Dynamics of Forest Fragmentation and Connectivity Using Particle and Fractal Analysis

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The ever decreasing area of forests has lead to environmental and economical challenges and has brought with it a renewed interest in developing methodologies that quantify the extent of deforestation and reforestation. In this study we analyzed the deforested areas of the Apuseni Mountains, which has been under economic pressure in recent years and resulted in widespread deforestation as a means of income. Deforested surface dynamics modeling was based on images contained in the Global Forest Database, provided by the Department of Geographical Sciences at Maryland University between 2000 and 2014. The results of the image particle analysis and modelling were based on Total Area (ha), Count of patches and Average Size whereas deforested area distribution was based on the Local Connected Fractal Dimension, Fractal Fragmentation Index and Tug-of-War Lacunarity as indicators of forest fragmentation or heterogeneity. The major findings of the study indicated a reduction of the tree cover area by 3.8%, an increase in fragmentation of 17.7% and an increase in heterogeneity by 29%, while fractal connectivity decreased only by 0.1%. The fractal and particle analysis showed a clustering of forest loss areas with an average increase from 1.1 to 3.0 ha per loss site per year. In conclusion, the fractal and particle analysis provide a relevant methodological framework to further our understanding of the spatial effects of economic pressure on forestry.

In view of its effect on climate, deforestation is the threatening challenge for contemporary society. The major factors leading to the decline of forested areas include an expansion of agricultural land1–4, human settlements5, timber demand6, mining exploitations and population growth7 leading to environmental and economical challenges in the long term. Therefore the aim of the local or regional authorities is to reduce deforestation and to regenerate the existing forests wherever possible due to their importance in supporting the biotic system, regional and global climate change, the preservation of atmospheric oxygen and carbon, conservation of biodiversity and benefits to local communities8–12.

Forest fragmentation is a major result of deforestation13,14. It leads to habitat modification15, and subdivision of plant and animal populations. Thus, changes in species interactions occur13,14, leading to further tree mortality.

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and destruction as observed at the edges of forest fragments16. Previous studies have suggested that forest fragmentation may have profound effects on biodiversity27,28 and differ among plant species29 resulting in some plant species having lower survival rate20. Forest fragmentation also generates a decline in forest bird populations23 by reducing the nesting success22,23 and the diversity of mammalian species24. In addition, forest fragmentation generates microclimatic changes14 with the risk of extinction of thousands of species25,26 associated with a lack of food, shelter and increased risk of attacks by carnivorous mammals27. An analysis of forest cover also indicates large carbon emissions from fragmented forests due to higher tree mortality at forest edges28. However; fragmentation may exert positive effects on increasing the abundance of the lianas if the severity of forest fragmentation intensifies29. Research on the impact of deforestation has revealed the complexity of this process, determined by the size of the deforested areas and their fragmentation patterns. that can impact the environment in diverse ways including frequency of flooding depending on the degree and type of logging30.

A forest fragmentation model based on the principles of percolation theory has been previously used for evaluation of the state of fragmentation. Results indicate that forest fragmentation is close to the critical point of percolation, which means that the number of small forest fragments will expand exponentially with increasing deforestation31.

Additional measures describing the state of forest fragmentation such as the rank occupancy-abundance profile19, the relation between forest patch size and proximity of forest to non-forest edge26, mean patch size, patch density and edge density provide further evidence of the impact of deforestation32.

Remote sensing has largely improved analysis of forest exploitation through logging and its impact on forests by changes in satellite, airplanes or UAV’s images. Forests are currently monitored least annually by satellite images globally as well as at regionally or locally33.

The complexity of the deforestation phenomenon calls for new analytical approaches. The proposed methodology in this study complements the approaches that have proven useful in previous research by applying Local Connected Fractal Dimension (LCFD), Tug-of War Lacunarity (ΛT-o-W) and Fractal Fragmentation Index (FFI)34–39.

Results
Particle analysis was carried out alongside fractal analysis in an attempt to tangibly describe what a highly abstract fractal analysis actually measures. The aggregated results can be found in the Supplementary Material as Table S1.

Particle analysis of the forested, deforested (loss) and regenerated area dynamics. Figure 1a,b present the dynamics of the Apuseni Mountain tree cover and forest loss areas. The tree cover area has decreased by 3.8% from a total of 794,005 ha in 2000 to 764,002 ha in 2014. The spatial dynamics of forested, loss and gain areas was determined using Particle Analysis data (Table S1).

Until 2004, forest loss areas were dispersed in small patches. However since then a clustering process occurred through a cluster development in the Gilău, Muntele Mare and Vlădeasa Mountains (Fig. 2). This coincided with a more pronounced scatter of total forest and thus led to a higher fragility of tree cover areas. Our measures have shown that, between 2000 and 2014, only 46.6% of the total forest loss areas have been regenerated (Table S1, Fig. 3).

By a particle analysis particle count parameter, we showed that out of 19,771 ha of forest loss areas, 9,951 clusters were formed while the rest remained as isolated forest loss areas. As a result of forest loss areas, the tree cover has become more fragmented, with the appearance of 727 new independent forest loss areas which amounted to 3.7% of cumulative forest loss areas.

Interesting results were also obtained by the average size analysis of forest loss areas. In periods with intense logging the average size of the loss sites exceeded 1.5 ha but in years with less logging activity the average size was less than 1.0 ha per loss site (Fig. 1a). This has revealed a clustering process: the average forest loss areas increased from 1.1 to 3.0 ha per loss site, over the study period. The highest increases in forest loss areas occurred in 2007...
Figure 2. Dynamics of cumulative forest loss areas (Cumulative deforestation), in relation to cumulative gain areas (Cumulative reforestation) and tree cover (Total forests) in Apuseni Mountains between 2001 and 2014. From QGIS Development Team (2018), QGIS Geographic Information System. Open Source Geospatial Foundation Project. http://qgis.osgeo.org.

Figure 3. The local effects of heterogeneity of the forest loss areas (deforestation) on the tree cover (forests) measured by $\Lambda_{T-o-W}$ ($T-o-W \ L$) compared with tree cover area (ha.), forest loss areas (ha.) and forest fragmentation measured by FFI (violet), using standardized values. Spearman’s correlation coefficients are shown in Table S2 in Supplementary Material.
and 2012, years with the largest forest loss areas. Forest fragmentation also led to a decrease from 99.6 to 87.8 ha per average tree cover site (Table S1). The most intense fragmentation occurred in periods with the largest forest loss areas: 2009–2010 and 2012 (Fig. 1a).

Fractal analysis. Local Connected Fractal Dimension (LCFD) was employed for the first time in forest analysis to measure the degree of connectivity described as a connection of each forest pixel with eight neighboring forest pixels from satellite images, previous exploited only in biology and medicine.

LCFD analysis of forest loss areas indicated that the greatest connectivity was during years with the largest forest loss areas, because the deforestation made in several patches. The least connectivity of forest loss areas, was found in years with very small forest loss areas. The highest increase of connectivity was recorded when forest loss areas were moderate, below average, but homogeneously organized and compact. As the cumulative loss area increased, its connectivity decreased. This finding suggested that forest loss areas did not have a strong influence on the spatial tree cover complexity in the Apuseni Mountains, because were done in small patches. (Fig. 2), though this decrease was only 0.1%. LCFD actually reflected the patch sizes, because of the strong correlation (0.95–1.00) between LCFD with tree cover and cumulative forest loss areas size (Fig. 2). Between 2001 and 2014 LCFDs of regenerated areas were lower by 51% compared to LCFDs of forest loss areas. This may be due to a regeneration occurring in smaller and highly spatially fragmented areas, leading to a lower connectivity between the forest patches (Table S1). Using LCFD analysis has revealed that forest loss areas increase has little effect on the tree cover fractal connectivity and may therefore contribute substantially to fragmentation.

The FFI index offers information regarding the fragmentation or the degree of compaction of an object. For the analyzed period, the forest areas decreased by 3.8% with a FFI decrease of 17%, thus indicating an increase in fragmentation of the tree cover (Table S1).

The highest decrease in FFI for the tree cover areas was registered in 2001 and 2007 when forest loss areas were characterized by low-fragmentation and 68% of forest loss areas occurring in new locations. The smallest decrease in tree cover FFI was in 2002 when forest loss areas distribution occurred mainly in small forest patches (Table S1).

Further minimal fragmentation occurred in 2007 and 2011, but fragmented loss areas of 34–39% were registered in 2013–2014 (Fig. 3). The higher the loss surface, the more compact it was. Thus, the years with intense forest loss areas were also associated with their increased compactness.

The FFI of regenerated areas between 2001 and 2014 was 51% lower compared to FFI of the deforestation areas (Table S1).

Interesting results were obtained by the Tug-of-War Lacunarity (A_{T-O-W}) analysis. It revealed maximal heterogeneity in years with dominant forest loss areas in new, and relatively large areas (Table S1). In contrast, the maximum homogeneity of the spatial forest loss areas distribution occurred when forest loss areas occurred as continuation of loss patches and in relatively small areas. A_{T-O-W} of the tree cover did not show a continuous downward trend. Because the deforestation was heterogeneous, the value of A_{T-O-W} increased by 29%, even though the forested areas decreased by only 3.8%. This fractal parameter therefore provided independent information as it showed low correlation with the standard forest parameters such as tree cover and forest loss areas (Table 2 Supplementary Material).

Discussion

The increasing fragmentation observed during the study period was most likely due to legislative changes in the management of the forests, the most important being the retrocession of large areas and the fast logging, as well as illegal logging. Fragmentation of forests is a stage in the loss of compact forest areas. The way forests are fragmented provides information on how to intervene in their exploitation. Illegal exploitation of wood masses is manifested by large fragmentation, and legal logging through compact cuts. Analysis of fragmentation over extended periods of time helps to forecast an evolution of economic pressure on forest resources globally.

This study measured the dynamics of forest loss areas by use of fractal and particle analysis features for a large region in Romania.

The results indicated that a tree cover decreased every year of the study while fragmentation increased. Such continuous decrease in tree cover was due to increased legal and illegal deforestation in the period of economic and legislative changes that encouraged logging. (Fig. S1, in Supplementary Material). Furthermore, forest loss areas have occurred in “jumps” corresponding to a transfer of significant portions of forested land from state property to the former owners prior to nationalization in 1948 (Fig. 1a).

The fractal indicators complement each other by providing different information. Connectivity information obtained by LCFD is supplemented with fragmentation/compaction (FFI) and heterogeneity/homogeneity (A_{T-O-W}). This complementary analysis has allowed us to highlight how the loss in forest areas occurred and how it spatially affects the tree cover of the Apuseni Mountains.

LCFD quantified the local effects of forest loss areas on connectivity of the forests through analyzing changes in connectivity of the forest. LCFD analysis of deforestation indicated that the largest connectivity occurred in years when large fragmented and heterogeneous deforestation alternated with homogenous forest loss areas. The lowest connectivity was registered during the years with very small fragmented but homogenous forest loss areas. This occurred by the merging of tree clusters in forest loss areas. LCFD analyses of forest loss areas showed that connectivity was directly proportional to the expansion of forest loss areas and also to the degree of homogeneity of the tree cover area clustering.

We have shown that LCFD might also be useful in assessing the local variations in complexity for forest loss areas or regeneration, unlike the global fractal dimension approach used in previous studies.

FFI analysis was used for determining the extent of forest fragmentation. Dynamics of FFI showed that the trend in forest loss areas clustering is based on their spatial extensions, especially after 2005 and that forest loss...
areas were less influenced by fragmentation compared to regeneration. Moreover, in this study we provide a substantial improvement in FFI’s ability to quantify fragmentation by correlating the results for the first time with fractal connectivity and particle analysis of binary images.

We have already reported that mountainous, well-forested counties have a low degree of forest fragmentation, with the FFI of 0.13, which was 0.08 higher compared to hilly counties with less forest.

Another recent study has shown a high degree of fragmentation in 2014 of forests in Maramures County with FFI of 0.09. Drăghici et al. (2017) reported a lower degree of fragmentation for the Northern Carpathian Mountains of Romania, with FFI of 0.11 in 2014 compared to the current results. Higher FFI values for the Apsen Mountains of 0.15 in 2014 were found in the current study. This indicates that the forests of the Apsen Mountains compared to the Northern Carpathian Mountains of Romania or the Maramures and Suceava counties still have a low degree of fragmentation despite the widespread emergence of forest loss areas in the period between 2000–2014. The results are clearly different due to the different patterns of deforestation, the greater severity of deforestation in the northern counties of Maramures and Suceava, together with the presence of several protected areas in the Apsen Mountains, which are very compact.

Previous studies have shown that the largest increase of forest fragmentation occurred during the most aggressive loss area expansion in Romania: in Suceava County FFI was 0.06, followed by 0.04 in the Northern Carpathian Mountains and 0.02 in Maramures County. With the same reference range and use of new images, we now report a FFI reduction of 0.03 calculated for the Apsen Mountains, comparable to that for Maramures County. This was due to only 3.8% of the tree cover being lost between 2000 to 2014. Previously, it was reported that for the same period Maramures County lost 5.06% of the tree cover, the Nordic Group 6.75%, while Suceava County lost 9.5%.

Another limitation of fractal analysis is that represents the years of cumulative forest cover loss event from 2001 to 2014 compared to year 2000.
and one image of year of cumulative forest cover loss event. For the gain areas only cumulative regeneration from 2001 to 2014 for each year was analyzed33.

The three images were post processed by GIS methods (reprojecting the images from WGS84 to Stereo70, the national coordinate system, to obtain metric results) by extracting a subset of the study area from each image and computing the loss area in meters for each year between 2000 and 2014. The pixel resolution for each image was about 30 m. Both Figs 2 and 4 were firstly generated with QuantumGIS (Version 2.2.0 available at http://download.osgeo.org/qgis/windows/). For image stacking in Fig. 2 was used ImageJ Fractal software, and for cartographic layout in Fig. 4 Inkscape (0.48.2) was used after the main images were made in QuantumGIS. The Administrative boundaries were downloaded from the Romanian Authority which reports data to Eurostat (European Statistical Office) from which both national boundaries and European countries border were downloaded.

GIS methods were used to extract vector data from the metric projected images in GeoTIFF format with 30 m resolution from the Global Forest Change 2000–2014 database and to create grayscale TIFF images. The images were produced by keeping the same scale, orientation, chromatic and exporting resolution from the vector data classified for each loss year. Keeping the mentioned parameters, the fractal analysis is more precise. The 14 TIFF images exported from the initial data were automatically binarized using ImageJ 1.51p software (Wayne Rasband, National Institute of Health, USA, 1997)44,45.

Particle analysis. The loss and gain areas and their impact on the dynamics of forest fragmentation were investigated by particle analysis including particle count, size, and average size, where a particle refers to a forest patch. Gain areas were also evaluated. Particle counter plug-in of ImageJ was used for this analysis47.

Fractal analysis. Because the forests analysed here are morphologically complex, showing very often fragmented and non-uniform patterns and because the particle descriptors depend on the scale of observation48, the forest images were further examined by fractal analysis as this is a scale-invariant method. Fractal dimension (FD) as the main fractal parameter predominantly describes the degree of morphological complexity49.

Fractal Fragmentation Index ($\text{FFI}$) measures the fragmentation/compaction of the forest patches. Tug-of-War Lacunarity ($\Lambda_{T-o-W}$) was used to measure the degree of the heterogeneity, i.e. to investigate whether the forest patches are arranged chaotically or more regularly.

Local Connected Fractal Dimension ($\text{LCFD}$) is a fractal index of complexity, quantifying connectivity changes at varying scales. The relationship is expressed in (Eq. (1):)

$$M(\varepsilon) \propto F \varepsilon^{\text{LCFD}}$$

and (Eq. (2)):  

$$\text{LCFD} = \frac{\log[M(\varepsilon)]}{\log(\varepsilon)}$$

where F is a mass pre-factor, $M(\varepsilon)$ is the number of locally connected pixels (a connection with eight neighbors) in a side-by-side box $\varepsilon^{50}$. 

![Figure 4. Geographical study area of Apuseni Mountains (QGIS Development Team (2018). QGIS Geographic Information System. Open Source Geospatial Foundation Project. http://qgis.osgeo.org).](image-url)
The LCFD value equals 1.0 when the object is a one-dimensional straight line. LCFD equals 2.0 when the object is two-dimensional and completely covered. Pixels in the $8 \times 8$ environment of the seed pixel are considered to be connected. This basic rule is applied to find the set connected for a certain predetermined, arbitrary distance around the seed pixel.

LFD was computed using ImageJ software and FracLac 2016 Apr 12048 a 502 plugin.

The Fractal Fragmentation Index (FFI) provides information on the degree of fragmentation using the Box-Counting algorithm. FFI can be interpreted as a compaction index (Eq. (3)):

$$\text{FFI} = D_{BC} - D_{max} \frac{\log N(\epsilon)}{\log 2} - \frac{\log N' (\epsilon)}{\log 2}$$

where $D_{BC}$ is the fractal dimension of the summed-up areas, $D_{max}$ is the fractal dimension of the being the total number of boxes.

$V_{nom}$ $V_{min}$

According to a previous study of Andronache et al., FFI values close to 1.0 indicate compact objects, while FFI values approaching zero indicate very small and fragmented objects. $FFI = 0$ reflects a very small forest area, equal to the size of one pixel in an image with $D_{BC} = D_{max}$. $FFI$ was calculated by using the FFD plugin for the IQM 3.5 software.

While FFI quantifies how much compact or fragmented the space occupied by the forest is, the lacunarity quantifies how space is occupied. In order to assess the degree of heterogeneity of forest loss areas compared to gain areas and their effects on forest, the Tug-of-War lacunarities ($\Lambda$) were used. $\Lambda$ indicates the manner of forest loss areas where increasing values indicate a chaotic distribution of the forest loss areas and vice versa. $\Lambda(T-o-W)$ was calculated based on the equation (Eq. (4)):

$$\Lambda(T-o-W) = \frac{N(r)Z^2}{L^2}$$

with $N(r)$ being the total number of boxes.

$Z^2$ is the second moment for each width and is approximated by

$$Z^2 \approx \sum_{i=1}^{N(r)} p(r, i)^2$$

With $p(r, i)$ the number of occupied sites in the $i$-th box and finally, $L$ is approximated by the mean of the occupied sites by

$$L^2 \approx \left( \sum_{i=1}^{N(r)} p(r, i) \right)^2$$

Actually, $\Lambda(T-o-W)$ was calculated by using the Fractal 2D Dimension plugin for the IQM 3.2 software.

For a better graphic representation we used standardized values because particle and fractal analyses have different units and implicitly different maximum and minimum values. Standardization according to Eq. (7) allowed us to present results comparably and conveniently in a graphical format.

$$\text{Standard value} = \frac{V_{nom} - V_{min}}{V_{max} - V_{min}}$$

Where $V_{nom}$ = nominal value, $V_{max}$ = maximum value, $V_{min}$ = minimum value

Standardized values are between 0–1.0. Correlations were determined by computing the Spearman’s rank correlation coefficient.

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**Author Contributions**

Ion Andronache - fractal analysis, data analysis, preparation of final draft; Marian Marin and Rico Fischer - analysis tools, preparation of final draft; Helmut Ahammer, Marko Radulovic, Herbert F. Jelinek and Antonio Di Leva - analysis tools; fractal analysis, preparation of final draft; Ana-Maria Ciobotaru, Radu-Daniel Pintilii, Cristian-Constantin Drăghici, Grigore-Vasile Herman, Alexandru-Sabin Nicula, Daniel Constantin Diaconu - data analysis; Adrian-Gabriel Simion and Vlad Loghin - GIS analysis; Daniel Peptenatu - data analysis, institutional coordination, preparation of final draft. These authors contributed equally to this work.

**Additional Information**

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