2	0	28	31	0.81
Total	35	35	35	35	35	156	
PA	0.91	0.89	0.89	0.97	0.80		
OA	0.91						
Kappa	0.89						

HDNV: High-Density Natural Vegetation; MDNV: Medium-Density Natural Vegetation; LDNV: Low-Density Natural Vegetation; OR: Open and Rocky Areas; AA: Agricultural Area, OA: Overall Accuracy, PA: Producer's Accuracy, UA: User's Accuracy.

Table A3. RF models accuracy setting different values on "ntrees" parameter.

	50 m		250 m		500 m	
ntrees	R^2 (OOB)	R^2 (NOT OOB)	R^2 (OOB)	R^2 (NOT OOB)	R^2 (OOB)	R^2 (NOT OOB)
100	83.43%	92.86%	86.97%	95.42%	86.99%	96.84%
200	83.88%	92.88%	87.24%	95.53%	87.09%	97.11%
300	84.04%	92.92%	87.38%	95.69%	87.28%	97.26%
400	84.18%	93.16%	87.45%	95.78%	87.52%	97.49%
500	86.64%	93.45%	87.42%	95.74%	87.64%	97.56%
600	86.47%	93.34%	87.37%	95.67%	87.63%	97.51%
700	86.42%	93.12%	87.26%	95.53%	87.56%	97.42%
800	85.64%	92.83%	87.14%	95.41%	87.37%	97.36%
900	85.51%	92.74%	87.01%	95.39%	87.09%	97.17%
1000	84.98%	92.68%	86.92%	95.22%	87.00%	97.05%

Table A4. Descriptive statistics of the selected two explanatory variables outputting from GRF models.

		Min	Max	Mean	SD
50	Cohesion_HDNV	0.00	1.57	0.27	0.24
	MESH_HDNV	0.00	1.46	0.24	0.20
250	Contagion	0.02	0.49	0.15	0.07
	ED_HDNV	0.00	0.23	0.07	0.04
500	LPI_HDNV	0.00	0.10	0.02	0.02
	Cohesion_HDNV	0.00	0.09	0.02	0.02

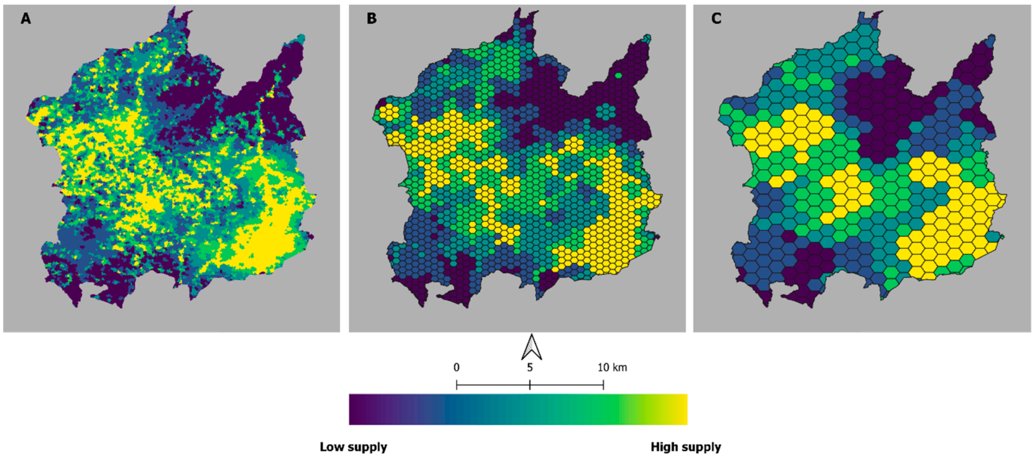

Figure A1. Graphs (**A**–**C**) are the ES supply maps at 50 m, 250 m, and 500 m scale analysis, respectively.

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