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SURVEY OF FOREST COVER CHANGES BY MEANS OF MULTIFRACTAL ANALYSIS

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Abstract: Land cover and land cover changes affect the environment in such ways that they can influence the human health by changing the climate, weather, water, air, biodiversity, wildlife, disease risk and food security. Comparing aerial or satellite images from the same region recorded at different times, known as post-classification comparison, is an approach that aims to identify changes in land coverage and understand forest spatial pattern change over time. These patterns are extremely complex, therefore, for their description and understanding a better approach would be multifractal geometry. In this paper, by using the multifractal analysis the evolution of the forest spatial model in southern Moldova over a decade has been investigated. We explored the potential of aerial image processing, lacunarity and textural analysis to detect a correlation between lacunarity, fractal dimensions and coverage crowns areas. This analysis leads to the determination of the percentage of land coverage, the dynamics of the natural reforestation process, the location of mature trees and the determination of areas where the landscape has changed drastically due to deforestation and / or reforestation. Two opposite forest spatial patterns were identified. For four studied forests, the rate of deforestation was continuously increased between 2005 and 2010. For only one forest, the Valeni forest, the coverage crown area has increased over the analyzed time period.

Keywords: Forest landscape change, Fractal analysis, Multifractal, Multifractal spectra, Deforestation.

1. INTRODUCTION

Nowadays, a major challenge for environmental sciences is to understand the changes in spatial patterns of land cover, to identify the processes that govern them and to find solutions to their negative effects. In recent years, dramatic changes have occurred in the area covered by forests and, in order to quantify and mitigate the undesirable effects of changes on the land cover detailed information, with sufficient spatial and temporal extent, is needed. An understanding of land cover and changes in ecosystem evolution are necessary to properly manage the negative effects of the forest cover changes. A practical tool for this operation is the remote observation of large areas of the Earth's surface, for a sufficiently long period. Earth observation technology has progressively been recognized for its usefulness in mapping land cover characteristics over a variety of spatial scales and over time.

To collect information and for data processing, some methods with an increasing accuracy which can be used at smaller or larger areas, have been developed. These methods can detect the vertical structure of forest vegetation and estimate the subcanopy density. Most commonly used methods are MODIS imagery (Bucha, & Stibig, 2008, Pouliot et al., 2009), integrating MODIS and Landsat data (Hansen et al., 2008), Landsat data (Do-Hyung Kim et al., 2014, Roy et al., 2014), LiDAR data (light detection and ranging) (Falkowski et al., 2009) or aerial images (Dube, 2008).

In order to explore new techniques to monitor the forest systems, the limitations of the Euclidean geometry in describing and modeling natural features related to landscapes and land cover were surpassed by using the fractal geometry (Zeide, 1991, Milne, 1991). According to Levin (1992) and Wiens (1989), processes and models are scale dependent, and in order to describe some natural characteristics such as patterns of spatial distribution, models capable of reproducing nature on several scales are required. Also, a power law type occurs frequently during the natural processes modelling. The same type of law underpins the development of fractal geometry (Pagnutti et al., 2007). The distribution of species, populations and communities in forest landscapes have been shown to have power-law related fractal properties (Mandelbrot, 1983) and thus it is possible to generalize these patterns.

In addition to the intrinsic factors, the spatial configuration of forests is also determined by extrinsic factors such as climate or soil (Forman, 1995). In nature, these factors have a fractal distribution (Caniego et al., 2005; Deidda et al., 1999). Interaction between extrinsic and intrinsic factors leads to increased complexity of the picture. Then, we can not hope that a single scale factor describes the configuration, but only a whole spectrum of such exponents (Scheuring & Riedi, 1994). Multifractal analysis is the technique in which not a single fractal dimension describes patterns observed in nature (Feder, 1988; Milne, 1991).

Multifractals analysis (Sole & Manrubia 1995) is the mechanism that drives both the spatial pattern and time distributions and are associated with the complex dynamics of forest systems. Multifractal analysis was used by Zhang et al., (2011) to identify changes in forest areas from LANDSAT data. Based on an idealized fractal growth model, they have shown that the changes in the forest landscape over time are governed by a fractal growth process. The multifractal spectra were used to highlight the reforestation of inaccessible mountainous areas by natural regeneration. A quantitative method based on the lacunarity analysis and analysis of the main components was presented by Frazer et al., (2005). The method was designed to analyze the continuity data of the crown areas and canopy gaps generated by the LiDAR systems. They reported a strong association between the lacunarity statistics and canopy cover and gap volume but they do not provide a clear relationship between lacunarity and the canopy cover.

In 1800, Romania had around 8.5 million ha of forest, i.e. 35-45% of the land surface. It has decreased continuously, so that now it reaches 6.4 million hectares, representing 27% of the land surface. This rate is weak compared to the European average of 32%. The illegal logging of forest is rife in Romania, while the people are not aware of the potential negative consequences of deforestation, so it is important to develop a method for fast identification of illegal exploitation and to act against it. The fractal analysis is an innovative method in shaping the economic pressure on the forest's resources as it provides additional information in the spatial analysis of the effects incurred by deforestation and quantifies the degree of fragmentation of the forested areas (Pintilii et al., 2017, Andronache, 2017).

In this paper, aerial images showing the same forest region at different time moments were analyzed and the multifractal formalism was used to highlight some possible landscape changes. Multifractal analysis of the forest areas characterizes changes in forest resources, the degree of uniformity, fragmentation, heterogeneity and homogeneity and estimates changes in the spatial extent of deforestation and reforestation. The multifractal measures are correlated to changes in the forest structure in order to identify the percentage of crown areas in the forest area, the existence of natural reforestation, the areas with mature trees, to determine those areas where the landscape has changed drastically due to deforestation and reforestation, the vertical development of the forest floors and finally, to give an automatic method to investigate the aerial images for surveilling, understanding and predicting the forest changes. The proposed method can also be used for satellite imagery.

2. MATERIALS AND METHODS

2.1. Field site and forest spatial

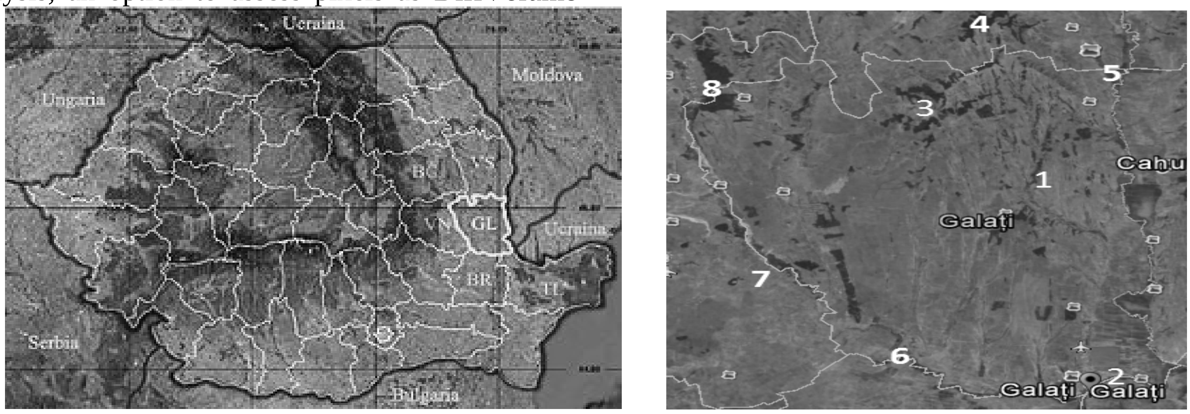
The study was conducted in the forested areas within the Galati Department of Silviculture (45°15′N – 46°15′N, 27°15′ - 28°15′ E) (Fig. 1). The studied forests are located in southern Moldova Plateau, between Siret and Prut river meadows and reach towards the core, the high plateau, altitudes of up to 300 m. The structure of forest ecosystems is also very different. In the region of the Siret meadow (areas 2 and 6) forests contain mostly willow, poplar and other species of softwood. In the higher regions (areas 1, 3, 4, 5, 7 and 8), the forests contain mostly hornbeam, oak and acacia. Some useful information about these forest areas are provided in Table 1. Specifically, these forests were selected for our study because the results can be easily validated by *in situ* visits. These forests are easily accessible and all data necessary to validate our study were provided by the Department of Forestry of the region Galati.

2.2. Multifractal analysis and lacunarity

Most of the process and natural phenomena are driven by mathematical and physical models that cannot be understood and studied by meaning of Euclidean geometry. Fractal geometry is the solution for these models. Upon careful examination of structure and coverage patterns, subsets of different scale exponents can be identified. There are fractals inserted into fractals. These models are called multifractals and are often associated with the dynamics of forest systems (Mandelbrot, 1983, Rényi, 1970 and Feder, 1998).

We used the free software ImageJ for aerial image processing, lacunarity and textural analysis and correlation between lacunarity, fractal dimensions and coverage crowns areas. It can be used either online as an applet or can be downloaded and installed on any computer with a Java virtual machine (Schneider et al., 2012). In addition, FracLac as a free plugin to ImageJ has been used to perform the multifractal analysis (Karperien, 2013). To obtain information on the distribution of pixel values in the aerial images, so called mass distribution, FracLac software uses the box counting grid technique. In the FracLac setup for multifractal analysis, an option to assess pixels as DiffVolume plus 1 was used. From this measure, FracLac calculates a series of numerical coefficients and provides some plots called multifractal spectra. FracLac allow us to compute the following parameters:

(i) plot D(q) against q. FracLac infers a scaling rule for a pattern, in our case the generalized fractal dimension D, by taking many measurements over many box sizes and approximates a log-log relationship from the slope of the regression line. The plot D vs. q is one of the multifractal spectra. D(q) basically addresses how mass distribution varies with ε (i.e. resolution or box size) in an image, indicating how it behaves when the image is scaled into a series of ε-sized pieces. The function D(q) vs. q sigmoidal decreases to q=0, and the following fractal dimensions can be determined: D_0 (D for q=0) ≥ D_1 (D for q=1) ≥ D2 (D for q=2). In a general sense, the generalized dimension, D_0 (q=0) describes the "Capacity Dimension", which can be understood as the box counting dimension. D_1 (q=1) is the "Information Dimension", and D_2 (q=2) is the "Correlation Dimension" (Zhang et al., 2011). A multifractal approach based on the generalized fractal dimension and the singularity spectra were used to correlate the structural variability and the



a b

Figure 1. The location of the studied forest areas. (Galati Department of Silviculture)

Table 1. Brief information about the studied forest areas

Nr.	Forest	Coverage crown areas (%)	The average age (years)	The average temperature (^{0}C)	Altitude (m)		Average rainfall (mm/year)	Aridity index
					limits	average		
1	Tg Bujor	74%	19	10.2	30- 200	100	446	21
2	Zatun	78%	17	10.5	6-10	7	426	20.7
3	Balabanesti	83%	37	9.8	60- 310	230	437.3	22
4	Valeni	85%	53	9.6	170- 300	220	485.2	20
5	Aldesti	84%	21	9.8	170- 290	200	437.3	22
6	Independenta	76%	14	10.5	4 -40	7	419.6	26.3
7	Furceni	69%	33	10.8	20- 45	40	467	27
8	Buciumeni	80%	46	10.8	125- 250	130	467	27

surface heterogeneity of an analyzed surface by some physical parameters that determine this heterogeneity (Dănilă et al., 2018).

(ii) f(α) spectrum of multifractal measures.

(iii) lacunarity. Lacunarity is based on the variation of pixel density at different box sizes either in fixed scans or sliding scans (Mandelbrot, 1983). Lacunarity involves both gaps and heterogeneity estimation. Lacunarity analysis provides a texture description for spatial features selection in multi-fractal and non-fractal approach for one-, two-, and three-dimensional data. Gefen et al., (1983) provide a precise definition of lacunarity or gappiness as a measure of the deviation of a geometric object, such as a fractal, from translational invariance. Low lacunarity geometric objects are homogeneous and translationally invariant because all gap sizes are the same. In contrast, objects with a wide range of gap sizes are heterogeneous and not translationally invariant; they show high lacunarity. However, we have to note that translational invariance is highly scale dependent, namely the small-scale heterogeneous objects could be considered homogeneous at larger scales. Also, the reciprocal statement is valid. In this study, lacunarity is correlated to the texture of aerial images in order to quantify the forest canopy structure. A low lacunarity index means a homogeneous forest canopy structure with narrow range of gap size. Conversely, high lacunarity index means a heterogeneous forest canopy structure with wide range of gap size. Let denote $n(R)$ the total number of boxes of size R and σ is the number of occupied sites of each box. Then, the number of the boxes with size R containing σ occupied sites (or mass σ) is $n(\sigma, R)$ and the probability distribution of the occupied boxes is as follows (Allain and Cloitre, 1991):

$$Q(\sigma, R) = \frac{n(\sigma,R)}{n(R)} \qquad (1)$$

Lacunarity is defined as:

$$\lambda = \frac{\sum \sigma Q(\sigma,R)}{\sum \sigma^2 Q(\sigma,R)} \qquad (2)$$

where summation is performed over the entire pixel distribution. The main advantage of using lacunarity analysis is that two forest sites showing the same fraction of vegetated coverage can have different lacunarities that, in turn, indicates variability in gaps distribution.

Ianăș & Germain, 2018, estimated the rate of deforestation over an analyzed period by using the following equation:

$$r = \left[1 - \left(\frac{A_t}{A_0}\right)^{\frac{1}{t}}\right] * 100 \qquad (3)$$

where r is the annual rate of deforestation, A_0 is the land-use coverage in the initial year, A_t is the land-use coverage in the final year, and t is the duration in years.

3. RESULTS AND DISCUSSION

We use the data provided by multifractal analysis to identify the forested areas where deforestation occurs and areas where either by planting or by natural regeneration the forests are restored. To obtain these results we addressed the crown coverage area that is defined as the fraction of the forest floor covered by the vertical projection of the tree crowns.

True color aerial images are converted to gray scale images to be used in multifractal analysis (Fig. 2). In order to compare the multifractal analysis results, all images were resized to 1065 × 580 pixels, so D_0 will have the same value for all images. The grayscale images are stored in a .tiff file format.

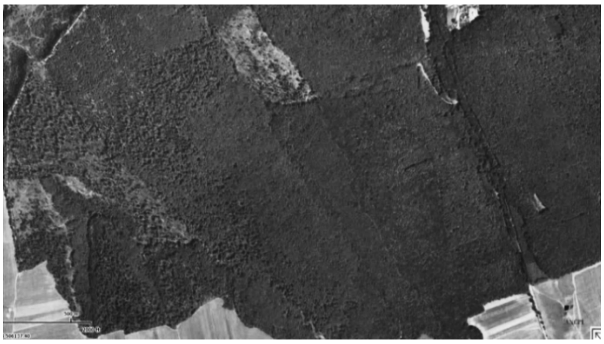


Figure 2. Aerial image displayed as a grey scale image of *Valeni* forest (*http://geoportal.ancpi.ro/geoportal/viewer/index.html*)

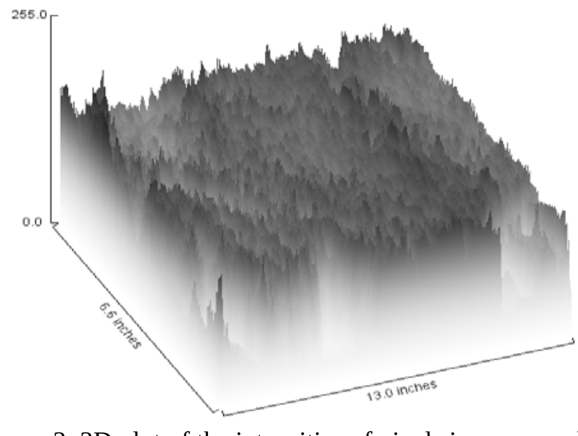


Figure 3. 3D plot of the intensities of pixels in a grayscale image for forest image in figure 2.

In order to extract information about the percentage of crown coverage area from the total forest surface by using the gap calculation, a multifractal analysis is applied to a 3D image, that is a three-dimensional plot of the intensities of pixels in a grayscale image (Fig. 3). Multifractal analysis better emphasizes placement and consistency of forest floors, gaps and discontinuities into a 3D image approach.

3.1. Lacunarity and the rate of deforestation

The potential of multifractal analysis and lacunarity in a textural approach to detect variations in the structure of forest canopies, of the main forests in the region of Galati has been materialized in the results presented in table 2. The coverage crown area has been correlated to lacunarity and has been estimated as $(1-\lambda)*100$ (%). By using eq. (3), we quantified the landscape changes by this landscape metric, using coverage crowns determined on site, and coverage crowns determined as $1-\lambda$. The results are presented in the last column of table 2. The negative values obtained for area 4 (Valeni forest) indicate an increasing crown coverage for this area.

It can be noticed that for 2005 and 2010, coverage crown areas estimated as $(1-\lambda)*100$ (%), are very close to the percentages of coverage crown determined by in situ measurements (differences are less than 2%). A comparison between the lacunarity values for 2005 and 2010 indicates that coverage crown area has decreased as a result of exploitation.

The only exception is the Valeni forest where the coverage crown area has increased. This first result is very important for our study in a very intuitive sense. In the case of forests with uniform composition and age, the tree crowns can be assumed to have the same size and, in the multifractals approach, the canopy appears to be self-similar. This allows for a fast and simple estimation of the number of trees per hectare.

Similarly, using *in situ* estimation of the volume of lumber in cubic meters for a tree, then the volume of lumber in cubic meters per hectare can be also estimated. However, we have to mention that for our studied cases, the homogeneity condition is not meet, all analyzed forests being heterogeneous as species and age.

3.2. Forest land cover

The plots of fractal dimension D vs. q and the singularity spectra $f(\alpha)$ vs. α provide information on the land cover trends. Figure 4 (a and b) shows the multifractal spectrum of the Buciumeni and Valeni forests, for the analyzed years.

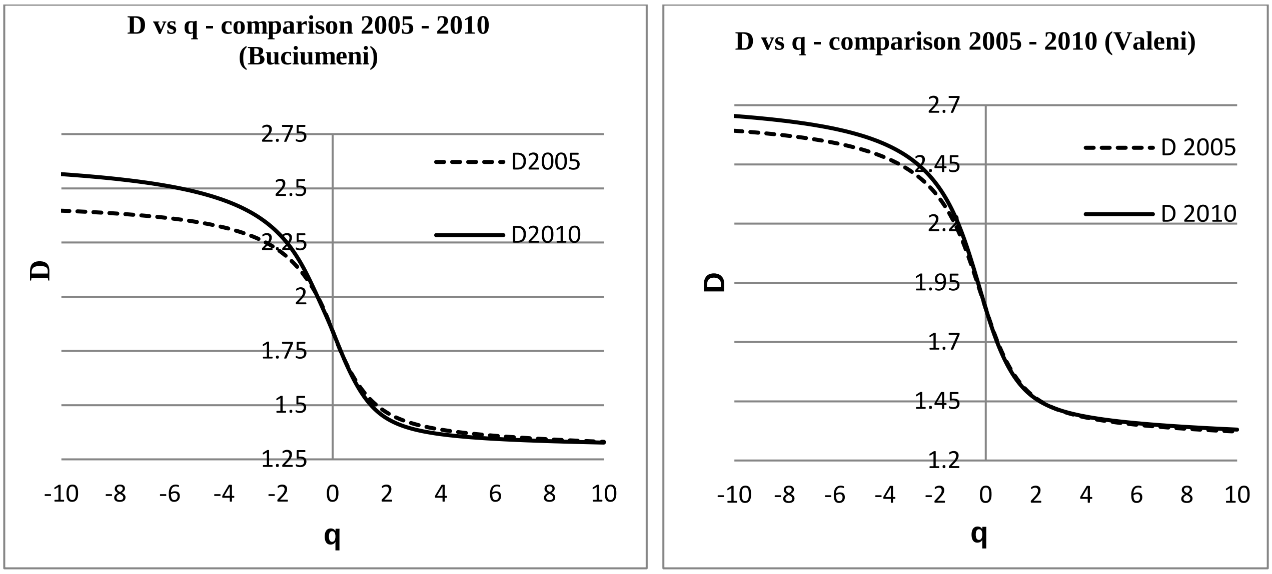
Zhang et al., (2011) used one of the most important models of fractal growth, so called the diffusion-limited aggregation (DLA) model to simulate the forest growth process. They concluded that smaller patches contribute more to the left part of the D vs. q spectra, and large patches contribute more to the right part of the spectra. They also associated the increase in the difference in time (D_{qmax}-D_{qmin}) with the natural growth of the forest vegetation.

In our case, the left side of the spectra grows faster than the right side. Accordingly, small forest landscape patches decrease faster than the larger patches increase. Also, the natural growth of vegetation is highlighted in the last column of Table 3, where the values of the difference $\mathbf{D_{-10} - D_{10}}$ increase. In this paper we propose an improvement of the fractals approach through linking the values of the fractal dimension D to the different vegetation levels in the forests.

The fractal dimension $D_{-\infty}$ (the fractal values for $q \to -\infty$ is $D_{-\infty}=D_{-10}$) in multifractal spectra increased for 2010 compared to 2005 in the left part of the spectra, but in different weights. This effect is more pronounced for Buciumeni forest and is due to natural growth. In the right part ($D_{\infty}=D_{10}$; D_{∞} is for $q \to \infty$) there are small differences over time, but the curve distribution is reversed for the analyzed cases.

Table 2. Lacunarity and rate of deforestation in a multifractal approach

Forest	Coverage crowns (%) determined on site (2010)	Lacunarity λ (%) (2010)	Coverage crowns (%) determined as $1-\lambda$ (2010)	Coverage crowns (%) determined on site (2005)	Lacunarity λ(%) (2005)	Coverage crowns (%) determined as $1-\lambda$ (2005)	*r* (%) (from eq.3)
Tg Bujor	74	27.31	72.69	77	23.50	76.50	0.7916
Zatun	78	20.70	79,30	80	19,70	80,30	0,5050
Balabanesti	73	25.42	74.58	76	22.74	77.26	0.8022
Valeni	85	16.71	83.29	75	23.25	76.75	-2,535
Aldesti	84	15.31	84.19	87	12.50	87.50	0,6993
Independenta	76	23.15	76.85	76	22.97	77.03	0
Furceni	69	29.31	70.69	73	27.20	72.80	1,1207
Buciumeni	77	24.64	75.66	78	22.67	77.33	0.2577



(a) (b)

Figure 4. Fractal dimension D vs. q. (a) Forest 8 – Buciumeni; (b) forest 3 - Valeni. For $q >> 1$, regions with a high degree of tree concentration are expanded for year 2010 for case (b).

Table 3. Fractal dimensions for analyzed forests

		D_{-10} (q=-10)	D_0 (q=0)	D_1 (q=1)	D_2 (q=2)	D_{10} (q=10)	D_{-10} - D_{10}
Aldesti	2005	2.5248	1.8416	1.5834	1.4834	1.3345	1.1903
	2010	2.5394	1.8416	1.5687	1.4765	1.3281	1.2113
Balabanesti	2005	2.4111	1.8416	1.5922	1.4775	1.3299	1.0812
	2010	2.4608	1.8416	1.5882	1.4712	1.3189	1.1419
Buciumeni	2005	2.3968	1.8416	1.5856	1.4657	1.3309	1.0659
	2010	2.5652	1.8416	1.57	1.4387	1.3273	1.2379
Furceni	2005	2.6457	1.8416	1.5798	1.4635	1.3324	1,3133
	2010	2.6724	1.8416	1.5704	1.4521	1.3259	1.3465
Independenta	2005	2.6642	1.8416	1.5629	1.4434	1.3248	1.3394
	2010	2.731	1.8416	1.5608	1.44	1.3236	1.4074
Targu Bujor	2005	2.521	1.8416	1.5984	1.4979	1.382	1.139
	2010	2.5633	1.8416	1.5622	1.4306	1.3201	1.2432
Valeni	2005	2.5921	1.8416	1.5843	1.4629	1.322	1.2699
	2010	2.6543	1.8416	1.5771	1.4599	1.3304	1.3239
Zatun	2005	2.5864	1.8416	1.5984	1.4752	1.3254	1.2614
	2010	2.6012	1.8416	1.5876	1.4632	1.3158	1,2854

For $q >> 1$, the regions with a high tree concentration have decreased and have small contribution to this part of the spectra, for year 2010 (for Buciumeni forest). Contrary, the Valeni forest has shown a slight increased contribution on the right part of the spectra for the year 2010, indicating that certain regions with a high degree of tree concentration are expanded.

A comprehensive multifractals data for all analyzed forests is presented in Table 3. The small differences between the generalized fractal dimensions D_{10}, show that the weights of the larger trees do not change over studied period.

The forests numbered 1, 3, 6 and 8 are characterized by smaller values of in the aerial images from 2010 than in the images from 2005. Similar results are for generalized fractal dimensions D_{-10}. This also indicates an intensive forest exploitation and asks for restoring by controlling forest exploitation.

The location and consistency of the forest floors give useful information about the forest evolution and health. It is well known that in order to stimulate certain tree species to develop a strong crown, fast-growing tree species are planted to force the species of interest to speed up growth. This strategy can be validated analyzing the fractal dimension values for different values of q. So, the multifractal analysis, allows to gather information about the scaling properties of forest spatial distribution over time at the intermediate forest levels of vegetation, by addressing to the fractal dimensions D_1, D_2 and D_{10} to intermediate forest levels. According to data in table 3, these values are almost similar for 2005 and 2010, but are slightly higher for 2005. However, we have to emphasize that this analysis takes into consideration the year 2004 that was a normal year in terms of temperatures and rainfall, and 2005 was a year with normal temperatures but with an excess rainfall regime, the development of shrubs and bushes, which are the lower vegetation affinities of the forest, have been favored. Instead, the years 2008, 2009 and early 2010 had an excessive thermal regime and a pluviometric one far below normal; the development of these floors in the forest was slower.

$\Delta\alpha$ and Δf are two essential parameters in multifractal analysis. Figure 5 shows the singularity spectrum $f(\alpha)$ vs. α for two forests with two different patterns, Balabanesti and Valeni. As shown in the figure, there are important differences between two forests, but in the case of Balabenesti forest no important variation in the spectrum of singularities of 2005 and 2010 is highlighted.

Finally, the measured values from the singularity spectra have been correlated to the information provided by the spectrum D vs. q and the fractal dimensions (Table 4).

An increase in $\Delta\alpha$ values means a wider pattern variability and indicates a transition from a homogeneous (random space filling) to a heterogeneous (clustered) pattern. Both extremes of the spectrum, i.e. $\alpha_{for\ q=10} = \alpha_{min}$ and the right terminal $\alpha_{for\ q=-10} = \alpha_{max}$, indicate the compactness of the higher concentrations and lower concentrations or the spread in the data space, respectively. A greater singularity is represented by a smaller α_{max} or a greater α_{min} (Zhang et al., 2011). $\Delta f(\alpha)$ values are positive for all forests, excepting the area 4 – Valeni forest, for which $\Delta f(\alpha)$ is negative. $\Delta f(\alpha) < 0$ indicates a significant increase in the crown coverage and the same result has been found by analyzing the D vs q spectra.

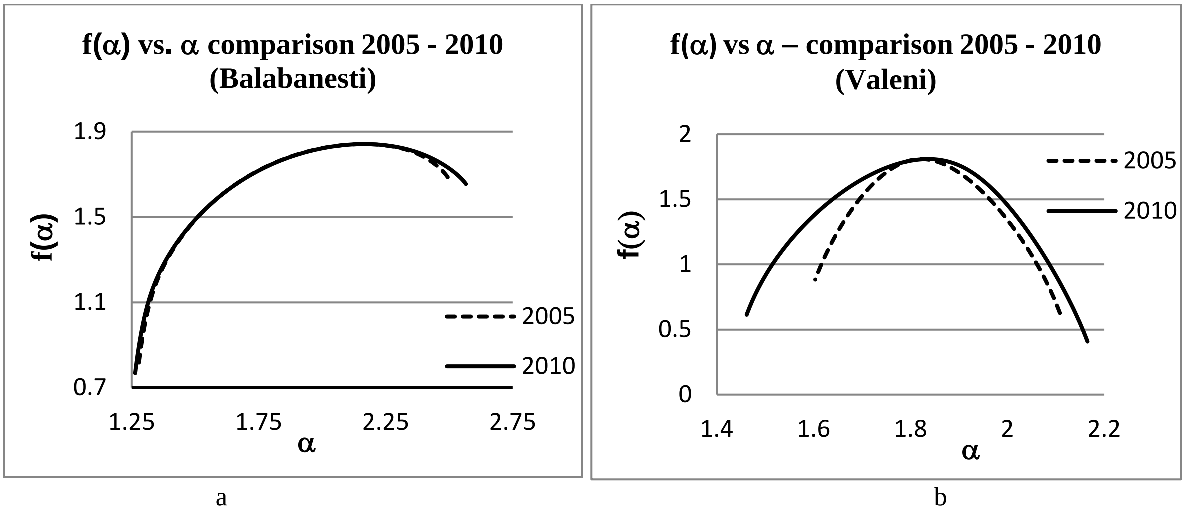


Figure 5. Singularity spectra $f(\alpha)$ vs. α. (a) Area 3 - Balabanesti forest; (b) Area 4 – Valeni forest

Table 4. Multifractal analysis: $\Delta\alpha$ and Δf from the singularity spectra. The extremum singularities are presented in bold.

		α_{max} (q=-10)	α_{min} (q=10)	$\Delta\alpha$	$f(\alpha)$ (q=-10)	$f(\alpha)$ (q=10)	$\Delta f(\alpha)$
Aldesti	2005	2.3452	1.2135	1.1317	1.2135	0.4521	0.7614
	2010	2.3724	1.2058	1.1666	1.2036	0.4425	0.7611
Balabanesti	2005	2.4941	1.277	1.2171	1.6863	0.8014	0,8849
	2010	2.5657	1.2638	1.3019	1.6545	0.7675	0,887
Buciumeni	2005	2.4531	1.2873	1.1558	1.8343	0.8949	0,9394
	2010	2.6608	**1.6095**	1.3513	1.303	1.0845	0,2185
Furceni	2005	2.5612	1.3564	1.2048	1.6459	1.0241	0.6218
	2010	2.5861	1.2856	1.3005	1.6325	0.9951	0.6375
Independenta	2005	2.7749	1.294	1.4809	1.5826	1.0161	0,5665
	2010	2.8566	1.3025	1.5541	1.514	1.0586	0,4554
Targu Bujor	2005	2.6861	1.3564	1.3297	1.6207	1.2952	0,3255
	2010	2.6209	1.1254	1.4955	1.5833	1.0706	0,5127
Valeni	2005	**2.1083**	**1.6033**	0.505	0.6268	0.884	-0,2572
	2010	**2.1653**	1.4616	0.7037	0.4073	0.6135	-0,2062
Zatun	2005	2.2598	1.3625	0.8973	1.0523	0.5524	0,4999
	2010	2.3251	1.3205	1.0046	1.0324	0.5329	0,4995

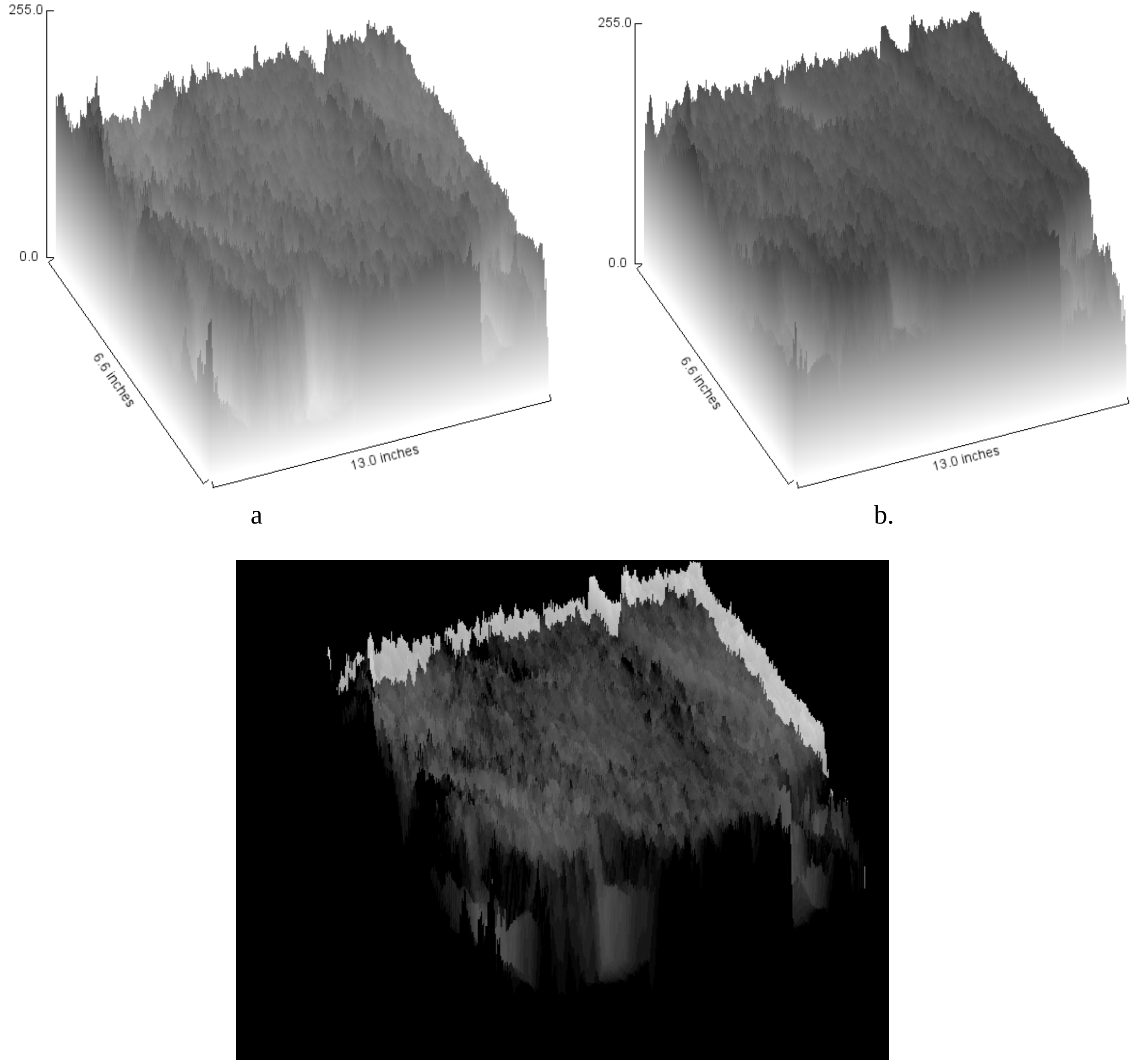


Figure 6. Multifractals analysis of Buciumeni forest. a) Forest distribution multifractals pattern in 2005 (initial image); b) Forest distribution multifractals pattern in 2010 (final image); c) Difference in the forest distribution multifractals pattern between 2005 and 2010

3.3. Deforested areas. Reforested areas

To underline the efficacy and utility of the aerial images in the forest dynamics surveillance, we also address the deforested and reforested areas analysis by comparing two images of the same area taken at same time period, namely 2005 and 2010. The Image calculator from the menu Process of ImageJ has been used. Figure 6 a and b represents the images of the Buciumeni forest (site 8 in fig. 1) in 2005 and 2010. The subtraction operation result is displayed in figure c.

As shown in figure 6, the black area represents deforested areas (group of trees that exist on the original image – 2005, and no longer appear on the final image - 2010) while light gray area represents reforested patches (group of trees that not exist on the original image and appear on the final image) mainly by natural growth or plantation, in the same time interval. The shades of gray in figure difference correspond to natural growth of the forest. The similarity analysis between aerial images into time series allows a fast identification of those regions affected by illegal forest exploitation. It is also possible to appreciate the degree of natural regeneration of surfaces, growth condition in forests and to estimate the health of the forest.

All results obtained in this study, were confirmed by *in situ* measurements and observations. After this validation of the results, further studies in more difficult accessible forested regions of the Carpathian Mountains are suggested.

4. CONCLUSIONS

The paper presents the application of the multifractal analysis of the aerial images of eight forest regions taken during the same period of vegetation, at the interval of five years. The proposed multifractals analysis method is suitable to identify changes in land use, deforestation and natural regeneration of the forest as well as changes occurring due to the natural vegetation growth.

It was shown that lacunarity analysis can be used as an effective index in assessing the coverage crown areas. Forests showing a uniform composition and age, are suitable candidates for a good estimation of the number of trees per hectare and the amount of wood in cubic meters per hectare. Land cover trend was estimated based on the singularity spectra analysis because it also correlates measures of compactness of the higher concentrations and lower concentrations vegetation patches. The multifractal analysis approach allows to gather information about the intermediate forest levels of vegetation, by addressing to the fractal dimensions. All results provided by this study have been confirmed by in situ measurements and observations.

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