fractal and fractional

Article

Particularities of Forest Dynamics Using Higuchi Dimension. Parâng Mountains as a Case Study

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Citation: Simion, A.G.; Andronache, I.; Ahammer, H.; Marin, M.; Loghin, V.; Nedelcu, I.D.; Popa, C.M.; Peptenatu, D.; Jelinek, H.F. Particularities of Forest Dynamics Using Higuchi Dimension. Parâng Mountains as a Case Study. *Fractal Fract.* **2021**, *5*, 96. https://doi.org/10.3390/fractalfract5030096

Academic Editors: Mikolaj Karpinski and Svitlana Kuznichenko

Received: 31 May 2021
Accepted: 11 August 2021
Published: 13 August 2021

Abstract: The legal or illegal losses and the natural disturbance regime of forest areas in Romania generate major imbalances in territorial systems. The main purpose of the current research was to examine the dynamics of the complexity of forests under the influence of forest loss but also to compare the applicability of Higuchi dimension. In this study, two fractal algorithms, Higuchi 1D (H1D) and Higuchi 2D (H2D), were used to determine qualitative and quantitative aspects based on images obtained from a Geographic Information System (GIS) database. The H1D analysis showed that the impact of forest loss has led to increased fragmentation of the forests, generating a continuous increase in the complexity of forest areas. The H2D analysis identified the complexity of forest morphology by the relationship between each pixel and the neighboring pixels from analyzed images, which allowed us to highlight the local characteristics of the forest loss. The H1D and H2D methods showed that they have the speed and simplicity required for forest loss analysis. Using this methodology complementary to GIS analyses, a relevant status of how forest loss occurred and their impact on tree-cover dynamics was obtained.

Keywords: forest; forest loss; fractal dimension; Higuchi dimension; anisotropy

1. Introduction

Forest pressure is one of the greatest challenges of contemporary society, generating major imbalances in both natural components of territorial systems and anthropic ones. The increasing need for wood as raw material, the need for agricultural land, and in general, population growth, has generated increasing pressure on forests [1–7]. In the last century, although forest area has declined, the global rate of global deforestation has slowed down by more than 50% because of the implementation of a specific forestry management policy by some states. Thus, stricter legislation has emerged, involving both governments and local communities [8,9].

In Eastern Europe, illegal logging has increased, in some countries being similar in spread to legal logging. The real forest exploitation trend and area are different from the official statistical reporting by recognized institutions because of the defective systems of recording forest data. The analysis performed on satellite images on the deforestation have highlighted a series of spatial-temporal peculiarities that require new methodological approaches. The result of the analysis highlighted important differences in the deforestation pattern between the peripheral area of the study area and the inner inaccessible area of the mountains. The most affected and fragmented forests being the old and mature ones, which in the European Union are mainly part of the Natura 2000 sites. Landsat imagery analysis provided more accurate information than official statistics, in which illegal deforestation and sometimes reforestation were not registered. To approach sustainable public policies, the use of the technologies provided by remote sensing, geographical information systems and fractal analysis can be useful in determining particularities of forest evolution. There are several studies on change detection of forests in the Eastern European Carpathian ecoregion, of which Romania is part. The forests of the Carpathian Mountains represent the largest temperate forest ecosystem in Europe, generating benefits over a much larger area than the Carpathians themselves. The most important political decision in Eastern Europe, which has led to the encouragement of logging in the last 50 years, is the restitution of forests to their former owners without a vision of how these resources can be managed [10–16].

Romania is one of the few countries within the European temperate region with virgin natural forests [17] and with a large number of protected areas and national parks, which are part of the European Natura 2000 network. Furthermore, a part of the area is protected by national legislation, located especially in mountainous regions [18]. After the fall of communism, a period with massive deforestation followed that generated the decrease of the annual forest fund [19]. The main causes of deforestation in Romania are both timber exports and traditional home heating, which is particularly important for the rural population [15,19]. Marinescu et al. in the analysis of forest cover changes in the Parang Mountains [20], identified three main time periods of major anthropogenic interventions in the forest ecosystem. The first identified stage was at the beginning of the twentieth century when the most significant forest changes occurred where human influence was largely generated by the need of expanding the grazing areas and by creating settlements at high-altitude closely related to pastoral activities. The second stage was characterized by drastic deforestation in the 1970s and is due to hydrotechnical constructions, especially on the Lotru and Sebes river basins, associated with adjacent logging. The third identified stage was the post-socialist era due to the changes in ownership and institutional policies that favored overexploitation of forests. According to official data, about 170 square kilometers of forest disappeared each year in Romania, but an exhaustive understanding of the phenomenon, considering the time frame, the spatial extent and the generating factors, requires a quantitative spatiotemporal analysis.

To determine the extent of tree cover areas and their dynamics, remote sensing and aerial imaging play an important role. By using remote sensing imagery, global changes in forests can be assessed annually [21]. Various classical metrics have been created that quantify the texture or characteristics of the continuous data surface [22,23], and connectivity, suggesting the degree to which the landscape impedes or facilitates the movement of organisms [24]. Simultaneously, metrics of the spatial structure of binary forest image maps incorporate an extensive diversity of measures: allometric-based model [25], patch number, area and perimeter measures, the edge length, edge area ratios, [26,27], the largest patch index [28], forest area density metrics [29], the contagion metric [30,31], the spatial heterogeneity of populations and communities, the spatial autocorrelation [32], and the patch isolation with the proximity index [33].

Fractal analysis has several advantages over these linear approaches, as fractal geometry is better suited to describe natural objects such as trees. Trees are self-similar objects that can be described with their fractal dimension. The actual value of the fractal dimension is in the range of the topological dimension of the object and the embedding dimension. The fractal dimension is also a measure of the space-filling property (how an object fills the embedding space) and is therefore a very good measure for distributions such as landscape images of forests. In this paper, we proposed to quantify forest dynamics through a textural fractal analysis by applying the Higuchi dimension [34]. The expected advantage of Higuchi 1D is to provide information about the isotropic or anisotropic behavior of forest loss, that cannot be obtained by applying the classical methods. By applying the Higuchi

2D we expect to see an image of the spatial complexity of the loss area considering the tree density per pixel. The chosen approach will allow both the spatiotemporal quantification of post-processed satellite imagery and the determination of the degree of complexity of the analyzed loss area. Through the methods chosen in this study, it is possible to quantify the degree of complexity and the anisotropic properties of forest loss as a manifestation of the pressure on the forestry fund. Higuchi dimension was proposed by transforming 2D image data into 1D data series and then applying the genuine Higuchi algorithm as a time-series analysis method. An additional benefit of this approach is that fractal dimensions can be computed for regions of interest excluding the background information [35]. In one of our previous studies [36] we used Higuchi 1D (H1D) analysis in modeling economic trends, where we have shown that H1D values increases with the growth of the economic influence of the main development centers, highlighting the moment when the economic crisis emerged. By computing Higuchi 2D (H2D) we quantify the complexity of the relationship between pixels and their neighboring pixels. This approach allows the identification of the spatial manifestation of forest loss. Higuchi 2D analysis was proposed by Spasic [37] and further developed by Ahammer [38]. They demonstrated that the generalization of the original 1D algorithm to two dimensions is useful for investigating digital images. The added value of this research is to extend the H1D analysis to grayscale (single-band) forest imagery, by analyzing only the forest areas pixels and excluding the background pixels. This study presents a spatial-temporal analysis and quantitative results of forest loss in the Parâng Mountains, Romania, using H1D and H2D fractal analyses to better understand how forest loss affects forest morphology.

2. Materials

2.1. Study Area

The study was applied to images of the Parâng Mountains, which are a part of the Southern Carpathians, the highest Carpathian chain in Romania, with altitudes over 2000 m. The Parâng Mountains are located between the Olt (West) and Jiu (East) valleys, in the north they are bordered by the hilly Transylvanian Basin and the Hunedoara Basin and in the south by the Getic Subcarpathians. The Parâng Mountains consist of the Parâng, Căpățânii, Lotrului, Leaota, Șureanu, and Cindrel Mountains (Figure 1). The vegetation is specific to the mountains, with coniferous forests, secondary meadows, and mixed forests, most of them being part of the European Natura 2000 sites. We have chosen the Parâng group as a case study due to the high degree of forest density, which is reflected by high compaction of tree cover areas and due to the anisotropic character of forest loss areas.

2.2. Data and Image Processing

For the spatial evaluation of the forest, the Global Forest Change database provided by the Department of Geographic Sciences, Maryland University, was used. The database is the result of the analysis of 654,178 Landsat 7 ETM+ images, and offers a worldwide dataset of the forest evolution between 2000 and 2016 in the form of GeoTIFF images, which contain relevant data and metadata. Global Forest Change puts more emphasis on forest loss than on forest dynamics overall. Thus, the forest dynamics were analyzed considering only the forest loss because it is the only evolutive dataset from the Global Forest Change database. In this study the Tree Cover for Year 2000 (treecover2000) and Year of the Gross Forest Loss Event (lossyear) datasets were used. The dataset Tree Cover for Year 2000 (treecover2000) provides the forest background image of year 2000 and is defined as a canopy coverage for vegetation taller than 5 m and also provides a tree density per pixel represented by values ranging from 0 to 100%. Year of the Gross Forest Loss Event (lossyear) indicates the forest loss area during the study period 2001–2016, giving values for each year of the mentioned interval [21].

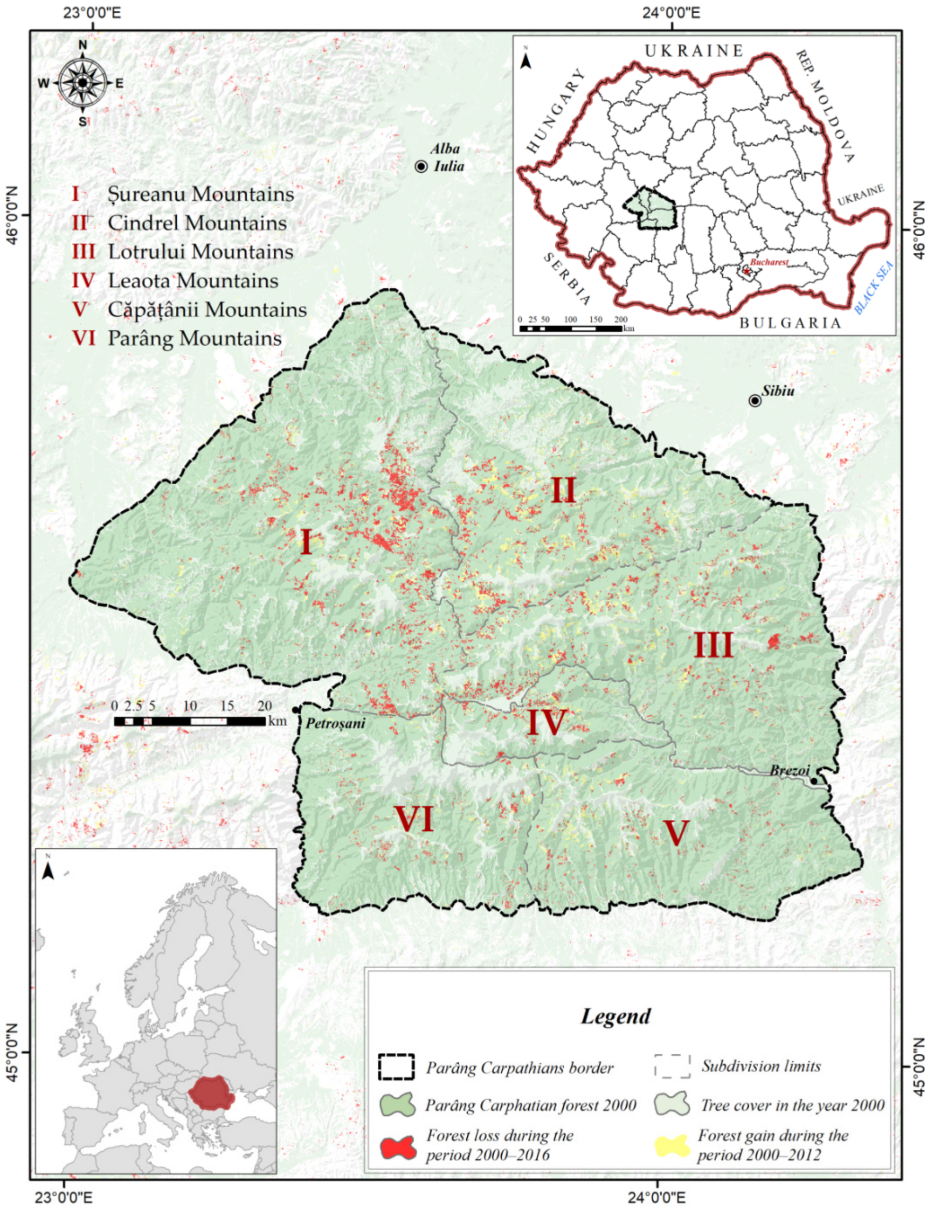

Figure 1. The geographic position of the Parâng Mountains.

Using the ESRI ArcGIS platform, the images used for fractal analysis were prepared and exported in tiff format. Each original raster dataset was exported as an image, considering a single scale and histogram for all the images in the temporally analyzed range. From the initial dataset, a tiff image for fractal processing was generated for each year of the analyzed period, resulting in 16 images. The forest cover image of the year 2000 (treecover2000) was used as a reference image for assessing the degree of forest cover. The forest coverage, meaning the total forest area extracted from treecover2000 and the forest cover degree, defined by the tree density per pixel are represented in this dataset with values between 0–100%. Through the forest cover degree calculation, we applied a precision correction for the initial area results, extracted from the forest coverage, and calculated the forest loss considering the tree density within the image. The results were used to analyze the patterns of loss areas within certain ranges of forest coverage. Based on the raw GeoTIFF images, the forest loss and gain areas were determined by spatial reprojecting the images to the national projection (EPSG:3844) using the ESRI ArcGIS software and by converting the raster data into vector data (polygons). Through the reprojection phase we did not change the spatial resolution of the images but converted the data from decimal degrees (0.00025′) to metric units (2451 m), and through data conversion from raster to vector representation, which provided more precise areas of interest, especially at the border of the forest. All images used in this study had the same resolution. This is important because the algorithms applied are extremely sensitive even to the smallest variation in the size of the pixels and shape of the image. However, being a large study area, such variations in the size of the pixels and shape of the image will not affect the pattern of the phenomenon.

To quantify the evolution of the morphological complexity of the forest loss and its impact on tree cover areas, textural fractal analysis methods were used. Thus, based on the resulting TIFF format images, specific fractal methods were applied using the Interactive Quantitative Morphology (IQM) 3.5.0 software tool [39]. Fractal textural analysis is an analysis that no longer requires binarization, the method by which quantitative and qualitative elements are lost in most situations and uses grayscale images directly [40]. The textural fractal analysis methods Higuchi 1D (H1D) and Higuchi 2D (H2D) allowed us to quantify the changing complexity of forest patterns. Due to the anisotropic properties of the analyzed images, we also qualitatively and quantitatively investigated this anisotropy and its influence on the computations of the fractal dimension [41]. It turned out that H1D is sensitive to anisotropy because of computing separate dimensions for the vertical and horizontal directions.

2.3. Higuchi 1D

The Geographic Information System (GIS) processed images for the forests, loss and gain areas are anisotropic; and required quantifying directional dependencies and checking whether it largely affected the results by calculating two independent fractal dimensions, which is not possible by applying classical 2D methods such as the differential box-counting dimension method [42]. For this procedure, a one-dimensional Higuchi 1D method is required. The genuine Higuchi method is a fast algorithm for calculating the fractal dimension of one-dimensional signals. Therefore, 2D processed GIS images are projected into one-dimensional signals (in the form of rows and columns), theoretically representing the intersection of the gray value of the surface with the 2D image. The images were sliced into strips, each of which had one-pixel width, in both vertical and horizontal directions, and analyzed one by one. The mathematical formula underlying the Higuchi 1D analysis method for 2D images was proposed by Ahammer in 2011 [43]:

$$H1D = \frac{1}{2}\left(\frac{1}{M}\sum_{j=1}^{M} H1D(r_j) + \frac{1}{N}\sum_{i=1}^{N} H1D(c_i)\right),$$

where M represents the height of the image (rows), N represents the width of the image (columns), r_j represents M rows with a constant length N, c_i represents N columns with constant length M, j represents the individual values of the rows, and i represent the individual values of the columns [43].

Computations were carried ut using open-source software IQM 3.5 developed by one of the authors. We chose the option of projecting rows and columns to two separate and one-dimensional signals (Higuchi 1D-*D_HˆPro*), due to the very high processing speed. The scaling value k of the Higuchi algorithm was set to a maximum value of 332, to obtain the most accurate information. Further details about the algorithm can be found in Ahammer 2011 [35,43]. Resulting values fall between Euclidian dimension 1 and Euclidian dimension 2.

2.4. Higuchi 2D

In contrast to H1D, the H2D method is based on calculating the fractal complexity of an image, considering the pixel grayscale ratios relative to the grey values of pixels in the proximity. The H2D method represents a generalization of the genuine one-dimensional

Higuchi method to compute the fractal dimension of a planar curve [37]. The H2D fractal dimension is the negative trend on log-log plot consistent across all k values:

$$H2D^{KfoldDiff} = -D,$$

D being obtained from the relation $A(k) \propto k^D$, where $A(k)$ is

$$A(k) = \frac{1}{k^2}\sum_{n=1}^{k}\sum_{m=1}^{k} A_{n,m}(k),$$

and $A_{n,m}(k)$ =

$$A_{n,m}(k) = \frac{1}{k^2}\left\{\left(\sum_{i=1}^{\omega_n^k}\sum_{j=1}^{\omega_m^k}\left[\left|x_{i-1,j}^k - x_{i-1,j-1}^k\right|k + \left|x_{i,j}^k - x_{i-1,j}^k\right|k + \left|x_{i,j-1}^k - x_{i-1,j-1}^k\right|k + \left|x_{i,j}^k - x_{i,j-1}^k\right|k\right]\frac{1}{4}\right)\Omega_{n,m}^k\right\},$$

where n and m are starting points going up to k, and i and j are indices of individual data points. ω_n^k and $\Omega_{n,m}^k$ are normalizing factors. Details can be found in Ahammer, 2015 [38]. Resulting values fall between Euclidian dimension 2 and Euclidian dimension 3.

2.5. Statistics

Statistical analysis was performed using SPSS v27 software (IBM Corp. Released 2020. IBM SPSS Statistics for Windows, Armonk, NY, USA). Correlations were determined by linear regressions and computing the coefficients of determination R^2, F-values, and their significance values as well as significance of the slope. Additionally, Spearman's rank correlation coefficients were determined.

3. Results and Discussion

The raster image processing has provided a detailed understanding of the forest area evolution in the Parâng Mountains (Figure 2), an evolution determined by legal and illegal forest exploitation, as well as by the context provided by forest management policies. We can see the increasing values of the loss surfaces between 2007 and 2012, when the legislation was amended to facilitate the exploitation of the restituted forest from the state property to the former owners who held these lands before being confiscated by the communist regime.

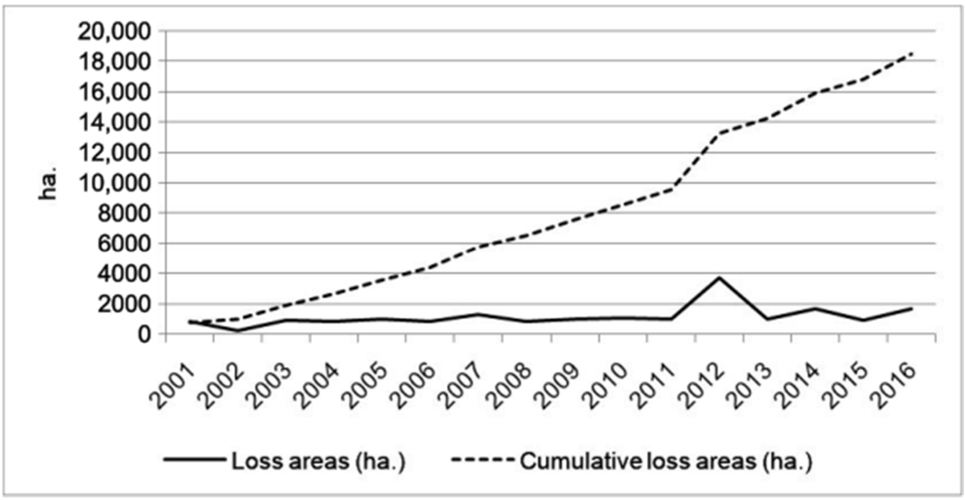

Figure 2. Evolution of the cumulative loss areas of the Parâng Mountains between 2000 and 2016.

Analyzing the evolution of forest dynamics and according to the five levels of forest pixel coverage, there is a distinction between the 2001 and 2004 period, when forest loss was dispersed in small areas, and 2005–2016, when there was a clustering of cumulative loss, mainly in the Șureanu Mountains, in the west of the Cindrel Mountains, and the northern part of the Parâng Mountains (Figure 3).

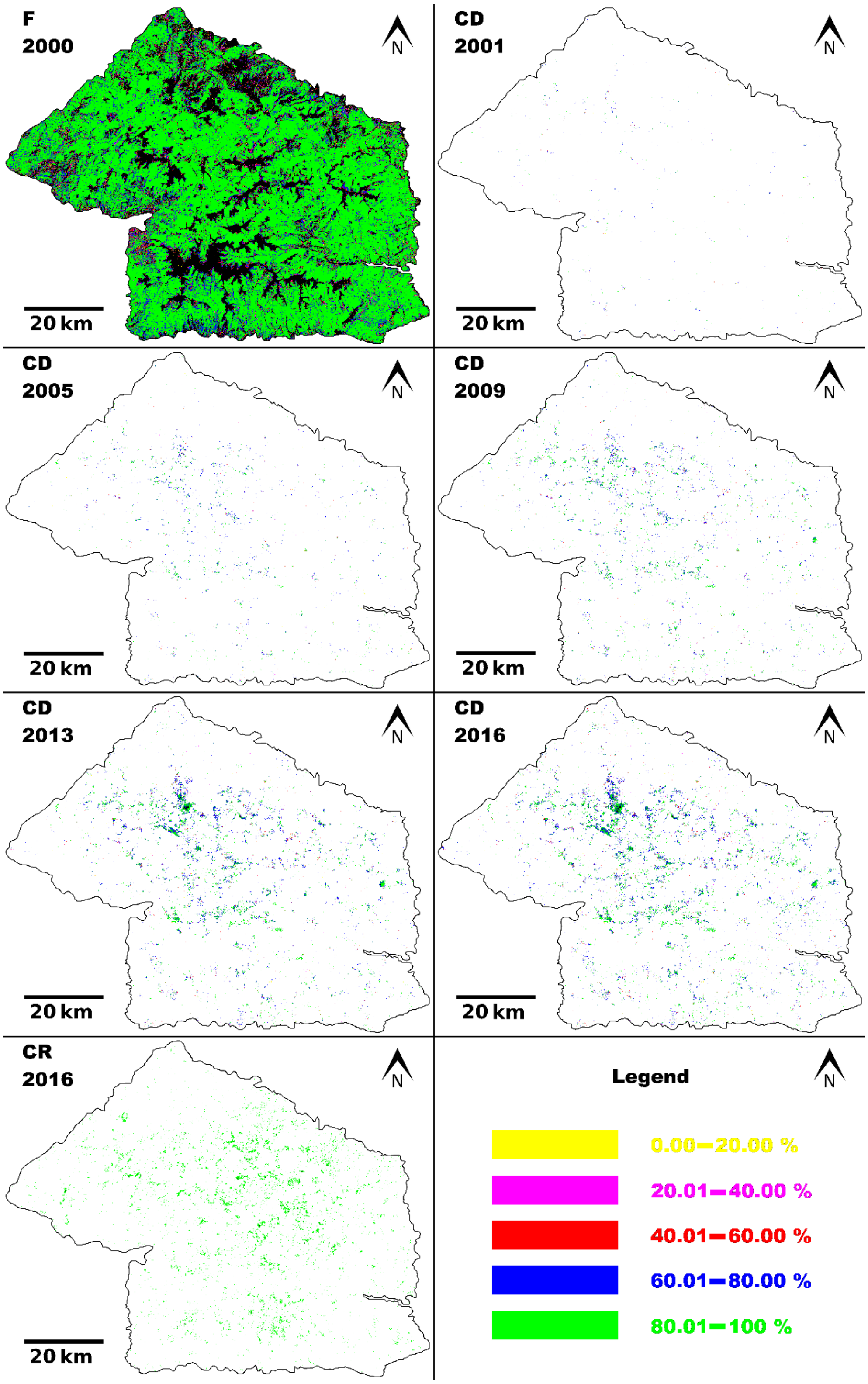

Figure 3. Spatial distribution of forests (F), cumulative loss (CD) and cumulative gain areas (CR), and differences between cumulative loss and cumulative gain areas (CD–CR) taking into account the degree of forest coverage per analyzed pixel.

The analysis of the five levels of forest coverage revealed that in 2000, the forest cover level was over 80.01% and represented 80% of the total forest specific pixels, followed by pixels with values of 60.01–80% coverage, which represents 12%, those with 40.01–60% (4%), 20.01–40% (2%), and those under 20% coverage (2%). The analysis of forest dynamics showed that forest loss occurred predominantly in compact tree cover areas, where the degree of forest cover was over 80.01% (representing 49% of the loss area), and 60.01–80% coverage (representing 38% of the loss area). In areas with a lower coverage (−≥60%), smaller surfaces have been lost: 8% of the total forest loss has a degree of coverage of 40.1–60%, 3% has a coverage level of less than 20%, and only 2% has a degree of coverage of 20.1–40% (Table 1).

Table 1. Evolution of the forest, loss and gain areas, taking into account the degree of forest coverage per pixel analyzed (as a percentage of total forest, loss and gain areas); L = loss, G = gain, and TC = tree cover areas.

	0–20%	**20.1–40%**	**40.1–60%**	**60.1–80%**	**80.1–100%**
TC 2000	1.7	2.1	3.9	12.4	79.8
L 2001	5.3	4.2	14.5	38.0	38.1
L 2002	3.2	2.3	8.7	40.1	45.8
L 2003	2.6	2.3	5.9	40.4	48.8
L 2004	3.6	3.5	9.1	36.0	47.8
L 2005	3.4	2.5	8.5	37.5	48.0
L 2006	2.9	2.7	7.8	36.0	50.7
L 2007	3.5	2.7	8.6	36.8	48.5
L 2008	2.6	2.1	8.1	37.0	50.2
L 2009	2.5	2.2	7.7	37.1	50.6
L 2010	2.7	2.2	7.8	36.2	51.1
L 2011	2.2	2.1	7.0	37.1	51.6
L 2012	2.7	2.3	7.2	38.6	49.4
L 2013	3.3	2.8	9.5	39.6	44.8
L 2014	2.7	2.0	7.9	36.6	50.8
L 2015	0.2	0.2	0.8	4.1	94.8
L 2016	1.1	1.1	5.9	41.1	50.8
L 2001–2016	2.1	1.7	6.5	41.7	48.0
G 2001–2014	1.4	1.1	2.6	4.1	90.8
TC 2016	5.2	2.4	4.0	12.1	76.3

Figure 4 shows the effects of the forest loss dynamics and their impacts on the forest, quantified by the H1D and H2D fractal methods. As the loss surfaces are larger, the complexity values highlighted by H1D and H2D are lower, because the impact on the forest is directly proportional to the size of the loss surfaces. Furthermore, in years with major loss, the forest loss phenomenon is more predominant in areas with high forest coverage than in years with reduced deforestation (Figure 4).

The corresponding statistical values of linear regressions between Higuchi dimensions 1D and 2D and between Higuchi dimensions and the corresponding areas can be seen in Tables 2–4. The H1D (second column) offered a better approach allowing a more detailed differential analysis, but also better correlations with cumulative loss areas and loss areas than H2D (third column), because in the case of images with only few pixels such as images of loss areas, anisotropy is very high. The correlation in terms of R^2 and F-values is slightly lower for H1D compared to H2D in the case of tree covered areas, but still very high and significant. The correlation between H1D and H2D is high, despite the loss areas. This is again due to the sparse distribution of pixels in that image. Additionally, all these correlations are confirmed with Spearman's rank correlation coefficients, which can be seen in Table 5. The maximum pixel count was found for loss areas in 2012, respectively

0.38% of the total pixels. H1D, mediating between the x-axis and the y-axis, diminishes the effects of image anisotropy. H2D does not diminish the effects of anisotropy because it takes into account the relationship between the analyzed pixels and the neighboring pixels. For example, 2003 marks the year with the smallest H2D complexity, although forest loss was reduced but performed in very small and homogeneously distributed areas. As cumulative loss surfaces grow, clusters begin to form and develop, thus further reducing the complexity of cumulative loss. Due to the larger number of pixels analyzed and cluster formation by agglutination, the correlation with cumulative loss areas is better. At the same time, a wide gap value is retained and superior correlations with the cumulative loss area for H1D versus H2D are also present. As in the loss areas, the cause is the total number of analyzed forest pixels, which is well below the background pixels number (maximum = 1.4% of total cumulative loss 2001–2016). Thus, anisotropy has an important role in differentiating the results obtained with H1D and H2D. For these reasons, using the H2D method, it was possible to emphasize that the year 2003 had a smaller complexity than the years from 2004 to 2011, when included with existing clusters and also the presence of small chaotic forest patches. The expansion of the clusters in the years 2012–2016, by including about 50% of isolated patches, generated a decrease in complexity, excluding the effects of reduced complexity in 2003.

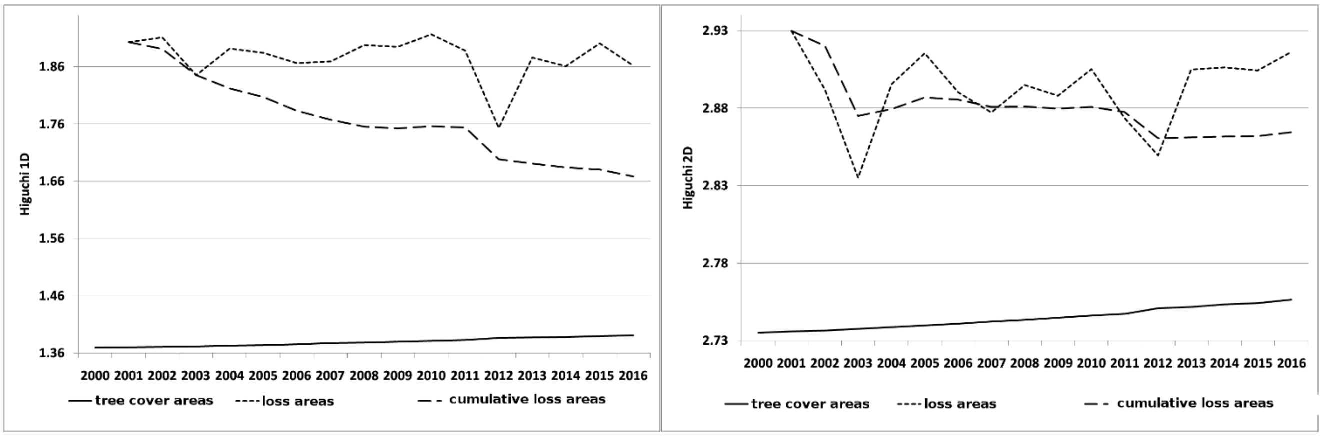

Figure 4. Higuchi dimensions 1D and 2D of loss, cumulative loss, and tree cover areas from Parâng Mountains.

Table 2. Coefficients of determination R^2 for linear regressions between Higuchi dimensions 1D and 2D and between Higuchi dimensions and corresponding areas.

	H1D and H2D	H1D and Areas (ha)	H2D and Areas (ha)
Cumulative loss areas	0.779	0.898	0.596
Loss areas	0.359	0.799	0.129
Tree cover areas	0.997	0.991	0.997

Table 3. F-values and corresponding degrees of freedom and p-values in brackets for linear regressions between Higuchi dimensions 1D and 2D and between Higuchi dimensions and corresponding areas.

	H1D and H2D	H1D and Areas (ha)	H2D and Areas (ha)
Cumulative loss areas	49.5 (n = 15, <0.001)	123.1 (n = 15, <0.001)	20.7 (n = 16, <0.001)
Loss areas	7.8 (n = 15, 0.014)	55.5 (n = 15, <0.001)	2.1 (n = 16, 0.172)
Tree cover areas	5257.5 (n = 15, <0.001)	1669.6 (n = 15, <0.001)	4506 (n = 16, <0.001)

Table 4. Significances of slope for linear regressions between Higuchi dimensions 1D and 2D and between Higuchi dimensions and corresponding areas.

	H1D and H2D	H1D and Areas (ha)	H2D and Areas (ha)
Cumulative loss areas	<0.001	<0.001	<0.001
Loss areas	0.014	<0.001	0.172
Tree cover areas	<0.001	<0.001	<0.001

Table 5. Spearman's rank correlation coefficients between Higuchi dimensions 1D and 2D and between Higuchi dimensions and corresponding areas.

	H1D and H2D	H1D and Areas (ha)	H2D and Areas (ha)
Cumulative loss areas	0.756	−0.985	−0.759
Loss areas	0.321	−0.565	−0.088
Tree cover areas	1.00	−1.00	−1.00

4. Discussion

This study was performed by using a combination of GIS and fractal analysis. The results obtained are an important contribution to the analysis of the impact of the economic pressure on the forestry fund.

Forest loss increased forest fragmentation, generating a continuous increase in the spatial complexity of tree cover areas. Because the number of pixels analyzed is almost equal to the number of background pixels (minimum = 43.88% in 2016), anisotropy does not significantly influence the result, the decrease in complexity being very close to the two H1D and H2D approaches. The increase in the spatial complexity of the forest area was noted by the presence of some thresholds on the evolution axis (Figure 4). The correlation between H1D and H2D of tree cover areas is very good for both H1D and H2D, due to an inversely proportional relationship between the reduction of the forest area and the increase in complexity (Table 2). Higuchi 1D and 2D fractal analysis showed that while the forest decreases, its spatial complexity increases. Thus, quantifying the evolution of these spatial complexes provides valuable information about the spatial effects of forest loss, effects reflected in legislative changes in this period.

Higuchi 1D and 2D dimensions, being methods of fractal analysis, are useful in quantifying the natural complexity of landscapes, these being scale invariant [44]. Therefore, in the analysis of ecological objects, the fractal geometry provides better results than the Euclidean analysis. In our study we applied the Higuchi dimensions on forest analysis for the first time and showed that comparing Higuchi 1D and 2D dimensions allow a first differentiation of the landscape pattern based on anisotropy. The results obtained can be used in forest policies.

In comparison with classic landscape ecology metrics such as the allometric-based model [25], patch number, area and perimeter ratio, edge to area ratios, the edge length, [26,27], the largest patch index [28], forest area density metrics [29], the contagion metric [30,31], the largest patch index [28], the spatial heterogeneity of populations and communities, the spatial autocorrelation [32], and the patch isolation with the proximity index [33], which uses binary images, Higuchi 1D and 2D dimensions use 8-bit gray-scale images. This allows an analysis of the image texture, in our case the analysis of the forest cover degree. Using gray-scale images eliminates binary bias. Compared to metrics that use 8-bit gray-scale images such as aggregation index [45], Higuchi 1D is sensitive to image anisotropy. Therefore, it can distinguish more or less anisotropic deforestation patterns. At the same time, Higuchi 2D allows the analysis of the complexity degree of the spatial distribution of the forests, thus providing additional information. At the same time, H1D and H2D being fractal dimensions are invariant with respect to scale.

The H1D and H2D analysis showed the effectiveness of this method in understanding how the forest loss process is evolving in the context of multiple factors. Along with particle analysis [46], this methodological approach provides significant additional knowledge by computing the fractal complexity of forest loss. The use of H1D and H2D in the analysis of forest images is innovative and provides additional information on the complexity of the forest, loss and gain areas. In this study, H1D and H2D were used to spatialize the effects of the economic pressure on the forests for the first time, which provides arguments for completing classical methods generally based on GIS algorithms [4,6,7,47–49]. The methodology applied in this study can make important contributions to the identification of illegally lost areas, with textural analyses highlighting qualitative aspects such as the complexity of the affected areas alongside results obtained by other fractal or GIS methods [5,17,19,36,50–58]. Similar findings were reported by Klonowski et al., 2018, for a clinical study of anal intraepithelial neoplasia stages applying H1D and H2D, which resulted in virtually the same results. In our study, in the analysis of images with a high degree of anisotropy, for forest loss and cumulative loss there were differences between the H1D and H2D values. We consider that in the case of strong anisotropic images that the use of H1D algorithms is at least complementary to H2D.

5. Conclusions

The use of H1D and H2D is an important contribution to the development of methodologies for modeling the anthropogenic pressure on forests. A methodological support is useful in adapting public policies to the sustainable development of the forest ecosystem. The H1D and H2D methods are very simple methods and allow a quick analysis of the computerized image. H1D and H2D have the advantage that image segmentation is no longer required. Typically, image segmentation introduces fully-automated algorithms and subjective parameters such as thresholds. Often, segmentation fails due to variations in brightness or sliding color. Our study has some limitations, the most important being that the primary resolution of the images is only 24.51 mm. Using more detailed images could solve this limitation and would increase the accuracy of fractal analysis. The extent of forest loss is currently one of the most important concerns of decision-makers. Accurately identifying legal and illegal loss areas as well as the complexity of how this vegetation loss exerts pressure on the forest system leads to anticipating the complex effects of this phenomenon. The proposed methodology allows us to quantify the fractal complexity of forest loss and its spatial impact on forests. We note that the H1D analysis of the loss areas indicated that as the loss areas are larger, the H1D complexity values are lower. As the cumulative loss areas grow annually, they begin to aggregate, thus increasingly reducing the complexity of cumulative loss. The forest loss has led to an increased fragmentation of forests, generating a continuous increase in the complexity of tree cover areas. Higuchi 2D analysis allowed us to quantify the complexity of the relationship between pixels and their neighboring pixels. This highlights the local effects of the spatial evolution of forest loss. Thus 2003 was an "anomalous" year with a smaller complexity than the period 2004–2011, when alongside the existing clusters, some small chaotic loss patches are present.

We have thus shown that H1D and H2D are useful tools that can be applied in complementary ways in quantifying the fractal complexity of forest loss and their spatial impact on forests. Moreover, in this study we confirmed the findings from previous studies [35] regarding anisotropic images. In conclusion, we have shown that the analysis of the spatial-temporal dynamics of the Parâng Mountains, using GIS and fractal analysis, provides qualitative elements in the quantification of forest dynamics and is a useful methodology that can be extended in further research.

Author Contributions: Conceptualization, A.G.S., I.A. and D.P.; methodology, H.A., A.G.S., I.A. and D.P.; software, H.A.; validation, H.A., H.F.J., M.M. and V.L.; formal analysis, I.A. and I.D.N.; investigation, V.L., I.D.N. and C.M.P.; resources, D.P. and H.F.J.; data curation, D.P. and V.L.; writing—original draft preparation, A.G.S. and D.P.; writing—review and editing, I.A. and D.P.; visualization, M.M. and C.M.P.; project administration, D.P.; funding acquisition, H.F.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: We choose to exclude this statement because the study did not report any data.

Acknowledgments: This work was supported by a grant from the Romanian National Authority for Scientific Research and Innovation, CNCS-UEFISCDI, project number PN-II-RU-TE-2014-4-0835 and by a grant of the University of Bucharest—Spatial projection of the human pressure on forest ecosystems in Romania (UB/1365). All authors were equally involved in analyzing and editing the paper.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Stickler, C.M.; Nepstad, D.C.; Coe, M.T.; McGrath, D.G.; Rodrigues, H.O.; Walker, W.S.; Soares-Filho, B.S.; Davidson, E.A. The potential ecological costs and cobenefits of REDD: A critical review and case study from the Amazon region. *Glob. Chang. Biol.* **2019**, *15*, 2803–2824. [CrossRef]
2. Fraser, E.D.G.; Stringer, L.C. Explaining agricultural collapse: Macro-forces, micro-crises and the emergence of land use vulnerability in southern Romania. *Glob. Environ. Chang.* **2009**, *19*, 45–53. [CrossRef]
3. Keenan, R.; Reams, G.; Freitas, J.; Lindquist, E.; Achard, F.; Grainger, A. Dynamics of global forest area: Results from the 2015 Global Forest Resources Assessment. *For. Ecol. Manag.* **2015**, *352*, 9–20. [CrossRef]
4. Lawrence, D.; Vandecar, K. Effects of tropical deforestation on climate and agriculture. *Nat. Clim. Chang.* **2015**, *5*, 27–36. [CrossRef]
5. Pintilii, R.D.; Papuc, R.M.; Draghici, C.C.; Simion, A.G.; Ciobotaru, A.M. The impact of deforestation on the structural dynamics of economic profile in the most affected territorial systems in Romania. In Proceedings of the 15th International Multidisciplinary Scientific Geoconference (SGEM), Albena, Bulgaria, 18–24 June 2015; Volume 3, pp. 567–573. [CrossRef]
6. Pintilii, R.D.; Andronache, I.; Diaconu, D.C.; Dobrea, R.C.; Zelenakova, M.; Fensholt, R.; Peptenatu, D.; Draghici, C.C.; Ciobotaru, A.M. Using Fractal Analysis in Modeling the Dynamics of Forest and Economic Impact Assessment: Maramureș County, Romania, as a Case Study. *Forests* **2017**, *8*, 25. [CrossRef]
7. Peptenatu, D.; Sirodoev, I.; Pravalie, R. Quantification of the aridity process in south-western Romania. *J. Environ. Health Sci. Eng.* **2013**, *11*, 5. [CrossRef] [PubMed]
8. FAO. *The State of Food and Agriculture. Innovation in Family Farming, Food and Agriculture*; FAO: Rome, Italy, 2014. Available online: http://www.fao.org/3/a-i4040e.pdf (accessed on 21 December 2017).
9. United Nations. Deforestation Slows, 'but We Need to Do Better' on Sustainable Forest Use—UN Agriculture Chief. Available online: http://www.un.org/apps/news/story.asp?NewsID=51814#.WLGdPFV97Dc (accessed on 11 February 2018).
10. Griffiths, P.; Kuemmerle, T.; Baumann, M.; Radeloff, V.C.; Abrudan, I.V.; Lieskovsky, J.; Munteanu, C.; Ostapowicz, K.; Hostert, P. Forest disturbance, forest recovery., and changes in forest types across the Carpathian ecoregion from 1985 to 2010 based on Landsat image composites. *Remote. Sens. Environ.* **2013**, *151*, 72–88. [CrossRef]
11. Hostert, P.; Kuemmerle, T.; Prishchepov, A.; Sieber, A.; Lambin, E.F.; Radeloff, V.C. Rapid land use change after socio-economic disturbances: The collapse of the Soviet Union versus Chernobyl. *Environ. Res. Lett.* **2011**, *6*, 045201. [CrossRef]
12. Knorn, J.; Kuemmerle, T.; Radeloff, V.C.; Szabo, A.; Mindrescu, M.; Keeton, W.S. Forest restitution and protected area effectiveness in post-socialist Romania. *Biol. Conserv.* **2012**, *146*, 204–212. [CrossRef]
13. Kummerle, T.; Chaskovskyy, O.; Knorn, J.; Radeloff, V.C.; Kruhlov, I.; Keeton, W.S.; Hostert, P. Forest cover change and illegal logging in the Ukrainian Carpathians in the transition period from 1988 to 2007. *Remote. Sens. Environ.* **2009**, *113*, 1194–1207. [CrossRef]
14. Kummerle, T.; Muller, D.; Griffiths, P.; Rusu, M. Land use change in Southern Romania after the collapse of socialism. *Reg. Environ. Change* **2008**, *9*, 1–12. [CrossRef]
15. FAO. *State of the World's Forests. Forest and Agriculture: Land-Use Challenge and Opportunities*; FAO: Rome, Italy, 2014. Available online: http://www.fao.org/3/a-i5588e.pdf (accessed on 22 December 2017).
16. Andersson, F.; Birot, Y.; Paivinen, R. Towards the Sustainable Use of Europe's Forests—Forest Ecosystem and Landscape Research: Scientific Challenges and Opportunities. In *Proceedings 49 of European Forest Institute, Joensuu, Finland*; European Forest Institute: Joensuu, Finland, 2004.
17. Andronache, I.; Fensholt, R.; Ahammer, H.; Ciobotaru, A.M.; Pintilii, R.D.; Peptenatu, D.; Draghici, C.C.; Diaconu, D.C.; Radulovic, M.; Pulighe, G.; et al. Assessment of Textural Differentiations in Forest Resources in Romania Using Fractal Analysis. *Forests* **2017**, *8*, 54. [CrossRef]
18. Guvernul României—Ministerul Mediului și Schimbărilor Climatice. Arii Naturale Protejate. 2017. Available online: http://www.mmediu.ro/beta/domenii/protectia-naturii-2/arii-naturale-protejate/ (accessed on 12 December 2017).

19. Pintilii, R.D.; Andronache, I.; Simion, A.G.; Draghici, C.C.; Peptenatu, D.; Ciobotaru, A.M.; Dobrea, R.C.; Papuc, R.M. Determining forest fund evolution by fractal analysis (Suceava-Romania). *Urban. Archit. Constr.* **2016**, *7*, 31–42.
20. Marinescu, E.; Marinescu, E.I.; Vladut, A.; Marinescu, S. *Forest Cover Change in the Parâng-Cindrel Mountains of the Southern Carpathians, Romania*; Springer: Berlin/Heidelberg, Germany, 2013; pp. 225–238. [CrossRef]
21. Hansen, M.C.; Potapov, P.V.; Moore, R.; Hancher, M.; Turubanova, S.A.; Tyukavina, A.; Thau, D.; Stehman, S.V.; Goetz, S.J.; Loveland, T.R.; et al. High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science* **2013**, *342*, 850–853. [CrossRef]
22. McGarigal, K.S.; Cushman, S.A. Surface metrics: An alternative to patch metrics for the quantification of landscape structure. *Landsc. Ecol.* **2009**, *24*, 433–450. [CrossRef]
23. Kedron, P.J.; Frazier, A.E.; Ovando-Montejo, G.A.; Wang, J. Surface metrics for landscape ecology: A comparison of landscape models across ecoregions and scales. *Landsc. Ecol.* **2018**, *33*, 1489–1504. [CrossRef]
24. Calabrese, J.M.; Fagan, W.F. A comparison-shopper's guide to connectivity metrics. *Front. Ecol. Environ.* **2004**, *2*, 529–536. [CrossRef]
25. Sellan, G.; Simini, F.; Maritan, A.; Banavar, J.R.; de Haulleville, T.; Bauters, M.; Anfodillo, T. Testing a general approach to assess the degree of disturbance in tropical forests. *J. Veg. Sci.* **2017**, *28*, 659–668. [CrossRef]
26. Stauffer, D.; Aharony, A. *Introduction to Percolation Theory*; Taylor & Francis: London, UK, 1992; 192p. [CrossRef]
27. McGarigal, K.; Marks, B.J. *FRAGSTATS: Spatial Analysis Program for Quantifying Landscape Structure. USDA Forest Service General Technical Report PNW-GTR-351*; U.S. Department of Agriculture: Portland, OR, USA, 1995; 122p. [CrossRef]
28. Romero, S.; Campbell, J.F.; Nechols, J.R.; With, K.A. Movement behavior in response to landscape structure: Role of functional grain. *Landsc. Ecol.* **2009**, *24*, 39–51. [CrossRef]
29. Riitters, K.; Wickham, J. Decline of forest interior conditions in the conterminous United States. *Sci. Rep.* **2012**, *2*, 653. [CrossRef] [PubMed]
30. O'Neill, R.V.; Krummel, J.; Gardner, R.H.; Sugihara, G.; Jackson, B.; DeAngelis, D.L.; Dale, V.H. Indices of landscape pattern. *Landsc. Ecol.* **1988**, *1*, 153–162. [CrossRef]
31. Li, H.; Reynolds, J.F. A new contagion index to quantify spatial patterns of landscapes. *Landsc. Ecol.* **1993**, *8*, 155–162. [CrossRef]
32. Legendre, P.; Fortin, M.J. Spatial pattern and ecological analysis. *Vegetatio* **1989**, *80*, 107. [CrossRef]
33. Gustafson, E.J.; Parker, G.R. Relationships between landcover proportion and indexes of landscape spatial pattern. *Landsc. Ecol.* **1992**, *7*, 101–110. [CrossRef]
34. Higuchi, T. Approach to an irregular time series on the basis of the fractal theory. *Phys. D Nonlinear Phenom.* **1988**, *31*, 277–283. [CrossRef]
35. Ahammer, H. Higuchi Dimension of Digital Images. *PLoS ONE* **2011**, *6*, e24796. [CrossRef]
36. Andronache, I.; Ahammer, H.; Jelinek, H.F.; Peptenatu, D.; Ciobotaru, A.M.; Draghici, C.C.; Pintilii, R.D.; Simion, A.G.; Teodorescu, C. Fractal analysis for studying the evolution of forests. *Chaos Solitons Fractals* **2016**, *91*, 310–318. [CrossRef]
37. Spasic, S. On 2D generalization of Higuchi's fractal dimension. *Chaos Solitons Fractals* **2014**, *69*, 179–187. [CrossRef]
38. Ahammer, H.; Sabathiel, N.; Reiss, M.A. Is a two-dimensional generalization of the Higuchi algorithm really necessary? *Chaos Solitons Fractals* **2015**, *25*, 073104. [CrossRef]
39. Kainz, P.; Mayrhofer-Reinhartshuber, M.; Ahammer, H. IQM: An Extensible and Portable Open Source Application for Image and Signal Analysis in Java. *PLoS ONE* **2015**, *10*, e0116329. [CrossRef] [PubMed]
40. Concezzi, M.; Spigler, R. An ADI Method for the Numerical Solution of 3D Fractional Reaction-Diffusion Equations. *Fractal Fract.* **2020**, *4*, 57. [CrossRef]
41. Di Ieva, A.; Grizzi, F.; Jelinek, H.F.; Pellionisz, A.J.; Losa, G.A. Fractals in the neurosciences, Part I: General principles and basic neurosciences. *Neuroscientist* **2013**, *20*, 403–417. [CrossRef]
42. Sarkar, N.; Chaudhuri, B. An efficient differential box-counting approach to compute fractal dimension of image. *IEEE Trans. Syst. Man Cybern.* **1994**, *24*, 115–120. [CrossRef]
43. Jelinek, H.F.; Ahammer, H.; Matthews, S.; Succar, P.; McLachlan, C.; Buckl, M. Establishing a reference range for oligodendroglioma classification using Higuchi dimension analysis. In Proceedings of the 9th IASTED International Conference on Biomedical Engineering, BioMed, Innsbruck, Austria, 28 February 2012; pp. 25–28. [CrossRef]
44. Halley, J.M.; Hartley, S.; Kallimanis, A.S.; Kunin, W.E.; Lennon, J.J.; Sgardelis, S.P. Uses and abuses of fractal methodology in ecology. *Ecol. Lett.* **2004**, *7*, 254–271. [CrossRef]
45. He, H.S.; DeZonia, B.E.; Mladenoff, D.J. An aggregation index (AI) to quantify spatial patterns of landscapes. *Landsc. Ecol.* **2000**, *15*, 591–601. [CrossRef]
46. Landini, G. Fractals in microscopy. *J. Microsc.* **2011**, *241*, 1–8. [CrossRef]
47. Phan, D.T.H.; Brouwer, R.; Davidson, M. The economic costs of avoided deforestation in the developing world: A meta-analysis. *J. For. Econ.* **2014**, *20*, 1–16. [CrossRef]
48. Parks, N. Deforestation-related climate impacts may vary by soil. *Front. Ecol. Environ.* **2014**, *12*, 204.
49. Botsch, J.C.; Walter, S.T.; Karubian, J.; Gonzalez, N.; Dobbs, E.K.; Brosi, B.J. Impacts of forest fragmentation on orchid bee (Hymenoptera: Apidae: Euglossini) communities in the Choc biodiversity hotspot of northwest Ecuador. *J. Insect Conserv.* **2017**, *21*, 633–643. [CrossRef]
50. Peptenatu, D.; Merciu, C.; Merciu, G.; Draghici, C.C.; Cercleux, L. Specific features of environment risk management in emerging territorial Structures. *Carpathian J. Earth Environ. Sci.* **2012**, *7*, 135–143.

51. Ciobotaru, A.M.; Peptenatu, D.; Andronache, I.; Simion, A.G. Fractal characteristics of the afforested, deforested and regenerated areas in Suceava County, Romania. In Proceedings of the International Scientific Conferences on Earth&Geo Sciences—SGEM Vienna Green Sessions 2016, Vienna, Austria, 2–5 November 2016; Stef92 Technology Ltd.: Sofia, Bulgaria, 2016; pp. 445–452.
52. Pravalie, R.; Sirodoev, I.; Patriche, C.V.; Bandoc, G.; Peptenatu, D. The analysis of the relationship between climatic water deficit and corn agricultural productivity in the Dobrogea plateau. *Carpathian J. Earth Environ. Sci.* **2014**, *9*, 201–214.
53. Pravalie, R.; Sîrdoev, I.; Peptenatu, D. Changes in the forest ecosystems in areas impacted by aridization in south-western Romania. *Iran. J. Environ. Health Sci. Eng.* **2014**, *12*, 2. [CrossRef]
54. Pravalie, R.; Patriche, C.V.; Sirodoev, I.; Bandoc, G.; Dumitrescu, M.; Peptenatu, D. Water deficit and corn productivity during the post-socialist period. Case study: Southern Oltenia drylands, Romania. *Arid. Land Res. Manag.* **2016**, *30*, 239–257. [CrossRef]
55. Braghină, C.; Peptenatu, D.; Draghici, C.C.; Pintilii, R.D.; Schvab, A. Territorial Management within the Systems Affected by Mining. Case study The South-Western Development region in Romania. *Iran. J. Environ. Health Sci. Eng.* **2011**, *8*, 343–352.
56. Diaconu, D.C.; Peptenatu, D.; Simion, A.G.; Pintilii, R.D.; Draghici, C.C.; Teodorescu, C.; Grecu, A.; Gruia, A.K.; Ilie, A.M. The restrictions imposed upon the urban development by the piezometric level. Case study: Otopeni-Tunari, Corbeanca. *Urban. Arhit. Constr.* **2017**, *8*, 27–36.
57. Draghici, C.C.; Peptenatu, D.; Simion, A.G.; Pintilii, R.D.; Diaconu, D.C.; Teodorescu, C.; Papuc, R.M.; Grigore, A.M.; Dobrea, C.R. Assessing economic pressure on the forest fund of Maramures County Romania. *J. For. Sci.* **2016**, *62*, 175–185. [CrossRef]
58. Draghici, C.C.; Andronache, I.; Ahammer, H.; Peptenatu, D.; Pintilii, R.D.; Ciobotaru, A.M.; Simion, A.G.; Dobrea, R.C.; Diaconu, D.C.; Vişan, M.C.; et al. Spatial evolution of forest areas in the Northern Carpathian Mountains of Romania. *Acta Montan. Slovaca* **2017**, *22*, 95–106.