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Article

Quantifying Forest Spatial Pattern Trends at Multiple Extents: An Approach to Detect Significant Changes at Different Scales

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Abstract: We propose a procedure to detect significant changes in forest spatial patterns and relevant scales. Our approach consists of four sequential steps. First, based on a series of multi-temporal forest maps, a set of geographic windows of increasing extents are extracted. Second, for each extent and date, specific stochastic simulations that replicate real-world spatial pattern characteristics are run. Third, by computing pattern metrics on both simulated and real maps, their empirical distributions and confidence intervals are derived. Finally, multi-temporal scalograms are built for each metric. Based on cover maps (1954, 2011) with a resolution of 10 m we analyze forest pattern changes in a central Apennines (Italy) reserve at multiple spatial extents (128, 256 and 512 pixels). We identify three types of multi-temporal scalograms, depending on pattern metric behaviors, describing different dynamics of natural reforestation process. The statistical distribution and variability of pattern metrics at multiple extents offers a new and powerful tool to detect forest variations over time. Similar procedures can (i) help to identify significant changes in spatial patterns and provide the bases to relate them to landscape processes; (ii) minimize the bias when comparing pattern metrics at a single extent and (iii) be extended to other landscapes and scales.

Keywords: modified random cluster algorithm; pattern metrics; scalogram; forest regrowth; stochastic simulations; central Italy; statistical significance of change

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1. Introduction

Forest ecosystems have played a major role in human history, and periodic deforestation has accompanied population growth and development throughout the world for thousands of years [1]. Although tropical forests are affected by intensive deforestation because of the dependence of local populations on land-based economic activities, harvesting practices, of vital importance in the postwar economy, have recently become moderate in temperate forests [1]. In particular, the current distribution of temperate forests in several hilly and mountainous landscapes of Europe derive from centuries of extensive forest exploitation followed by the abandonment of traditional agricultural practices [2–4]. In this context, the analysis of forest spatial pattern through time and, in particular, the study of the process of natural regrowth is of primary importance in ecological research because forest distributions could affect many ecosystem functions at multiple scales [4].

The most common approach for analyzing changes in forest spatial patterns over time is the mere comparison of pattern metrics extracted from areas of fixed size defined by administrative or natural limits [5,6]. However, such an approach could be problematic for at least three principal issues: (i) the arbitrary choice of the extent of the analyzed area [7]; (ii) the lack of specific scale breaks (thresholds) to identify significant changes in landscape structure and function [8]; and (iii) the negligence, or, in the worst cases, the absence of an analysis of statistical significance when comparing categorical maps [9]. Indeed, forests, like other ecological systems, are characterized by a hierarchical spatial structure [10–14] where specific patterns and processes may take place at certain "characteristic" spatial extents (scale effect) [15]. This means that, for example, different forest dynamics can be most effectively studied at a particular characteristic extent. Thus, identifying this characteristic extent provides a key to further understand the processes that occur in a specific ecological system. It follows that limiting the analysis of forest distribution to a single spatial extent could introduce potential bias or misleading conclusions in pattern analysis [16,17]. Furthermore, the majority of pattern metrics, commonly used to quantify and monitor forest spatial distribution, are scale-dependent, and their scale sensitivity has been demonstrated (see Šímová and Gdulová [7] for a review) for both empirical [18–22] and simulated landscapes [16,18,23]. In fact, the limitations and pitfalls introduced as a result of the use of landscape metrics to compare landscapes with different map sizes are well documented (see Sitzia *et al.* [24] for examples), and there is a critical need for further research addressing the influence of spatial extent on pattern analysis over time. An accurate knowledge of metric scaling relations could be given by empirical scalograms in which variations of pattern metrics are plotted directly against scale [25,26]. In this context, we believe that multi-temporal scalograms could help in both cases: Relate the observed patterns to underlying ecological processes and correctly extrapolate the recorded information across scales. Finally, although the observed spatial patterns are the realization of specific spatial processes [27], it is of great importance to understand whether the observed differences between two patterns could have arisen purely by chance or whether a specific process has promoted this differences [9]. Nevertheless, the attribution of statistical significance to differences in forest pattern over time is still one of the most important and complex challenges to be faced [27]. The statistical comparison of two different landscapes is quite difficult to perform because field studies usually address only one or a few landscapes so that no simple test is available for making statistical inferences [9,15,27]. One possible way to compare and test the statistical significance of pattern metric values between two maps is the use of computer-generated simulations (e.g., Neutral Landscape Models) to reproduce a set of maps with spatial characteristics (composition and configuration) that are similar to real-world characteristics [27–31]. Among the neutral landscape models [9,31], the Modified Random Cluster Method (MRC) [32] is able to correctly represent forest aggregation (or fragmentation) caused by human land use pressure [33]. By varying simulation parameters (the proportion of forest cover *pi* and the degree of aggregation *H*), it is possible to obtain different levels of habitat aggregation and patchiness [32]. In view of the above, we are strongly confident that such statistical methods, if extended to multi-temporal analysis, could offer a consistent framework for assessing forest pattern changes over time and sound information necessary for relating them to landscape processes.

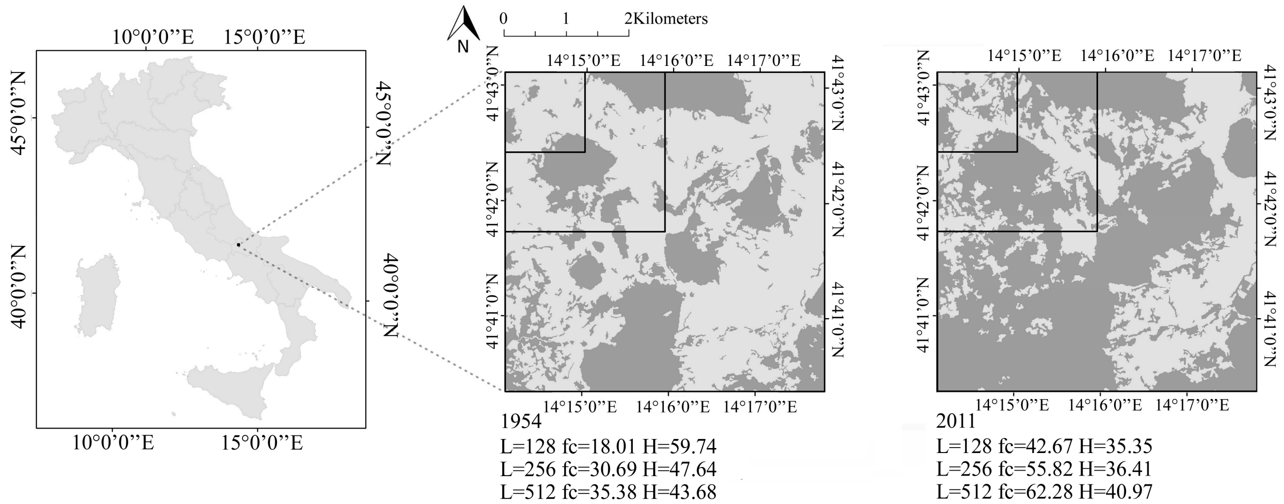
Based on consideration of the aforementioned points, we propose and test a procedure in this study to quantify the spatial pattern of forests over time at multiple spatial extents with statistically robust methods. As an application, we focus on forest cover dynamics in hilly landscapes. We analyze the spatial pattern of temperate forest patches in a Man and Biosphere Reserve (MAB-UNESCO) in central Italy as a representative example of landscape transformation occurring during the past 60 years in sub-Mediterranean hilly landscapes. In particular, we attempt to clarify the following questions by implementing the proposed procedure: (i) how did the forest pattern vary on the compared dates in relationship to various spatial extents? (ii) do specific scale breaks exist that indicate consistent changes in landscape structure and function? (iii) are the differences in the spatial pattern of forests over time statistically significant? To address this issue appropriately, we first used a set of pattern metrics to describe the forest spatial dynamics over time and across various extents and then assessed the statistical significance of any possible differences by comparing the metric values of real and simulated landscapes. An analysis at multiple spatial scales might help to better define the characteristic extents at which it is possible to focus on specific aspects of forest dynamics (e.g., forest loss or gain; forest fragmentation or coalescence of forest patches). The assessment of the statistical significance of forest pattern differences over time and across scales could also offer sound information to relate the observed spatial pattern to the specific underlying ecologic processes and to better understand the specificities of the study case, thus allowing for the application in other cases.

2. Materials and Methods

2.1. Study Area

The Collemeluccio-Montedimezzo Man and Biosphere Reserve (MAB-UNESCO) in Central Italy was selected for analysis (Figure 1). This MAB reserve was chosen because the recent historic changes occurring in this area offer a good example of the pattern of landscape transformation in all sub-Mediterranean hilly landscapes. Since the end of the Second World War, many socio-economic changes have occurred in Europe, where the abandonment of traditional rural activities has produced marked changes in the distribution of temperate forests [34–36]. The reserve and its buffer zone covers approximately 25,000 ha and currently consists of a hilly and mountain landscape dominated by broadleaved natural forests (60% of the area) and other semi-natural vegetation types, such as shrubs and meadows (20% of the area), along with agricultural land and pastures (20% of the area). Altitudes range from 380 m a.s.l., (the Verrino fluvial plain) to 1730 m a.s.l. (Mt. Capraro), and the climate is temperate [37]. The main potential natural vegetation (*sensu* Zerbe [38] and Ricotta *et al.* [39]) is a broadleaved temperate forest [36,37].

Figure 1. Location of the study area, with forest cover maps for the years 1954 and 2011 with a pixel resolution of 10 m. The multi-scale analysis was performed by expanding the extent diagonally, starting from the upper left corner of the original area. The dimension of the maps was 128 × 128, 256 × 256 and 512 × 512 pixels, corresponding to 163.84, 655.36 and 2621.44 hectares. The binary classification separates forest (dark grey) from no forest (light grey). fc is the proportion of forest cover, and H is the spatial autocorrelation or contagion of the map.



2.2. Forest Cover Maps

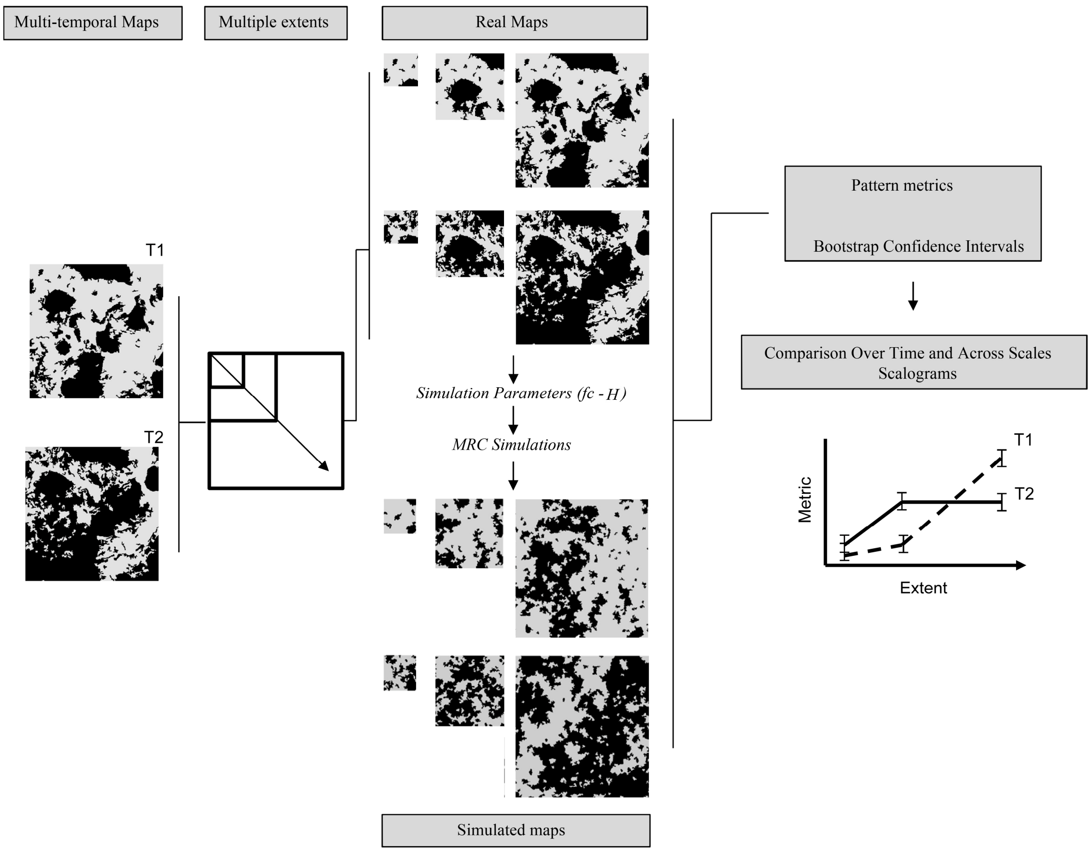
To assess changes in forest distribution, we used existing large-scale (1:8000) forest cover maps of the MAB reserve for the years 1954 and 2011. The 2011 forest cover map was derived by applying a manual classification process (manual segmentation and photointerpretation supported by field data performed in summer 2011) to panchromatic digital orthophotos (flight AGEA05) relative to the

Collemeluccio-Monte di Mezzo Reserve. For the preparation of the 1954 map, a series of greyscale aerial photographs (flight GAI) were acquired, georeferenced and digitized within a Geographic Information System. The 1954 aerial photos were scanned in 8-bit TIFF images with a resolution of 600 dpi and orthorectified using OrthoEngine software (PCI Geomatica) with a 10 m Digital Elevation Model (DEM). For each data frame, 30 ground control points were used for the orthorectification process, and the resulting Root Mean Square Error (RMSE) was less than 4 m. A manual classification process was applied to produce the 1954 forest cover map. Next, both forest cover maps (1954 and 2011) were rasterized with a spatial resolution of 10 m. To make the maps comparable, we set the minimum mapping unit to 0.5 ha by applying a majority filter.

2.3. Data Analysis

We quantified the spatial pattern of forests over time at multiple spatial extents using real and simulated maps and detected significant changes in forest spatial pattern relaying on bootstrapping procedures [29] to perform significance testing. The general framework is outlined in Figure 2.

Figure 2. Flowchart representing the different steps of the proposed procedure for detecting significant changes in forest spatial pattern at different scales. T1: 1954; T2: 2011.



2.4. Multi-Scale Analysis

To perform the multi-scale (extent) analysis over time, we selected from both forest maps (1954 and 2011), a set of three representative geographic windows of different dimensions. As suggested by Wu [22], we delineated a first window extent of 128 × 128 pixels (small) and diagonally expanded it starting from the upper left corner to the bottom right corner of the original area with the following increasing dimensions: 256 × 256 (medium) and 512 × 512 pixels (large). It is important to note that also the window direction can influence the result of a pattern metric analysis, since landscapes are commonly anisotropic [20]. However, we overcome this issue by using neutral simulations (as described below) able to reproduce isotropic landscapes. The analyzed extents correspond to 163.84 ha, 655.36 ha and 2621.44 ha, respectively (Figure 1). The selected widow dimensions are comparable with those commonly used for local and regional forest analysis at landscape scale [40]. As suggested by O'Neil *et al.* [19], the chosen extents are at least two times larger than the largest patch area in the year 1954 (see Figure 1). To frame the landscape transformation patterns in an ecologically significant manner, the wider window was entirely included in one homogeneous environmental type [36], *i.e.*, in one potential natural vegetation type [38,39], thus, in an area where in absence of human interventions or hazard events the vegetation would evolve in one potential natural type (see Zerbe [38] and Ricotta *et al.* [39] for details). Note that in our case the analysis on larger windows would include in the extent, areas with different and heterogeneous environmental characteristics (geology, morphology, soils and climate) and, thus, forest dynamics must be interpreted accounting of the presence of extra environmental heterogeneity.

2.5. Spatial Pattern Analysis

To analyze the spatial pattern of forests over time and across extents, we selected a set of eight pattern metrics that had been previously reported as ecologically meaningful and that have proven useful for describing and comparing the spatial structure of forests [41,42]. The selected metrics are adequate for describing forest patch size (MPS = Mean Patch Size), forest subdivision (NP = Number of Patches, PD = Patch Density), forest spatial geometry (LSI = Landscape Shape Index, ED = Edge Density TE = Total Edge), and connectivity (AI = Aggregation Index, CLUMPY = Clumpiness Index). The landscape pattern analysis software FRAGSTATS 4.0 [43] was used to calculate the metrics. The description of the pattern metrics used in the study (based on McGarigal and Marks [44]), along with their respective variation range, are provided in Table 1.

Table 1. List of pattern metrics used in the study. Landscape metrics and the relative acronyms, descriptions, variation ranges and scaling relations based on published references were provided. Symbols: ▲ increase, ▼ decrease, **?** unpredictable, = no sensitivity, ▲▼increase then decrease.

Landscape Metrics	Description	Range	Scaling Relation	References
Number of Patches (NP)	The number of forest patches	≥1	▲	(Baldwin *et al.* [21]; Shen *et al.* [23]; Wu [22])
Patch Density (PD)	The number of forest patches per unit area (patches/ha)	>0	? ▼	(Shen *et al.* [23]; Wu [22]) (Saura and Martínez-Millán [16]; Baldwin *et al.* [21])
Mean Patch Size (MPS)	The average area of all forest patches in the landscape (ha)	>0	?	(Shen *et al.* [23]; Wu [22])
Total Edge (TE)	The sum of the lengths of all forest edges in the landscape (m)	≥0	▲	(Turner *et al.* [18]; Baldwin *et al.* [21]; Shen *et al.* [23]; Wu [22])

Table 1. *Cont.*

Landscape Metrics	Description	Range	Scaling Relation	References
Edge Density (ED)	The total length of all forest edges per ha (m/ha)	≥0	**? =**	(Shen *et al.* [23]; Wu [22]) (Saura and Martínez-Millán [16]) (Baldwin *et al.* [21])
Landscape Shape Index (LSI)	Equals 0.25 times the sum of the entire forest boundary divided by the square root of the total landscape area	≥1	**▲▼**	(Shen *et al.* [23]; Wu [22])
Aggregation Index (AI)$AI = \left[\frac{g_{ii}}{max-g_{ii}}\right](100)$	Equals the number of like adjacencies involving the corresponding class *(g_{ii})*, divided by the maximum possible number of like adjacencies involving the corresponding class *(max-g_{ii})*, which is achieved when the class is maximally clumped into a single, compact patch (%)	0 ≤ AI ≤ 100	**▼ ?**	For the aggregation metrics (*sensu* McGarigal and Marks [44]) Baldwin *et al.* [21] reported a general decreasing function, while Wu *et al.* [20] reported unpredictable function
Clumpiness Index (CLUMPY)$CLUMPY = \left[\frac{G_i-P_i}{1-G_i}\right]$	Equals the proportional deviation of the proportion of like adjacencies *(Gi)* involving the corresponding class (*Pi*) from that expected under a spatially random distribution (%)	1≤ CLU ≤ +1		

The scaling behavior of the Number of Patches [21–23], the Total Edge [18,21,22] and the Shape Index [22,23] is well documented, whereas the relation between Mean Patch Size and the extent has been found to be unpredictable [22]. However, current information about the response of Edge Density, Aggregation, Clumpiness and Patch Density to changing scales is highly controversial (see Table 1 for details). Several studies have reported that Edge Density, Patch Density [16] Aggregation and Clumpiness [20] were insensitive or weakly sensitive to the spatial extent of the analysis, whereas several others have stated that they could show different types of scaling behaviors [21–23].

2.6. Map Simulations and Inference

In the real world, replications of a given landscape are often difficult to obtain because each single landscape shows a specific degree of land cover proportion and spatial autocorrelation [30]. To overcome the limited number of replications in natural landscapes, it is possible to rely upon simulations based on computer-generated models that serve to reproduce an expected pattern that shares statistical properties with an empirical pattern of interest [30]. Among the spatial models developed in ecology, Neutral Landscape Models (NLMs) can produce an expected pattern in the absence of specific landscape processes [45]. In this study, we used the Modified Random Cluster Method (MRC) implemented in the software SIMMAP 2.0 [32] to generate categorical (thematic) landscape spatial patterns in raster format (grid-based data). MRC is a stochastic simulation procedure that, through the variation of simulation parameters (the proportion of forest cover, fc, and the initial probability, p, which controls the degree of spatial autocorrelation), provides a wide range of simulated landscapes with intermediate levels of spatial dependence and in which the fragmentation and abundance of land-cover classes can be systematically and independently controlled (see, for details, Saura and Martínez-Millán [32]).

First, for each year and extent, we simulated 15 maps (see Appendix A) that adequately characterized the mean values for the metrics considered [46]. We ran specific simulations for each extent and date, using their corresponding actual fc and p values as input. Because the initial probability p is not an explicit spatial pattern metric, we iteratively generated landscapes with different levels of p and then chose those simulated landscapes in which the level of autocorrelation, measured as Contagion H [47], was similar (based on a 99% confidence interval) to those of the observed real landscapes. Thus, by computing selected pattern metrics (Table 1) on both real and simulated landscapes, their empirical distributions (*sensu* Fortin *et al.* [29]) for each date and extent were derived. The empirical distributions, which are functions of the parameters used to generate the landscapes (fc and p), are often non-Gaussian but they provide the basis for determining confidence intervals [30]. Since pattern metrics are not statistics *per se*, that is their distributions are not derived analytically, to statistically compare them randomizations, resampling techniques or bootstrapping procedures are needed [48]. To compare real map pattern indices at different scales and time a bootstrap procedure (Bias-Corrected and accelerated bootstrap) was applied. By bootstrapping pattern metric values of each set of simulated MRC maps (three window sizes and two time periods) we derived the arithmetic mean and the 99% confidence intervals necessary to perform the significance testing [23,30,48]. If the confidence intervals (e.g., 99%) of a given spatial metric between different extents or time periods overlap, it can be stated that there are no significant differences between the compared landscapes. In order to better interpret the magnitude of the observed temporal processes, we measure the effect size of forest pattern change by computing the weighted average of the standardized difference (based on pooled variance measures) between mean metric values (for small medium and large windows) in 1954 and 2011 landscapes (that is, Hedges' g [49]). The effect size is positive when the metric value of the 2011 maps is greater than that of the 1954 ones and is negative when the metric value decrease in the recent time period. The magnitude of the effect size indicates which pattern metric has changed more than the others. We used a resampling procedure based on 10000 bootstrap samples (with replacement) to generate the mean effect size and 99% confidence intervals. All the analyses were performed in the R statistical computing program [50] by using the BootES package [51]. Then, for each metric, we built a multi-temporal scalogram by representing real map values (three map extents 128 × 128, 256 × 256 and 512 × 512 pixels and two temporal periods 1954 and 2011) and the 99% confidence intervals (obtained by bootstrapping procedures on metric values of simulated MRC maps). Each multi-temporal scalogram reported the response curve of one pattern metric to changing extents on both the compared time periods (1954 and 2011).

3. Results

3.1. Pattern Metrics across Extents

The analysis of the multi-temporal scalograms underlined the existence of many significant differences between the compared extents of analysis and pinpointed specific behaviors of pattern metrics for each date (Figure 3; Table 2). Note that although the changes in the 2011 response curves were strongly linear, the

1954 curves appear to show a scale break (*sensu* Wu *et al.* [25]). For most of the metrics measured on the 1954 maps, an abrupt variation in the response curve at medium scale is evident.

Figure 3. Multi-temporal scalograms showing the effects of changing extent on forest pattern metrics in the two years analyzed (1954 and 2011). Lines connect real map metric values. Error bars denote the 99% confidence intervals for each pattern metric, obtained by applying bootstrap procedures (BCa) on simulated MRC maps. For methodological details, see Figure 2; for pattern metric acronyms, refer to Table 1. Type A, where the pattern metric curves for the compared data did not intersect and did not converge with each other; Type B, in which scalograms intersected each other and diverged; and Type C, with metric curves that converged but did not intersect.

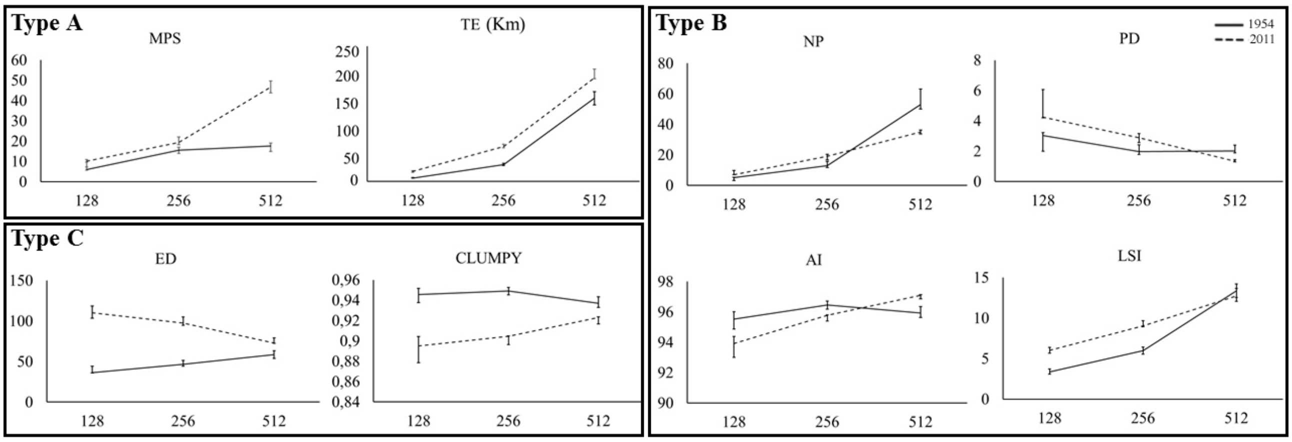


Table 2. Real values of pattern metrics obtained from three different map extents (128 × 128, 256 × 256 and 512 × 512 pixels) and two temporal periods (1954 and 2011) along with the 99% confidence intervals (CIs) obtained by applying bootstrapping procedures (BCa) on specific simulated MRC maps.

Landscape Metrics	1954				2011			
	Window Size	Real Value	Upper CI	Lower CI	Window Size	Real Value	Upper CI	Lower CI
	128 [a]	5 *	5.26	3.26	128 [a]	7 *	9.8	6.93
Number of Patches (NP)	256 [b]	13 *	15.73	11.73	256 [b]	19 *	20.42	16.79
	512 [c]	53 *	63.08	49.29	512 [c]	35 *	38.00	33.78
	128 [a]	3.03 *	3.23	1.99	128 [a]	4.24 *	6.06	4.19
Patch Density (PD)	256 [a]	1.98 *	2.42	1.79	256 [b]	2.89 *	3.15	2.56
	512 [a]	2.08 *	2.41	1.90	512 [c]	1.33 *	1.45	1.29
	128 [a]	5.95 ns	9.71	5.61	128 [a]	10.07 ns	10.94	7.19
Mean Patch Size (MPS)	256 [b]	15.53 *	16.92	13.88	256 [b]	19.33 *	22.05	18.27
	512 [b]	17.53 *	18.97	14.97	512 [c]	46.74 *	43.83	49.75
	128 [a]	6000 *	7226	5871	128 [a]	18,200 *	19,414	16,953
Total Edge (TE)	256 [b]	30,760 *	33,638	28,944	256 [b]	64,180 *	68,893	62,195
	512 [c]	153,680 *	165,624	141,188	512 [c]	191,730 *	207,541	190,012

Table 2. *Cont.*

Landscape Metrics	1954				2011			
	Window Size	Real Value	Upper CI	Lower CI	Window Size	Real Value	Upper CI	Lower CI
Edge Density (ED)	128 [a]	36.34 *	44.11	35.84	128 [a]	110.22 *	118.50	103.47
	256 [b]	46.75 *	51.33	44.17	256 [a]	97.55 *	105.12	94.902
	512 [c]	58.51 *	63.18	53.86	512 [b]	72.99 *	79.158	72.487
Landscape Shape Index (LSI)	128 [a]	3.37 *	3.73	3.07	128 [a]	6.04 *	6.39	5.64
	256 [b]	5.97 *	6.41	5.56	256 [b]	9.03 *	9.66	8.91
	512 [c]	13.37 ns	14.21	12.07	512 [c]	12.72 ns	13.63	12.55
Aggregation Index (AI)	128 [a]	95.53 *	96.01	95.53	128 [a]	93.93 *	94.39	93.01
	256 [b]	96.47 *	96.72	96.47	256 [b]	95.78 *	95.79	95.41
	512 [ab]	95.92 *	96.35	95.63	512 [c]	97.10 *	97.14	96.86
Clumpiness Index (CLUMPY)	128 [ab]	0.9455 *	0.9515	0.9376	128 [a]	0.8949 *	0.9043	0.8784
	256 [a]	0.9491 *	0.9526	0.9451	256 [ab]	0.9045 *	0.9049	0.8962
	512 [b]	0.9369 *	0.9434	0.9327	512 [c]	0.9230 *	0.9237	0.9166

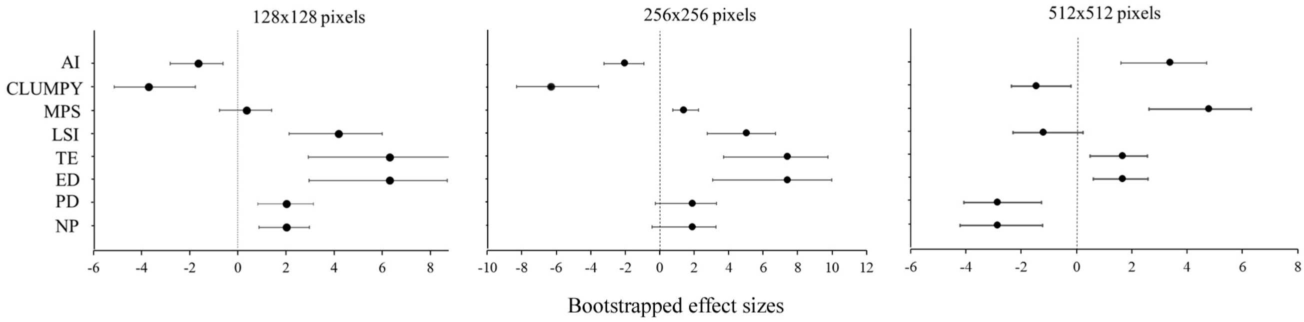
[a,b,c] Uppercase letters indicate significant differences among scales. [*] Asterisks indicate significant differences and ns, no significant differences, among time periods.

In the more recent landscape (2011), significant differences across all three compared extents were found for six of the eight metrics (except for ED and CLUMPY). In particular, ED significantly decreased between the small and the large extent as well as the medium and the large extent. The clumpiness index significantly increased from the smallest and the largest extents as well as between the medium and the large extents. The MPS, TE, NP, LSI and AI showed significant increases across the considered extents, whereas PD showed a significant decrease. The 1954 scalograms showed significant differences across all the extents for four of the analyzed parameters (TE, NP, SI and ED). All these metrics increased as the extent expanded. Mean Patch Size (MPS) significantly increased between small and medium extents as well as between small and large extents. The Aggregation Index (AI) significantly increased between the small and the medium extent, but no significant changes were evident between medium and large extents. Both patch density (PD) and Clumpiness Index (CLUMPY) tended to decrease across extents, but no significant changes were evident.

3.2. Pattern Metrics over Time

Comparing the maps for 1954 and 2011 (Figure 1), we found significant temporal changes in both the abundance and the spatial distribution of forests. Although the effect size varied between pattern metrics and scales (Figure 4). The magnitude of the effect sizes for each metric varies in correspondence of the different scales and tends to be higher on small and medium extents. For medium and small scales we found that TE and ED are the most sensitive metrics with an effect size substantially higher than that of the other metrics (Figure 4). For large extents, the most sensitive parameters are MPS and AI (Figure 4). Overall we found that all the significant changes on pattern metrics over time are relevant. The analysis of the multi-temporal scalograms (Figure 3) showed a strong influence of the spatial extent on forest pattern, and a specific response curve for the compared dates was also evident. The observed scaling relationships over time were schematically summarized in three main types of multi-temporal scalograms: Type A, where pattern metric curves for the compared data did not intersect and did not converge with each other; Type B, in which scalograms intersected each other and diverged; and Type C, with metric curves that converged but did not intersect.

Figure 4. Effect size estimations. Mean values and 99% confidence intervals of the effect sizes estimation (10,000 bootstrap resampling) are reported. The vertical dashed lines represent an effect size of zero. For pattern metric acronyms, refer to Table 1.



Type A metrics tend to increase over time regardless of the extent of analysis. Total Edge (TE) and Mean Patch Size (MPS), increased between 1954 and 2011 across all extents, and belonged to this group. However, note that the MPS values at the smallest extent were not significantly distant from each other (99% confidence interval overlap between them). The scalograms of Type B intersected each other; furthermore, depending on the chosen extent of analysis, opposite temporal changes in the spatial metrics emerged. Interestingly, most of the metrics belong to this Type B group: Number of Patches (NP), Patch Density (PD), Aggregation Index (AI) and Shape Index (SI). For example, the curves describing Number of Patches (NP) and Patch Density (PD) relative to the years 2011 and 1954 intersected each other after the medium extent. Thus, the analysis of forest pattern at medium and small extents showed significant increments in the number and density of forest patches. In contrast, at the largest extent, a significant decrease in the number and density of patches between 1954 and 2011 was found. SI showed similar behavior, but the decline in the 2011 map was not significant at the largest extent. For the Aggregation Index at smaller extents, the 1954 curve was higher than the 2011 curve, whereas the 1954 curve dropped below the 2011 curve at the largest extent. Specifically, the AI values decreased significantly between 1954 and 2011 at smaller extents but significantly increased at the largest extent. In the Type C scalograms, the 1954 and 2011 curves tended to converge but maintained significant distances at all the investigated spatial extents and did not intersect. Type C curves included ED and CLUMPY. In particular, CLUMPY significantly increased over time as ED significantly decreased.

4. Discussion

The observed increase in forest cover over the past 60 years, along with the significant changes in forest spatial pattern and the effect sizes analysis, suggest that the analyzed area has undergone an intense process of natural recolonization that began after World War II and that is still in progress. The phenomenon that we observed could be considered reforestation (*sensu* Sitzia *et al.* [24]), *i.e.*, the natural reestablishment of a forested landscape on disused agricultural lands following farm abandonment in regions where the potential natural vegetation (*sensu* Zerbe [38]) is a forest.

The statistical comparison of pattern metrics at different window sizes over time allows the recognition of the characteristic extent, highlighted by the scale breaks, at which specific patterns of the ongoing process of reforestation are more evident. For the compared dates, significant variations in many metric values were found to correspond with different map extents. The multi-temporal scalograms of type A summarize the behavior of metrics (MPS and TE) that describe similar temporal changes in forest pattern regardless of the extent of analysis. Even if such parameters can be sensitive to the map boundary effect [21,52], they unambiguously depict the ongoing landscape process of forest regrowth in our case. The increase in patch size and edge length over time suggests that forest regrowth has occurred evenly over the entire landscape. At small extents, the absence of significant differences in patch size in association with an increase in the total edge length depicts a landscape with many small patches that, most likely, are the new nuclei of young forests [34]. In the multi-temporal scalograms of type B, the curves intersect each other due to the presence of a scale break at the medium extent for the 1954 scalograms. The curves of type B include parameters such as NP, PD, AI and LSI that describe opposite temporal trends in the pattern of forests depending on the extent of analysis. Such findings serve as a warning to researchers and planners. If these parameters are used over time, it is strongly recommended to analyze them at multiple scales to avoid misleading or partial conclusions. In our case, the parameters of type B describe different aspects of the forest regrowth process. At small and medium extents, the general increase in the number of patches and their spatial density over time describe the ongoing process of natural recolonization. Indeed, the establishment of several new forest nuclei is characteristic of the natural colonization of abandoned lands in Mediterranean ecosystems [34]. In contrast, the observed decrease at larger extents in NP, PD and SI describes the expansion and the coalescence of several secondary forest patches into larger ones [31,34,35,53]. Similar behavior is also evident for the AI index. At smaller extents, decreasing values of AI pinpoint the typical disaggregated pattern that characterizes the initial stages of natural forest regrowth [34]. In contrast, at the larger extent, the significant decline in forest pattern aggregation over time highlights the process of coalescence of forest patches and the consequent increase in forest connectivity. In the scalograms of type C, the 1954 and 2011 curves are significantly distant but tend to converge at the largest extent. The growth of ED over time and the reduction of CLUMPY values clearly indicate a more dispersed distribution of present-day forests relative to past forests. The convergence of ED values in association with a significant increase in forest cover-from 35% (1954) to 62% (2011)-is most likely related to the parabolic distribution of the index as a function of forest cover [54,55]. In particular, ED values increase as forest cover expands and peak when the proportion of forest reaches 50% of the landscape extent. For this reason, markedly different landscapes exhibit very similar ED values. On the other hand, the significant decrease in CLUMPY values over time and across all the extents reveals an increase in forest dispersion. Most likely, the process of natural forest recolonization in abandoned lands occurs in a stochastic manner [34].

Overall, the observed differences in the scaling behaviors over the compared time periods are most likely related to the various ways in which humans exploited landscape resources in the compared years. In 1954, for example, land-based economic activities (such as grazing and agriculture) had forced forests into areas in which productivity was low [36] promoting the development of an anisotropic pattern. Instead, the more recent process of natural reforestation has been driving the entire landscape toward a more natural and homogeneous pattern [35]. Forest regrowth on abandoned lands occurs in a stochastic manner [34], with patches that expand isotropically (in all directions) and tend to be uniformly distributed over the entire landscape (statistically stationary). In such situations, pattern metrics manifest predictable and simple scaling relations. Note that the obtained results are strongly dependent on the specific type of landscape, which, in our case, is characterized by a homogeneous underlying environmental structure [36] (geology, morphology, climate, soil). Indeed, we are observing the natural reestablishment of a forested landscape in regions where the potential natural vegetation (*sensu* Zerbe [38]) is a temperate forest. Different results should emerge in landscapes with high environmental heterogeneity, in which, by tuning the extent of analysis, specific scalograms and metric behaviors could emerge.

Many of the understandings and conclusions obtained in this study have been facilitated by the proposed statistical framework. The chosen modeling procedure, which incorporates the temporal variation in landscape composition (forest cover) and configuration (spatial autocorrelation) occurring in real landscapes [16,19] offers useful insights to address the influence of spatial extent on pattern variation over time. In particular, the utilization of the observed proportions of forest (fc) and the values of spatial autocorrelation (H) as input parameters for the stochastic simulation procedures allows an adequate description of the process of forest regrowth and, at the same time, has yielded a robust statistical and defendable framework. In particular, the application of the MRC algorithm allows the following approaches: (i) modeling a plausible set of maps, with different levels of forest proportion and patchiness, that adequately describes the spatial pattern of forests through time and across scales; (ii) generating a set of landscape replications that recognizes the most relevant real landscape information; (iii) defining the landscape expectations, allowing the statistical comparison of patterns through time and across scales; and (iv) avoiding the effects of the window direction of analysis.

5. Conclusions

Although many authors have stressed the importance and limitations of employing pattern metrics for comparing landscapes [56], the use of these metrics for characterizing and monitoring forest distribution over time continues to be highly popular [57,58]. We proposed and tested a procedure to detect significant changes in forest spatial patterns and relevant scales. This approach enriches the set of the existing methods for multi-scale/multi-temporal landscape studies by including the statistical analysis of the observed differences. As a demonstration, we analyzed the change in the spatial pattern of temperate forests in a Mediterranean hilly landscape over the last 60 years across different extents.

Our results highlight that if landscape pattern is analyzed at a single extent that does not match the scale at which a given phenomenon occurs (e.g., reforestation), the results are incomplete and obscure the effective landscape variation over time. For example, we found that different patterns of the ongoing process of natural reforestation emerged (e.g., nucleation and coalescence of the existing patches in a unique bigger one) at different spatial extents.

The proposed multi-temporal analysis, which incorporates the effects of scale on pattern metrics and the statistical significance of the differences in metric values, have helped to relate the changes in pattern parameters to landscape processes. It overcame and minimized the potential bias introduced in traditional studies that simply resort to the comparison of pattern metrics at a single extent, ignoring information about the distribution and variability of the pattern metrics.

Even if the obtained results are strongly dependent on both the specific type of landscape and the chosen spatio-temporal scales, analogous methods could be used for the study of pattern changes and statistical expectations across a large ensemble of landscapes. In any case, consistent scale breaks could be expected in strongly human-shaped landscapes, where anthropogenic driving forces lead to the juxtaposition of different ecosystems (natural, semi-natural and artificial), whereas linear scaling relations should emerge in more natural landscapes.

From a practical point of view, the obtained results offer scientifically sound bases for orienting decisions in various fields, such as forest management and monitoring. For example, the correct choice of the spatial extent might help to better define conservation measures oriented to increase landscape connectivity values [59]. Furthermore, the proposed approach could allow for the examination of the long-term effects of the extent of the protected area on forest distribution and other conservation features, which is essential for assessing their effectiveness [60,61].

We believe that similar procedures, designed to perform statistically robust multi-temporal and multi-scale analyses, could become a standard method for the comparison of categorical maps, especially if the investigated landscapes, are samples extracted from areas of fixed size and shape [6]. Such procedures are particularly necessary in the consideration of change detection and when uncertainties about the scale and pattern metric values exist and could provide relevant indications regarding the changes in landscape structure over time and all the ecological and cultural consequences linked to this issue.

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Author Contributions

Conceived and designed the experiments, analyzed the data and wrote the manuscript: Ludovico Frate, Maria Laura Carranza. Produced data and reviewed the drafts: Michele Minotti, Carmen Giancola, Paolo Di Martino. Discussed main topics and reviewed the text: Santiago Saura.

Conflicts of Interest

The authors declare no conflict of interest.

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