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Spatial Variability of Forest Species: Case Study for Alto Alentejo, Portugal

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Abstract: Landscape evaluation and monitoring enable us to understand the interactions between its components and the effects of disturbances (whether they are natural or artificial) in its dynamics. Forests have a wide variability and diversity, and their analysis at the landscape level allows us to evaluate its spatial distribution pattern. This study focused on the analysis of the landscape spatial variability of forest species with data derived from remote sensing and landscape metrics of a case study in Alto Alentejo, Portugal. Sentinel-2 satellite images were used to produce a land use and land cover map with a random forest classification algorithm, where the bands, vegetation and texture indices were the explanatory variables. The obtained land use/cover map has classified five forest classes and one non-forest class. The map was used to evaluate the diversity with eleven composition and configuration landscape diversity metrics for Alto Alentejo and for four sub-regions delimited according to their edaphic-climatic characteristics. The results showed that the land use/cover map had a good precision (a global precision of 89% and a kappa of 86%) and that both Alto Alentejo and its sub-regions had high forest diversity both in composition and configuration.

Keywords: Sentinel-2; forest land use; landscape metrics; beta diversity modelling

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1. Introduction

The world's surface is in constant change, resulting in dynamic landscape patterns, and these can be due to natural (e.g., climate change) or anthropogenic (e.g., changes in land use/cover and forest management) disturbances. These changes at the local, regional and/or global levels affect many ecological processes [1]. The landscapes vary in space from simple homogenous to complex heterogeneous ones, and they are the result of a suite of factors from edaphic, climatic and topographic conditions to disturbances [2–4]. Actually, the wide variety of remote sensing data obtained from Earth observation satellites play a key role in the management of natural resources, the study of climate change, territorial and forest management and measures that promote sustainable development [5,6]. These data allow us to generate, periodically, land use/land cover (LULC) maps at several scales, and they are a relevant tool to identify and understand the effects of the landscape dynamics over time and space [1].

The landscape is heterogeneous, comprising several LULC classes with a certain spatial distribution [7]. Landscape encompasses a set of patches that can be characterised by composition (e.g., the quantity and proportion of patches) and configuration (e.g., the patches' form and their spatial arrangement) [8,9].

Landscape patterns are studied using LULC maps, either with existing maps (older or recent, from different data sources) or produced with remote sensing data [10–12]. The LULC maps result from satellite image classification methods using several algorithms, such as maximum likelihood, support vector machine or random forest [13]. The maps can be generated with only one data set or with the conjugation of different spatial resolution, temporal and/or sensors data [14]. The use of the abovementioned data sets enables us to improve the data quality and earth surface monitoring at low costs [15]. The independent variables used in the identification of LULC classes can be the multispectral bands from the satellite images, as well as auxiliary bands, such as the vegetation or texture indices. This is due to the different spectral response of each forest species [16]. In forest landscapes, the LULC maps are determinants for their protection, conservation, biomass and carbon evaluation and ecological processes [17]. The existing LULC maps and those derived from remote sensing data have different spatial and temporal scales that enable the evaluation of landscape composition and configuration [2,3] over space [18] and in time [10]. Based on these maps, several analyses have been conducted with a focus on a set of features such forest fires, forest monitoring and management [19], habitat fragmentation [10] and forest land loss [1,4,7,11,18,20].

From 1992 onwards, a set of software packages were developed to analyse the landscape patterns with landscape metrics. These software packages use geographic information systems tools with maps either in vectorial or in raster formats. The latter one is more frequently used due to the wider availability of the data, both spatial and temporal data [1]. From those, Fragstats has been widely used as it encompasses most of the landscape metrics [21].

Landscape patterns, both spatial and temporal ones, have been most frequently analysed with metrics. Landscape metrics are quantitative indices that allow us to evaluate the composition and configuration of the LULC classes [8,9]. Several landscape metrics are used, and some characterise the composition, whereas others characterise the configuration [1,9]. However, some landscape metrics may produce redundant results. Thus, the selection of the better suited metrics is of the utmost importance, and it is dependent on the area and the objectives of the study [1]. The eleven most frequently used indices are: the total area (TA), Shannon's evenness index (SHEI), Simpson's evenness index (SIEI), percentage of landscape (PLAND), largest patch index (LPI), patch area (AREA_MN), number of patches (NP), weighted mean shape (AWMSI), edge density (ED), core area percent of landscape (CPLAND) and interspersion juxtaposition index (IJI). These indices enable us to characterise the landscape patterns, and they complement each other [9,21,22].

Landscape composition is usually analysed with Shannon or Simpson indices, or even both of them as they complement each other. The former one places more emphasis on the most frequent classes, while the latter one highlights the influence of the less frequent classes [23]. The landscape configuration is analysed with the metrics percentage of landscape, largest patch index, mean patch area, number of patches, weighted mean shape index, edge density, core area percent of landscape and interspersion juxtaposition index [6,21,22]. The percentage of landscape quantifies the proportion of each LULC class in the landscape. The largest patch index is a measure of dominance at the class level, and it corresponds to the area of the largest patch. Mean patch area corresponds to the mean area per LULC class. The number of patches is the total number of patches, and it can be calculated at the landscape or class levels. The weighted mean shape index corresponds to the ratio of the edge length to the standard edge length (assuming a standard square patch). The edge density is the proportion of the length of the boundary of the patches in relation to the area of the landscape. The core area percent of landscape corresponds to the total core area of each LULC class. The interspersion juxtaposition index evaluates the distribution of the patches of the LULC classes in relation to their neighbours, evaluating the spatial pattern of the patches, which is their interspersion or mingling.

The advantage of using several landscape metrics is that it enables us to highlight the effect of the interaction between the different metrics [8,9,21,24,25]. For example, the analysis of the mean patch area and the number of patches are indicative of the fragmentation of the LULC classes: the smaller the mean patch area is and the larger the number of patches is, the more fragmented the landscape is. The weighted mean shape index, edge density and core area percent of landscape are indicative of the complexity of the form of the patches: the higher the weighted mean shape index and edge density are and the smaller the core area percent of the landscape is, the more complex the patch forms are. Core area percent of landscape is also dependent on the mean patch area, edge density and weighted mean shape index: the smaller the mean patch area is and the larger the edge density and weighted mean shape index are, the smaller the core area percent of the landscape is.

The goal of this study was the analysis of the spatial variability of the non-forest and forest areas in Alto Alentejo, Portugal with an LULC map derived from Sentinel-2 data. The three specific objectives were to: (i) produce an LULC map of the Alto Alentejo region with Sentinel-2 images; (ii) use landscape metrics to evaluate the composition and configuration of the landscapelevel; (iii) compare the landscape diversity in Alto Alentejo and in four sub-regions with homogeneous edaphic and climatic conditions.

2. Materials and Methods

2.1. Study Area and Sentinel-2 Data

The study area, Alto Alentejo, is located in Eastern Central Portugal (Figure 1). It is characterised by a Mediterranean climate, with high temperatures and dry summers, and precipitation that is concentrated in the autumn and winter. The relief is irregular, with it ranging from 400 to 1027 m in the Serra de São Mamede (northeast of the study area), and in the remaining area, there is a mean elevation of around 250 m. The climate is under Atlantic influence in the higher elevations, whereas the lower ones are influenced by the Mediterranean climate [1]. The soils have a spatial heterogeneous distribution, and they include cambisoils, litosoils, luvisoils, vertisoils and podzols [5]. It comprises two watershed basins, Tagus and Guadiana [1].

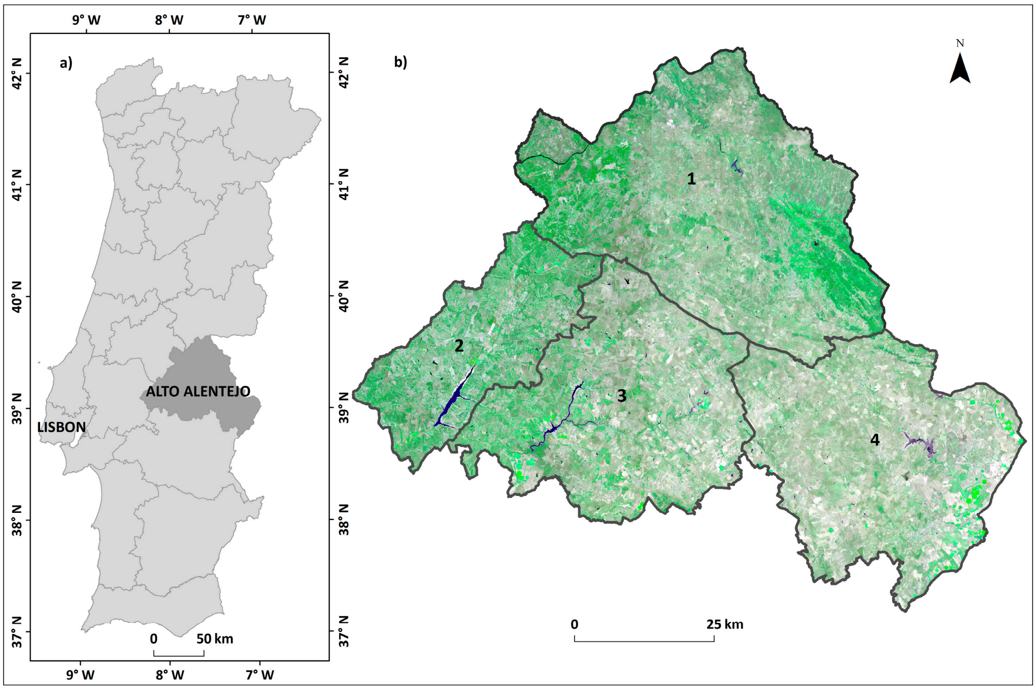

Figure 1. Portugal administrative division NUTIII, Alto Alentejo, (**a**) and false colour composite of Sentinel 2 image (RGB-b483) with homogeneous sub-regions delimited with grey lines (**b**).

The Sentinel-2 satellite images used in this study were obtained from the Europe Spatial Agency (ESA) Copernicus open access hub portal [6]. The Sentinel-2 product at level 2 A corresponds to the bottom of atmosphere (BOA) reflectance. To enable a stronger contrast between the forest cover and other LULC classes, the image acquisition dates were selected during the dry months. Additionally, the images with less than 10% cloud cover were selected. Two images were needed to cover Alto Alentejo, and were acquired in September 2019. From the thirteen available multispectral bands, ten were used (Table 1), as these were the better suited for the LULC evaluation [6,7].

Table 1. Characteristics of Sentinel-2 bands used in this study.

Bands	Description	Spatial Resolution (m)	Central Wavelength (nm)
B2	Blue	10	490
B3	Green	10	560
B4	Red	10	665
B5	Red Edge 1	20	705
B6	Red Edge 2	20	749
B7	Red Edge 3	20	783
B8	Near infrared (NIR)	10	842
B8A	Red Edge 4	20	865
B11	Shortwave infrared (SWIR 1)	20	1610
B12	Shortwave infrared (SWIR 2)	20	2190

2.2. Methods

This study was developed in two phases: in the first phase, the LULC map was produced, and in the second phase, this map was used to evaluate the diversity at the landscape level (Figure 2).

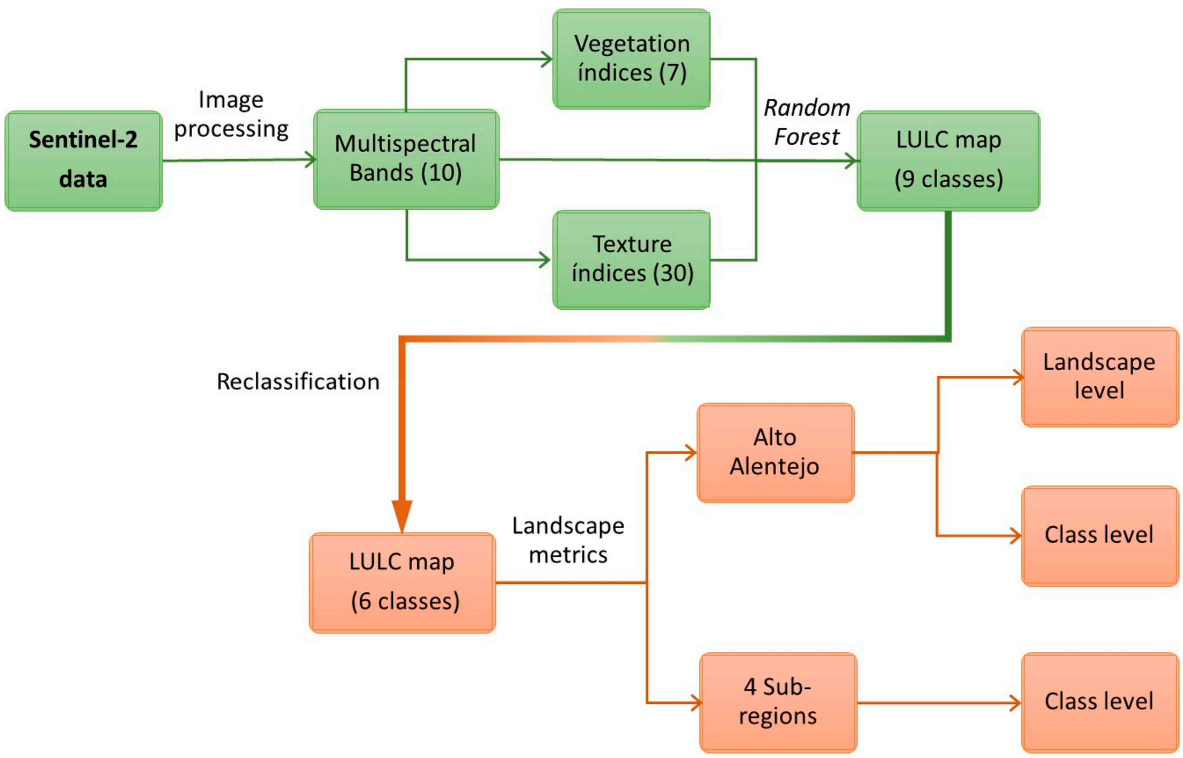

Figure 2. Flowchart of the methodology of this study.

First, the LULC map was produced using the following sequential steps: (i) the creation of the mosaic with the two satellite images; (ii) resampling the spatial resolution of the bands from 20 m (B5, B6, B7, B8A, B11 and B12) to 10m using the nearest neighbour algorithm; (iii) image classification using the supervised method with Random Forest (RF) algorithm, which included the definition of the LULC classes, the definition of the training areas, the selection of the exploratory variables and RF parameters (the number of decision trees and knots).

In this study, nine classes of LULC were defined: five of them were forest species, and four of them were non-forest. The forest classes correspond to the following forest species: holm oak (*Quercus rotundifolia*, hereafter, HO), cork oak (*Quercus suber*, hereafter, CO), eucalyptus (*Eucalyptus* spp., hereafter, EC), umbrella pine (*Pinus pinea*, hereafter, UP) and maritime pine (*Pinus pinaster*, hereafter, MP). The non-forest (NF) classes encompass the classes social area and soil, water, agricultural areas and shrubland. For each class, a set of sampling areas were selected per LULC class.

The RF classification algorithm was selected due to its ability to derive LULC maps with good accuracy and a shorter processing time [2,8,9]. The RF algorithm requires the definition of the number of decision trees and knots. According to the literature [3,4,10], good accuracy is attained with 500 decision trees and 20 knots, which were used in this study. Additionally, RF requires the data set to be divided into two subsets: one is used for fitting (corresponding to two thirds of the data set), and another one is used for validation (one third of the data set), according to the suggestion by Pageot et al. [10]. The exploratory variables selected for the classification included ten multispectral bands (Table 1), seven vegetation indices and thirty texture indices (three for each original band) (Table 2). From the existing vegetation indices, those with a better ability to discriminate between the different LULC classes were selected. For example, the vegetatipon indices that differentiate vegetation from other uses, different types of vegetation, water minimise the effect of soil in areas with sparse vegetation, noise and atmospheric influence [11–15]. Similarly, the selected gray-level co-occurrence matrix (GLCM) texture indices were the ones which attained better performances in image classification in former studies [12,16–18], namely, mean, variance and correlation.

Table 2. Vegetation and texture indices.

	Indices	Formula	Eq.
Vegetation Indices	NDVI	$\frac{(B8-B4)}{(B8+B4)}$	1
	SAVI	$\frac{1.5\times(B8-B4)}{8\times(B8+B4+0.5)}$	2
	MSAVI2	$0.5 \times \left\{2\times(B8+1)-\sqrt{(2\times B8+1\times(2\times B8+1)-8\times(B8-B4)}\right\}$	3
	EVI	$\frac{2.5\times(B8-B4)}{(B8+6\times B4-(7.5\times B2)+1)}$	4
	NDRE1	$\frac{(B8A-B5)}{(B8A+B5)}$	5
	NDRE2	$\frac{(B8A-B6)}{(B8A+B6)}$	6
	NDII	$\frac{(B8A-B11)}{(B8A+B11)}$	7
Texture indices	GLCM Mean	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} i \times P(i,j)$	8
	GLCM Variance	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(i-u)^2 p(i,j)$	9
	GLCM Correlation	$\frac{\sum_i\sum_j(ij)P(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$	10

B2-Blue; B4-Red; B5-Red Edge 1; B6-Red Edge 2; B8-Near infrared; B8A-RedEdge 4; B11-Shortwave infrared 1; p(i,j) is (i,j) gray-level co-occurrence matrix input; N_g—total number of grey levels in the image; μ_x and μ_y—Mean deviation in row (x) and column (y), respectively; σ_x and σ_y—Standard deviation in row (x) and column (y), respectively.

The classification accuracy was evaluated with the confusion matrix, overall accuracy (OA) and the kappa statistic (Table 3), according to the suggestion by several authors [19–21].

Table 3. Accuracy precision measures.

	Formula	Eq.
Overall accuracy	$\sum_{i=1}^{k} \frac{N_{ii}}{N}$	11
Kappa statistic	$\frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} . x_{+i})} \times 100$	12

N is the total value of observations included in the matrix; r is the number of rows in the matrix; x_{ii} is the total number of observations in row i; x_{i+} is the total number of observations in column i; x_{+i} is the total number of observations in column i.

As the focus of this study was the analysis of the forest species, the LULC map was reclassified into six classes: five forest ones, corresponding to the five forest species and one non-forest one, corresponding to social area and soil, water, agricultural areas and shrubland.

The data processing was performed using the software ENVI 4.8 [22]; the vegetation indices and texture indices were calculated in ArcGIS 10.7.1 [23] and in SNAP (Sentinel Application Platform) 8.0.0 [24], respectively; the training areas identification and delimitation were conducted using ArcGIS 10.7.1 [23] with the help of the images available in the platform Google Earth Pro [25] and Portuguese cover map (COS) of 2018 [26]; the RF algorithm was used in the Orfeo 7.1 tool of QGIS 3.16 [27].

In the second phase, the LULC map, in a raster format, with a spatial resolution of 10m, was used to evaluate the diversity at the landscape level. For this analysis, two levels were considered: Alto Alentejo and four homogenous sub-regions of Alto Alentejo (Figure 1). The latter areas were considered as Alto Alentejo has topographic and ecological differences in its territory. The division into homogeneous sub-regions according to the ecological, edaphic and topographic characteristics was conducted to uncover further details in the analysis of the study area.

Heterogeneity at the landscape level is frequently evaluated for the LULC classes' diversity and number, size and spatial arrangement of the patches [28]. From the existing landscape metrics, eleven (Table 4) of them were chosen, which enabled us to evaluate the study area and its sub-regions. For the landscape metrics calculation, two parameters had to be defined: the number of neighbours and the sampling approach. The number of neighbours that were considered was four, as recommended by Mcgarigal et al. [29]. In terms of the sampling approach, two levels were considered, the landscape and the class [29,30]. The total area, Shannon and Simpson evenness indices were calculated for the former one, and for the latter one, the percentage of landscape, largest patch index, mean patch area, number of patches, weighted mean shape, edge density, core area percent of landscape and interspersion juxtaposition index were considered (Table 4).

The differences in the metrics per sub-region were tested with ANOVA and a post hoc Tukey test at a significance level of 0.05 [31] as the data did not meet the normality criteria (evaluated with Shapiro–Wilk normality test). This analysis was implemented in IBM SPSS Statistics 25 [32].

Table 4. Landscape metrics.

Level	Indices	Formula	Units	Range	Eq.
Landscape	TA	$A\left(\frac{1}{10{,}000}\right)$	ha	[0, +∞]	13
	SHEI	$\frac{-\sum_{i=1}^{m}(P_i\ o\ InP_i)}{Inm}$	Dimensionless	[0, 1]	14
	SIEI	$\frac{1-\sum_{i=1}^{m}P_i^2}{1-\left(\frac{1}{m}\right)}$	Dimensionless	[0, 1]	15
Class	PLAND	$\frac{\sum_{j=1}^{n}a_{ij}}{A}\times 100$	%	[0, 100]	16
	LPI	$\frac{\overset{n}{\underset{j=1}{\max}}(a_{ij})}{A}\times 100$	%	[0, 100]	17
	AREA_MN	$\frac{a_{ij}}{N_i}\left(\frac{1}{10{,}000}\right)$	ha	[0, +∞]	18
	NP	$\sum_{j=1}^{n}n_i$	Dimensionless	[0, +∞]	19
	AWMSI	$\sum_{j=1}^{n}\left[\left(\frac{0.25p_{ij}}{\sqrt{a_{ij}}}\right)\left(\frac{a_{ij}}{\sum_{j=1}^{n}a_{ij}}\right)\right]$	Dimensionless	[0, +∞]	20
	ED	$\frac{\sum_{k=1}^{m}e_{ik}}{A}\times 100{,}000$	m/ha	[0, +∞]	21
	CPLAND	$\frac{\sum_{j=1}^{n}a_{ij}^{c}}{A}\times 100$	%	[0, 100]	22
	IJI	$\frac{-\sum_{K=1}^{m}\left[\left(\frac{e_{ik}}{\sum_{k=1}^{m}e_{ik}}\right)In\left(\frac{e_{ik}}{\sum_{k=1}^{m}e_{ik}}\right)\right]}{In\ (m-1)}\times 100$	%	[0, 100]	23

A-total area of the landscape; P_i-proportion of the landscape occupied by the patch of class i; m-number of classes in the landscape; a_{ij}-area of the patch ij; N_i-number of patches of the class i; n_i-number of patches; p_{ij}-perimeter of the ij patch; e_{ik}-total length of the border of all patches of classes; $_k$; a^c_{ij}-central area of the ij patch.

3. Results

3.1. Land Use/Cover Map

The land use/cover map (Figure 3) showed a predominance of cork oak and umbrella pine in the southwest area, while holm oak prevailed in the central and south-eastern areas. The non-forest class did not seem to have a clear distribution pattern, it is scattered all over the area. Eucalyptus was scattered over the west of Alto Alentejo, and maritime pine was concentrated in the central eastern area.

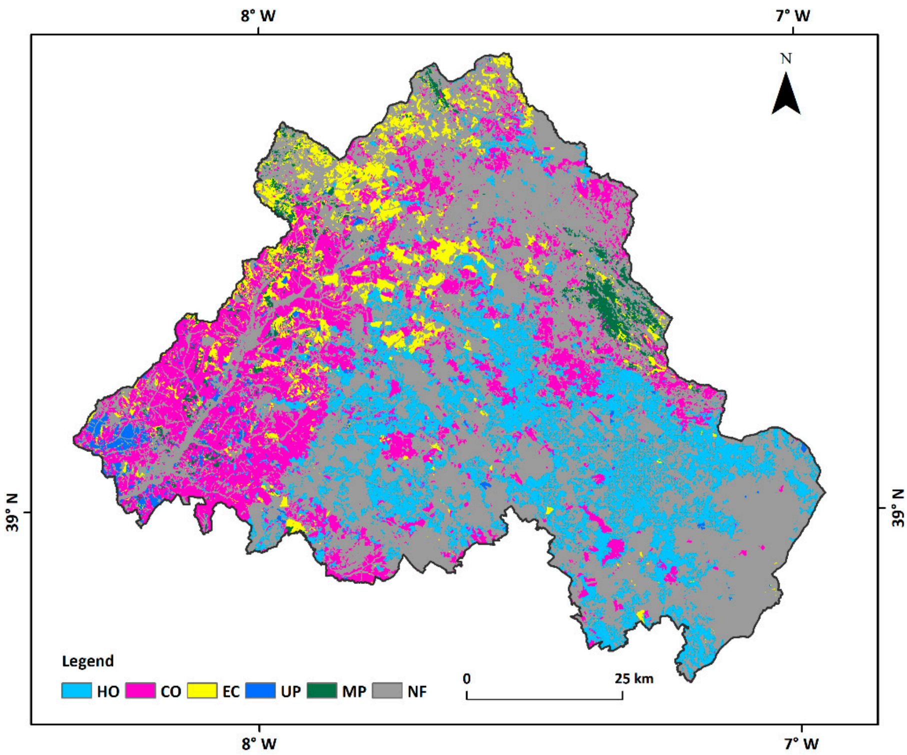

Figure 3. Land use/cover map for Alto Alentejo region.

The overall precision of the classification was good, with a producer precision and user precision that is above 80% (Table 5) for all of the LULC classes. The overall accuracy and kappa statistic were 89% and 86%, respectively. Thus, there was a high agreement between the estimated and the observed values. Moreover, the higher commission errors were observed in the holm oak, eucalyptus and umbrella pine classes, whereas higher omission errors were observed in the remaining classes. These errors were related to the spectral behaviour of the forest tree species: some of them have similar spectral behaviour, making it difficult to separate them, e.g., holm oak vs. cork oak, eucalyptus vs. maritime pine and umbrella pine vs. maritime pine.

Table 5. Confusion matrix.

LULC Class	HO	CO	BG	UP	MP	NF	Total	PP
HO	25,519	1414	267	215	3	668	28,086	91%
CO	2017	22,357	375	1049	659	1629	28,086	80%
BG	737	344	24,321	1236	545	903	28,086	87%
UP	649	915	1095	24,452	587	388	28,086	87%
MP	63	305	1579	1609	23,388	1142	28,086	83%
NF	1186	1234	587	1045	2467	105,825	112,344	94%
Total	30,171	26,569	28,224	29,606	27,649	110,555		
PU	85%	84%	86%	83%	85%	96%		
OA	89%							
Kappa	86%							

3.2. Diversity at Alto Alentejo Level

Alto Alentejo has a total area of 608 435ha, and the landscape was composed of 55% non-forest areas, 19% cork oak, 17% holm oak, 6% eucalyptus, 2% maritime pine and 1% umbrella pine. The Shannon evenness and Simpson evenness indices (0.70 and 0.76, respectively) corresponded to a high degree of diversity.

The largest patch index was the biggest for cork oak (2.48% of the total area), which was followed by holm oak (1.82% of the total area). For the other three forest species (eucalyptus, maritime pine and umbrella pine), the largest patch index was smaller than 1% of the total area.

The number of patches was the largest for the non-forest class. For the forest classes, the larger number of patches was observed for cork oak (3697 patches) and holm oak (3059 patches). Umbrella pine had the lowest number of patches (618 patches). The mean patch area was larger for cork oak and holm oak than that of eucalyptus, maritime pine and umbrella pine. The comparison of the number of patches and the mean area patches (Figure 4) indicated higher fragmentation for eucalyptus, corresponding to 1939 patches, with a mean area of 18.4 ha. The lowest patch fragmentation was observed for umbrella pine, with 618 patches and a mean area of 11.5 ha.

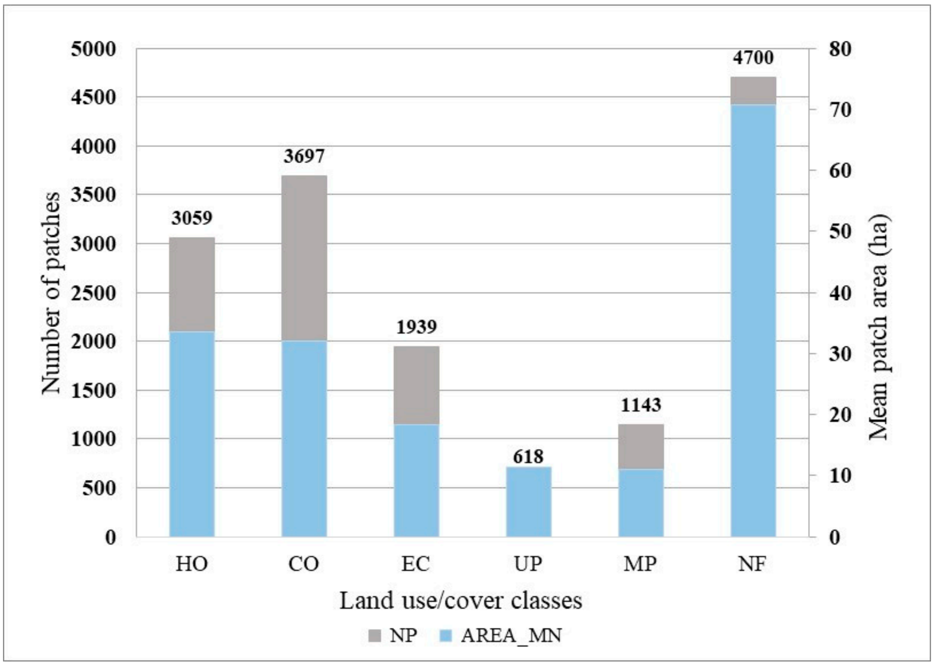

Figure 4. The number of patches (NP) and mean patch area (AREA_MN).

The weighted mean shape index and edge density are directly related to and characterise the patch complexity. The highest values were attained for the non-forest class (Table 6), while for the forest classes, the larger values were for cork oak and holm oak. Overall, these three classes had more complex patches, with irregular shapes and higher neighbourhood diversity. The weighted mean shape index and edge density were clearly larger for holm oak and cork oak than they were for the other three forest species. The irregularity of the patch form was higher for cork oak than it was for holm oak, which is denoted by the smaller weighted mean shape index and larger edge density of the former one. This difference can be explained by the largest patch index, which was larger for cork oak than it was for holm oak (circa 2.5% and 1.8% of the total area, respectively. Umbrella pine, maritime pine and eucalyptus, in spite of their low edge density, had some patch form irregularity, which is denoted by the weighted mean shape index. This can be, at least partially, explained by the terrain topography (e.g., slope and/or elevation).

Table 6. Weighted mean shape index (AWMSI) and edge density (ED).

LULC Class	AWMSI	ED (m/ha)
HO	11.18	19.36
CO	7.85	20.56
EC	3.70	7.74
UP	2.05	1.89
MP	4.60	3.62
NF	63.61	39.16

The core area percent of the landscape, corresponding to the central area of a patch, attained the largest values for non-forest, cork oak and holm oak classes (Figure 5). This is indicative of high fragmentation. Inversely, the lowest core area percent of the landscape, and consequently, the lowest fragmentation was observed in the other three forest classes. The analysis of the largest patch index, mean area patch and weighted mean shape index gives insights about the heterogeneity of the landscape. The non-forest, cork oak and holm oak classes had a larger mean area patch, thus reducing the effect of edge density due to its larger weighted mean shape index. The interspersion of the LULC classes, which was evaluated by the interspersion juxtaposition index, was the largest for the non-forest class, whereas for the forest classes, it was larger for maritime pine and eucalyptus (67% for both of them), umbrella pine (61%), and cork oak (59%) than it was for holm oak (26%).

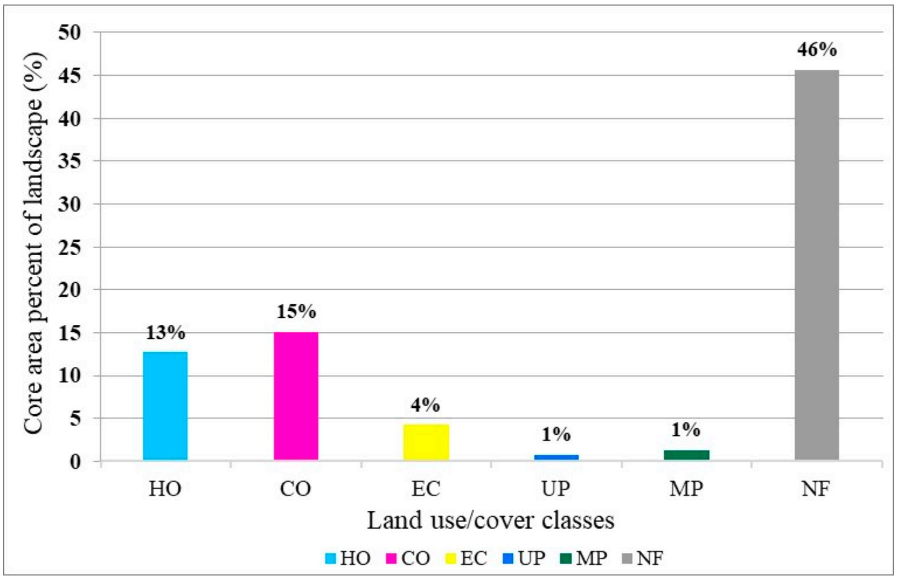

Figure 5. Core area percent of landscape (CPLAND).

3.3. Diversity at Sub-Region level

The analysis per sub-region enabled us to evaluate the spatial variability of the diversity in Alto Alentejo. The percentage of the landscape showed significant differences among the four sub-regions (all $p > 0.05$) (Figure 1). The non-forest class in sub-regions 1 and 3 occupied more than half of their areas, while in sub-regions 2 and 4, it occupied considerably less area (Table 7). Considering the forest classes for all of the sub-regions, cork oak and holm oak comprised the largest percentage of the landscape, but in different proportions. Eucalyptus and maritime pine had some expression (4–8% of the total area of the sub-regions) in sub-regions 1 and 2.

Table 7. Percentage of landscape (PLAND) per sub-region.

LULC Class	PLAND (%)			
	1	2	3	4
HO	10.85	49.80	26.93	53.31
CO	16.74	32.51	19.46	20.98
EC	8.02	8.14	0.25	2.63
UP	0.18	2.74	0.19	0.62
MP	4.28	6.12	0.05	0.24
NF	59.94	0.68	53.12	22.31

The number of patches, the largest patch index and the patch area showed significant differences between the sub-regions (all $p > 0.05$) (Table 8). In sub-region 1, holm oak, cork oak and maritime pine were the forest classes with the higher number of patches, while in the sub-regions 2 and 4, these were cork oak and holm oak. The largest patch index was higher for holm oak in sub-regions 1 and 3 and for cork oak in sub-regions 2 and 4, which is indicative of a lower level of fragmentation. For the other three species, the higher number of patches was found for eucalyptus in sub-regions 3 and 1, for umbrella pine in sub-regions 4 and 1 and for maritime pine in sub-regions 1 and 2.

Table 8. Number of patches index (NP), largest patch index (LPI) and patch area (AREA_MN) per sub-region.

LULC Class	NP				LPI				AREA_MN			
	1	2	3	4	1	2	3	4	1	2	3	4
HO	568	369	179	642	48.56	0.46	51.24	0.41	173.56	26.36	164.60	35.07
CO	737	711	671	399	1.30	17.75	0.47	35.44	40.75	113.11	40.18	124.10
EC	483	259	618	212	0.06	0.16	6.44	3.11	13.57	11.20	76.68	54.33
UP	211	105	12	277	1.34	13.23	0.02	10.14	27.75	38.32	6.33	83.27
MP	729	225	20	20	1.48	1.29	0.08	0.06	37.97	22.79	20.40	17.60
NF	28	42	17	63	2.79	0.14	0.05	0.08	44.68	13.62	18.12	14.67

For sub-regions 1 and 3, the largest patch index was about half of the landscape area for holm oak, which was much larger than it was for the other sub-regions and LULC classes. The highest landscape fragmentation was observed in the sub-regions 1 and 2 with a higher number of patches, a lower largest patch index and a lower patch area. The LULC class with the lowest level of fragmentation was eucalyptus in the sub-regions 1 and 2, umbrella pine in sub-region 3 and maritime pine in sub-region 4, which is denoted by the lower patch area and number of patches.

Significant differences were found among the sub-regions for the weighted mean shape index, edge density and core area percent of the landscape (all $p > 0.05$) (Table 9). The largest irregularity and complexity of the patch form was found in sub-regions 1 and 3 for holm oak due to the large mean area and edge density of the patches. A similar trend was observed for cork oak in sub-regions 2 and 4. Inversely, in sub-regions 2 and 4, the holm oak patches were more regular due to their smaller mean area and edge density. Eucalyptus, umbrella pine and maritime pine were the classes with a more regular form, and they were less complex and had a smaller edge density. The core area percent of landscape was the largest for holm oak in sub-regions 1 and 3, for cork oak and umbrella pine in sub-regions 2 and 4, for eucalyptus in sub-regions 3 and 4 and for maritime pine in sub-region 1.

Table 9. Weighted mean shape index (AWMSI), edge density (ED) and core area percent of landscape (CPLAND) per sub-region.

LULC Class	AWMSI				ED				CPLAND			
	1	2	3	4	1	2	3	4	1	2	3	4
HO	18.66	1.80	13.31	1.70	20.71	6.66	18.66	1.70	59.94	8.15	63.12	2.63
CO	2.45	6.19	2.03	10.62	7.14	23.26	2.98	18.91	10.85	49.80	4.46	53.31
EC	1.24	1.18	5.20	3.22	0.20	3.26	17.43	13.25	0.18	2.74	31.93	20.98
UP	2.74	4.94	1.07	5.28	3.32	21.42	0.07	10.00	4.28	32.51	0.05	22.23
MP	2.61	1.90	1.25	1.53	11.47	5.11	0.21	0.23	16.74	6.12	0.25	0.24
NF	3.72	1.31	1.19	1.28	5.03	0.71	0.19	0.64	8.02	0.68	0.19	0.62

4. Discussion

4.1. Land Use/Cover Map

Alonso et al. [33] produced a LULC map for Galicia, Spain. In the classification, the authors used multitemporal images from satellite Sentinel-2 with the RF algorithm, obtaining an overall accuracy of circa 92% and a kappa statistic of 90%. In this study, the accuracy was slightly lower (an overall accuracy of 89%, and a Kappa of 86%) using mono-temporal Sentinel-2 image with RF. The difference in precision between the two studies can be explained by the difference in the LULC classes. Kupidura [34] used two approaches using multispectral bands and texture indices to classify images from satellites Pléiades and Sentinel-2 to produce an LULC map. The approach with multispectral bands attained overall accuracies of 78% and 93% and Kappa values of 71% and 90%, respectively. In the second approach, the inclusion of the texture indices resulted in the improvement of both the overall accuracy and kappa statistic. For the Pléiades image, the overall accuracy was 90%, and the kappa statistic 87%, while for the Sentinel-2 image, these were 95% and 93%, respectively. In another study by Dobrinić et al. [35], the precision of the LULC map using the Sentinel-2 images with multispectral bands had an overall accuracy of 89%, whereas when the multispectral bands and vegetation indices were used as independent variables, the overall accuracy increased to circa 90%. Dobrinić et al. [35] and Kupidura [34] showed the importance of the vegetation and texture indices in the classification process. Shao and Wu [36] noted that the precision should be circa 90% to allow for consistency in the landscape metrics. In this study, the abovementioned threshold was attained.

4.2. Landscape Level Analysis

The landscape metrics in this study were indicative of a high level of diversity [29,37]. This was the result of the arrangement of the six LULC classes in the landscape, whether the analysis is made by number, form or dimension [38]. This can be explained by the topography, climate and soil type distribution, as well as the ecological and cultural characteristics of the species. This variability was highlighted in the analysis of the sub-regions. Cork oak and holm oak were present in all of the sub-regions, occupying the areas under Mediterranean climate influence and at lower elevations. This is in accordance with the suitability maps for these species of Ferreira et al. [39]. Inversely, most of the areas occupied by maritime pine are under Atlantic influence and at higher elevations, such as Serra de São Mamede (sub-region 1), as this species is more sensitive to high temperatures [39,40]. Eucalyptus and umbrella pine were mainly in sub-regions 1 and 2, which are under a Mediterranean climate, at lower elevations, and this is due to the sensitivity of these two species to frost [39,41]. The number and area of patches per LULC class, both for Alto Alentejo and for the sub-regions, presented a high variability, showing a matrix for the six LULC classes. Although fragmentation was observed more for some classes than it was others, it was the result of natural and artificial disturbances [38,42–45]. It was the largest for the classes that occupied a larger area. Moreover, the highest number of patches was found in sub-region 1 (2756, of which 2728 correspond to the five forest classes), which was followed by sub-region 2 (1711, of which 1669 belong to the five forest classes) and sub-regions 3 and 4 (1517 and 1615, 1500 and 1550 of forest classes, respectively). The mean patch area was the largest in sub-regions 3 and 4 for the forest classes (61.6 ha and 62.9 ha, respectively), which were followed by sub-regions 1 (58.7 ha) and 2 (42.4 ha). This also reflected the effect of relief and edaphic and climatic conditions on the forest species distribution due to their ecological and cultural traits [39]. Furthermore, in the study area, it was observed that the patches varied from a rather regular form, with a low edge density and a small area to very irregular form, with a high edge density and a large area. These three metrics are related; the larger the area, the edge density and form irregularity are, then the larger the complexity of the patches and the edges between the different patches are [46–50].

The core area percent of landscape can be indicative of habitat degradation, where the number of patches is high and the area is small. In this study, the classes non-forest, holm oak and cork oak comprised a large core area percent of the landscape in spite of the high number of patches, whereas eucalyptus, maritime pine and umbrella pine comprised a lower core area percent of the landscape and number of patches. The variability of the core area percent of the landscape of the forest classes in the four sub-regions seemed to be also related to relief, climate and soils, with a trend towards its decrease with the increase in the elevation. In all of the sub-regions, the more irregular classes had large mean areas, and thus, they had less influence in the central areas. Inversely, in the more fragmented classes, the mean areas were small, and the central areas were even smaller, thus increasing the influence of edge density and the edge effect. Although all of the forest classes were managed forest systems, some differences have to be noted. Holm oak and cork oak and umbrella pine are managed as agroforestry systems with low density and high diversity levels, [51] while eucalyptus and maritime pine are timber oriented systems [39]. The classes of eucalyptus, umbrella pine and maritime pine had a lower number and area of patches. This can be related to the suitability of the sites for these species traits. Yet, they can contribute to the reduction of the isolation of the large patches, thus, increasing the connectivity between the patches [52].

The interspersion juxtaposition index values of this study indicate that the forest classes of cork oak, eucalyptus, umbrella pine and maritime pine were spatially mingled with other LULC classes. The number of patches of each class influences the mingling between the LULC patches. For example, in the classes with a lower number of patches, they can be spatially interspersed with other LULC classes [53]. The non-forest class included several lands uses/covers (e.g., social area, water and agricultural areas), resulting in patches that are more interspersed.

The diversity analysis in this study showed significant differences between the sub-regions. Casimiro [46] performed a spatial analysis with sixteen metrics for the municipality of Mértola (Southeastern Portugal), considering three sub-regions, and they attained significant differences among the sub-regions. The differences were explained, at least partially, by the edaphic-climatic characteristics of the sub-regions and the ecological-cultural traits of the species. Other studies [48,54] evaluating the dynamics of LULC in time with landscape metrics also observed differences, and these indicated that the number of patches index is a primordial metric.

5. Conclusions

An updated LULC map is of the utmost importance for the monitoring of the landscape dynamics. The data sets derived from Sentinel-2 satellite images, namely, multispectral bands, vegetation and texture indices with the random forest classification algorithm enable us to obtain accurate LULC maps, such as that which was produced in this study with an overall accuracy of 89%.

Alto Alentejo and the four sub-regions showed a landscape pattern of high variability in terms of composition and configuration. The spatial heterogeneity increased with the increase in the variability of relief, climate and soils. For Alto Alentejo, there was a trend towards the irregularity and mingling of the patches. The forest classes with larger areas had the higher edge density and form irregularity (holm oak and cork oak), whereas the others (eucalyptus, umbrella pine and maritime pine) had a smaller number of patches and more regular areas. The central areas were larger for holm oak and cork oak, where edge density did not have a strong influence as it did in the other forest classes due to the mean patch area dimension. All of the classes presented a high level of interspersion. This trend was also observed at the sub-region level. The differences between the sub-regions are related to the variability edaphic, climatic and topographic characteristics and their suitability to the ecological and cultural traits of the forest species. All six classes exist in the four sub-regions, but the proportion and fragmentation of each forest class varied from one sub-region to another. In sub-regions 2 and 4, the predominant LULCs were the forest classes, while for sub-regions 1 and 3, these were non-forest ones. Additionally, the former two sub-regions were more fragmented than the latter two sub-regions were.

This study highlights the importance of updated and accurate LULC maps. Further improvements to the maps can be made with multitemporal data and other vegetation and texture indices. In the diversity analysis, the importance of the analysis at two spatial scales was stressed (Alto Alentejo and sub-regions), which gave further insights about the dynamics of the spatial arrangement of the landscape. Again, data sets that include more detailed forest data, such as density measures (number of forest trees, basal area, volume and biomass) would enable a more detailed diversity analysis at the landscape level.

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