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Research Article

Application of fractal analysis in interpreting 2D and 3D grayscale images: Methodologies and case studies

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Abstract

This study investigates the application and performance of several fractal analysis methods for interpreting complex spatial patterns in 2D and 3D grayscale images. Using synthetic datasets with known properties, we systematically evaluate the accuracy of multiple fractal metrics. Among these, Fast Fourier Transform (FFT) dimension and Higuchi dimension proved the most effective in capturing both isotropic and anisotropic structural complexity. The methods were then applied to case studies that address land use change, deforestation, reveal fragmentation patterns, and spatial heterogeneity. Notably, fractal metrics offer consistent and scalable tools for monitoring landscape transformations over time, providing valuable insights for environmental assessment and biodiversity conservation.

Key words: 2D surface analysis, 3D volumetric analysis, biodiversity conservation, deforestation, fractal analysis, land use and land cover (LULC), sustainable development, synthetic data

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1. Introduction

Fractal analysis has emerged as a valuable tool in geographical sciences due to its ability to characterize complexity and irregularity across spatial scales. Rooted in self-similarity and scale invariance (Mandelbrot 1983), fractal methods allow the quantification of spatial heterogeneity, fragmentation, and structural connectivity in natural and anthropogenic systems. These capabilities make fractal analysis indispensable for studying terrain irregularities (Mark and Aronson 1984), forest dynamics (Wu and Loucks 1995), and the spatial distribution of urban patterns and economic activities (Batty and Longley 1994).

In environmental contexts, fractal metrics have been used to investigate hydrological processes (Rodríguez-Iturbe and Rinaldo 2001; Diaconu et al. 2017; Andronache et al. 2019b), forest fragmentation (Andronache et al. 2019a), and temperature-humidity patterns affecting urban environments (Ciobotaru et al. 2019c). Their integration with remote sensing and GIS data enables an enhanced understanding of land use and land cover dynamics, aiding in ecological planning and biodiversity conservation (Sugihara and May 1990; Myint et al. 2004; Wu et al. 2013).

While previous studies have successfully applied fractal metrics to 2D spatial data for analyzing landscape fragmentation, hydrological patterns, or urban morphology, there remains a significant gap regarding systematic comparisons across methods and the inclusion of 3D volumetric analysis.

This study addresses that gap by proposing a comparative framework for evaluating multiple fractal techniques applied to both 2D and 3D grayscale images. The objectives are twofold: (i) to validate each method using synthetic datasets with known fractal properties, and (ii) to demonstrate their interpretive value through real-world case studies involving forest degradation and land use dynamics. A key innovation lies in the integration of 3D fractal analysis, offering a novel dimension for exploring structural complexity in geographical imagery.

By combining theoretical consistency with real-world relevance, this research highlights the potential of fractal analysis as a diagnostic and predictive tool in environmental studies. Its application may support the monitoring of landscape changes, assessment of spatial connectivity, and formulation of sustainable territorial development policies.

2. Theoretical framework

Fractal geometry provides a robust mathematical foundation for analyzing irregular and complex spatial patterns. Among the most widely used fractal metrics in image analysis are fractal dimension, lacunarity, and succolarity, each capturing a different aspect of spatial complexity (Mandelbrot 1983).

Fractal dimension (FD) is a scalar measure that quantifies the degree of space-filling capacity of an object or pattern. It is beneficial for assessing the structural complexity of natural features such as coastlines, forest edges, and river networks. In image analysis, FD helps characterize texture, roughness, and heterogeneity within grayscale images (Shanmugavadivu and Sivakumar 2012).

Lacunarity (Λ), a complementary measure to fractal dimension, provides insights into the texture and gaps within spatial structures. It helps differentiate between patterns that may have the same FD but different distributions of voids or heterogeneities. High lacunarity indicates a heterogeneous pattern with an uneven distribution of gaps, while low lacunarity corresponds to more homogeneous patterns (Plotnick et al. 1993; Reljin et al. 2000).

Succolarity is a fractal analysis metric that assesses the potential for movement or flow within a binary structure. It estimates the ability of a substance or agent to percolate through the spatial configuration, considering both connectivity and resistance. Succolarity is a metric that applies exclusively to binary images. It is conceptually mentioned here for completeness (De Melo and Conci 2013; Andronache 2024a), but it is not computed or analyzed in this study, which focuses strictly on grayscale image processing. However, it does not constitute a focus of the present study, which centers exclusively on grayscale image analysis.

Grayscale images are preferred in fractal analysis due to several key advantages. Representing intensity values through a single channel reduces data dimensionality and minimizes redundancy in color images, often including overlapping spectral information. This simplification leads to lower computational costs and facilitates more accurate quantification of self-similarity and spatial complexity (Aptoula and Lefèvre 2007, 2011; Gonzalez and Woods 2017). Fur-

thermore, grayscale images allow the direct application of fractal measures to pixel intensity variations, which is, often sufficient for detecting spatial heterogeneity and structural connectivity in geographical and ecological contexts.

These concepts—fractal dimension, lacunarity, and succolarity—are applied throughout this study to analyze spatial patterns in synthetic and real-world datasets. By quantifying texture, void distribution, and connectivity, fractal measures provide a nuanced understanding of spatial complexity. Their specific applications are illustrated in the subsequent case studies, demonstrating how each metric captures distinct aspects of structural organization in different geographical contexts (Svynchuk et al. 2021; Khudaiberdiev et al. 2024).

3. Methodology

3.1. Description of the datasets used

This section describes the datasets employed for fractal analysis, including synthetic images generated under controlled conditions and real-world images derived from geospatial sources.

The Gaussian, Random, Fractal Surface Fast Fourier Transform (FFT), and Fractal Surface Midpoint Displacement Method (MPD) datasets were generated using the ComsystanJ plugin collection (Ahammer et al. 2023) for Fiji/ImageJ2 software (Schindelin et al. 2012), employing the 2D Image Generator and 3D Image Generator modules. Two distinct generation methods were applied: the Fourier Transform for Fractal Surface FFT, which adjusts the frequency spectrum to ensure structural homogeneity, and the MPD, which creates surfaces exhibiting self-similarity properties. These datasets were selected based on their ability to isolate key structural properties, such as anisotropy, scale invariance, and noise sensitivity, providing a robust foundation for both validation and real-world transferability of fractal metrics. Moreover, they constitute a rigorously controlled experimental framework that supports the methodological calibration of fractal approaches and enables investigation of the relationships between fractal dimensions and the analyzed parameters.

The synthetic images were designed with controlled FD values ranging from 2.0 to 3.0 in 0.1 increments for 2D images, featuring resolutions of 512×512 pixels. For 3D volumes, the controlled FD values ranged from 3.0 to 4.0 in 0.1 increments, with resolutions of 256×256×256 voxels. This design enables comprehensive analysis and validation of fractal algorithms across both 2D and 3D spatial scales.

The overall analytical workflow, from image preprocessing to the interpretation of fractal measures in spatial case studies, is illustrated schematically in Fig. 1. These images were subjected to evaluation using a broad set of fractal metrics, organized into four distinct methodological categories as illustrated in Fig. 2:

- Space-covering methods (e.g., box-counting—ComsystanJ, Sasaki, FracLac; cube counting; triangulation; partitioning; Minkowski dimension),
- Distance- and correlation-based methods (e.g., mass-radius, mass vs. distance, correlation dimension, directional correlation),
- Frequency- and signal-transform methods (e.g., FFT dimension, Higuchi 1D/2D, power spectrum),

- Complementary texture and heterogeneity measures (e.g., lacunarity—Roy and Perfect (2014), Sengupta and Vinoy (2006)).

These categories reflect diverse analytical perspectives, enabling a comprehensive understanding of structural complexity in synthetic data. The complete experimental design for 3D volumes (FD 3.0 to 4.0) follows the same principles and is discussed in the following sections.

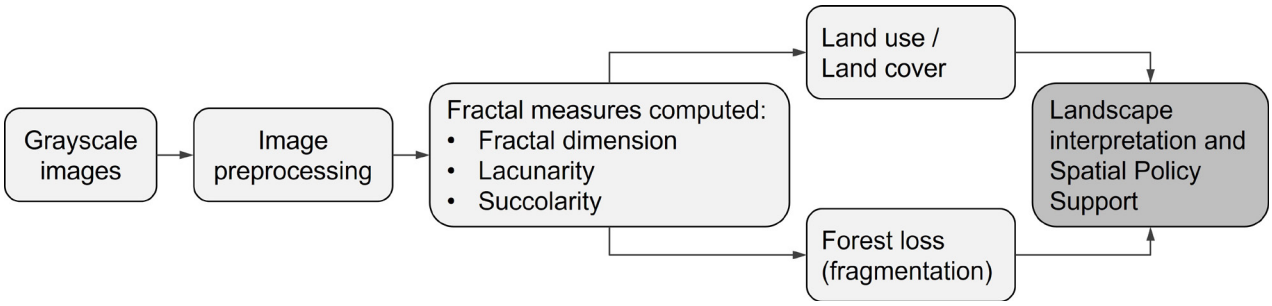

Figure 1. Schematic representation of the spatial analysis process using fractal metrics applied to grayscale images. The workflow illustrates the key steps, from image acquisition and preprocessing to interpreting structural patterns in environmental and land use change case studies.

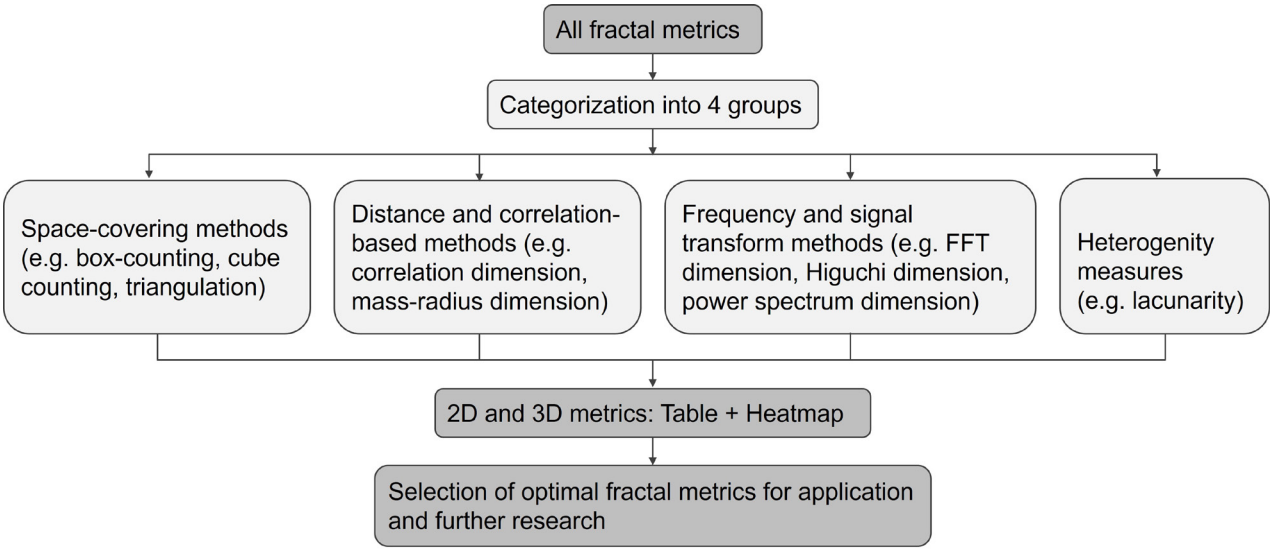

Figure 2. Flowchart illustrates fractal metrics' classification into four methodological categories used for synthetic 2D and 3D image analysis.

In addition to synthetic data, real-world images from applied studies in forestry (Ciobotaru et al. 2019a, 2019b) and the analysis of Byzantine icons (Peptenatu et al. 2022) were processed as raster images. For tree cover dynamics, data were sourced from remote sensing, utilizing Sentinel-2 imagery (Korah et al. 2024) and the Global Forest Change dataset (Hansen et al. 2013), with resolutions ranging from 10 to 30 meters. These datasets illustrate spatial and temporal variations in vegetation cover, highlighting ecological structures and processes across multiple scales. For land use/land cover (LULC) analysis, maps derived from remote sensing and GIS databases were used, with resolutions

between 30 and 100 meters, classifying land types (urban, agricultural, and forested areas). These maps were processed to differentiate classes through variations in grayscale tones (Olorunfemi et al. 2020; Fonseca et al. 2021).

By integrating synthetic and selected real-world data, fractal analysis can be applied rigorously across disciplines. Synthetic data offers a controlled experimental framework for validating methodologies, while ecological and landscape data demonstrate the applicability of the approach in interpreting complex spatial distributions in natural systems. These datasets contribute to a deeper understanding of spatial relationships and dynamics across diverse geographical contexts. Building on this foundation, the next step involves meticulous image preprocessing to ensure the accuracy and reliability of the derived fractal measures.

3.2. Image processing procedures

This section outlines the essential steps involved in image preprocessing, a critical phase in the application of fractal analysis, which ensures the validity of results by optimizing images for subsequent analysis. The procedures include grayscale conversion, noise filtering, normalization, resolution resizing, segmentation, and preprocessing quality assessment.

3.2.1. Grayscale conversion

Grayscale conversion simplifies image representation by removing color information that may introduce redundancies. This conversion ensures an appropriate representation of spatial structures, where variations in grayscale intensity can be analyzed fractally to characterize roughness, complexity, and spatial distributions (Aptoula and Lefèvre 2011; Panigrahy et al. 2020).

3.2.2. Noise filtering

Noise filtering is necessary to remove distortions that may influence the calculation of fractal dimensions. Noise, introduced by sensors or data acquisition methods, is mitigated using appropriate filters. Gaussian filters reduce fine details and high-frequency noise while preserving the primary structures of the image (Gonzalez and Woods 2018). Median filters eliminate salt-and-pepper noise without compromising object edges (Tomasi and Manduchi 1998). This filtering is particularly applied to remote sensing images and synthetic datasets, where noise can significantly affect fractal interpretations.

3.2.3. Normalization

Normalization aims to bring images to a unified pixel intensity scale, facilitating comparability between different images. This includes rescaling pixel values (e.g., to the 0–255 range for 8-bit images) and adjusting contrast through histogram equalization or contrast stretching (Parker 2011). Normalization is significant for real-world images with variations in illumination and contrast, such as those associated with tree cover or land use, ensuring uniformity of data for fractal analysis.

3.2.4. Resizing and resolution standardization

Resizing and resolution standardization are critical preprocessing steps to ensure comparability of images with varying spatial resolutions. Remote sensing images, such as Sentinel-2 (10 m) or Landsat (30 m), require resampling techniques like bilinear or cubic interpolation to achieve a standardized resolution. Resolution uniformity is essential for comparing fractal parameters across different datasets (Chen et al. 2023).

3.2.5. Preprocessing quality assessment

Finally, a preprocessing quality assessment is performed to validate the applied steps and ensure the integrity of processed data. Methods include visual inspections, histogram analyses, and the Signal-to-Noise Ratio (SNR) calculation to evaluate image fidelity (Sharma et al. 2025). These checks are essential for confirming image accuracy before applying fractal analysis. The overall sequence and role of each step in the preprocessing workflow are summarized in Table 1.

Table 1. Overview of preprocessing procedures and their functions in the context of fractal image analysis.

Preprocessing step	Purpose
Grayscale conversion	Simplifies image channels and enhances fractal interpretation
Noise filtering	Reduces distortions from sensors or simulation noise
Normalization	Standardizes intensity and contrast for inter-image comparability
Resolution resizing	Ensures spatial consistency across datasets with different resolutions
Preprocessing quality check	Validates image integrity before applying fractal measures

Precise and reproducible results can be achieved through rigorous preprocessing, including filtering, normalization, resizing, and quality validation. These steps ensure the practical application of fractal analysis to synthetic and real-world images. Having established a consistent and accurate preprocessing foundation, the next phase involves calculating fractal measures, which constitutes the core of the analytical workflow.

3.3. Calculation of fractal measures

This part outlines the procedure for determining fractal measures, a central step in fractal image analysis aimed at quantifying the complexity and self-similarity of spatial structures. The methods described below were selected to support theoretical comparison and practical application across synthetic and real-world datasets. Not all techniques were applied uniformly; each was used where appropriate based on the image type (2D or 3D) and context (e.g., synthetic or ecological data). The main measures analyzed include fractal dimension and complementary metrics such as lacunarity and succolarity, each offering distinct insights into the spatial characteristics of images (De Melo and Conci 2013; Andronache 2024a). Notably, 3D fractal analyses are obtained as direct expansions of 2D algorithms.

3.3.1. Fractal dimension

The fractal dimension (FD) is the primary metric used to characterize the complexity and self-similarity of an image or surface. It describes how a structure occupies space across different observation scales and can be calculated through various methods:

- Differential box-counting: An adaptation of the traditional box-counting method, incorporating grayscale intensity and spatial coordinates. The slope of the logarithmic plot of sums against box sizes is used for FD calculation (Sarkar and Chaudhuri 1992; Jin et al. 1995).
- Correlation dimension: Measures fractal complexity by evaluating grayscale pixel values as a distance function. The slope of a linear regression on a double-logarithmic plot provides this dimension (Grassberger and Procaccia 1983). A directional correlation extension analyzes textures along specific directions (e.g., horizontal, vertical, radial), offering detailed insights into the orientation and structure of objects.
- FFT dimension (Fast Fourier Transform): Analyzes fractal complexity based on frequency spectrum transformations, with the slope of the logarithmic power spectrum defining FD (Anguiano et al. 1993).
- Higuchi dimension: Applied in 1D and 2D, this method calculates FD using grayscale differences along rows, columns, or surfaces for global complexity measures (Ahammer 2011; Ahammer et al. 2015; Spasić 2014).
- Minkowski dimension: This dimension uses morphological dilations to treat grayscale images as 3D surfaces, where pixel intensities represent elevation. The slope of the logarithmic plot of dilated volumes versus distances defines FD (Dubuc et al. 1989).
- Cube counting and Triangulation: Evaluates FD by counting cubes required to cover the surface at various scales or through triangulation networks, offering insights into spatial distribution and fragmentation (Douketis et al. 1995; Zahn and Zösch 1999).
- Variance (Partitioning): Analyzes surface variation by dividing the image into square boxes and evaluating their heterogeneity. This method is beneficial for identifying patterns and distributions within textures (Van Put et al. 1994; Mannelquist et al. 1998).
- Power spectrum: Examines the frequency distribution by analyzing the power spectrum of image profiles, providing insights into dominant frequencies and their complexity (Van Put et al. 1994; Zahn and Zösch 1997; Mannelquist et al. 1998).
- Structure Function (HHCF): Extends power spectral analysis by quantifying height–height correlations, making it well-suited for assessing surface irregularities and spatial continuity (Van Put et al. 1994; Mannelquist et al. 1998).

These methods provide robust tools for analyzing complex textures and spatial distributions, offering complementary perspectives on ecological and geographical surface studies.

3.3.2. Lacunarity

Lacunarity quantifies the spatial distribution of voids and the degree of heterogeneity in an image by analyzing grayscale intensities within variably sized box-

es. Unlike fractal dimension, which focuses on self-similarity, lacunarity characterizes the "fullness", heterogeneity, and texture of a structure across different scales (Allain and Cloitre 1991; Dale 2000; Sengupta and Vinoy 2006; Roy and Perfect 2014). This metric is particularly relevant for analyzing textured images and fractal surfaces generated using the midpoint displacement method.

3.3.3. Succolarity

Succolarity measures the connectivity of spatial structures and complements the fractal dimension (Mandelbrot 1983; De Melo and Conci 2008). It evaluates how well the regions of an image are interconnected, making it useful for analyzing complex networks such as tree cover distributions or natural surface morphologies (Andronache 2024a). Succolarity only applies to binary images and is therefore not included in the analyses presented in this study. It is mentioned here solely for theoretical context and completeness.

The successful calculation of fractal measures relies not only on theoretical frameworks but also on the appropriate selection and application of computational tools. These tools facilitate the practical implementation of fractal methodologies, enabling accurate and efficient analysis of synthetic and real-world datasets. The following section discusses the specialized software employed for this purpose.

3.4. Software tools

A range of specialized software tools was employed for fractal analysis to ensure methodological versatility and computational accuracy. These tools support 2D and 3D processing, grayscale image handling, and customized algorithm development. Rather than listing each tool in narrative form, Table 2 provides a comparative overview of the software utilized in this study, highlighting their core functionalities, applicable image types, and distinctive features relevant to 2D and 3D fractal analysis.

These tools ensure robust and versatile fractal analysis across synthetic and real-world datasets, supporting research in ecology, geospatial studies, and more. The capabilities of these software tools not only facilitate the calculation of fractal measures but also underscore the importance of these metrics in uncovering intricate spatial patterns. With a solid computational foundation, the next step is to explore how fractal measures contribute to a deeper understanding of structural complexity and spatial distribution across diverse datasets.

3.5. Relevance of fractal measures

Fractal dimensions and complementary metrics such as lacunarity and succolarity allow a deeper understanding of spatial patterns and irregularities. Combined with advanced software tools, these measures enable precise interpretations of synthetic and real-world images, revealing undetectable patterns and structures through conventional approaches (Andronache et al. 2019a). Building on the significance of fractal measures, their practical utility can be demonstrated through specific applications. Selected case studies demonstrate how these measures, in conjunction with advanced methodologies, help interpret complex spatial distributions across synthetic and real-world datasets.

Table 2. Comparative summary of software tools used for fractal analysis, including central functions, image types, and specific features.

Software Tool	Main functions	Image type	Key features	Reference
Fiji/ImageJ2 + FracLac, ComsystanJ	Fractal dimension, lacunarity, succolarity, synthetic image generation	2D/3D	Plugins for automated analysis	Schindelin et al. 2012; Karperien 2013; Ahammer et al. 2023
MATLAB & Python (OpenCV, skimage)	Fractal dimension, lacunarity, succolarity	2D/3D	Customizable and script-based	The MathWorks Inc. 2022; Python Software Foundation 2024
ArcGIS / QGIS	Spatial integration of fractal metrics	Real-world	GIS support for mapping and overlays	Environmental Systems Research Institute 2020; QGIS Development Team 2024
Gwyddion	Cube counting, triangulation, power spectrum, variance (partitioning) method	2D	Open-source, SPM-compatible	Nečas and Klapetek 2012
FASW (Fractal Analysis System for Windows)	Box-counting fractal dimension	2D	Classic tool, legacy use	Sasaki et al. 1994

3.6. Case studies

These examples illustrate the application and validation of fractal metrics across both synthetic and real-world datasets, demonstrating their utility in analyzing complex spatial distributions.

3.6.1. Testing fractal metrics with synthetic images

This study validates fractal metrics using synthetic 2D images (Fig. 3) and 3D volumes (Fig. 4) generated with ComsystanJ. Fig. 5 presents 3D surface plots of the synthetic volumes for enhanced visualisation, using Thermal LUT to highlight the controlled fractal dimensions. The datasets, created with controlled fractal dimensions (FD = 2.0–3.0 for 2D images and FD = 3.0–4.0 for 3D volumes), employ Fractal Surface FFT and MPD methods.

These controlled conditions facilitate a precise evaluation of the relationship between theoretical fractal dimensions and the values calculated using various methods:

- 2D metrics: Differential box-counting, correlation dimension, directional correlation, FFT, Higuchi 1D and 2D, Minkowski, cube counting, triangulation, variance (partitioning), power spectrum, structure-function (HHCF), and lacunarity.
- 3D metrics: Extensions of the 2D algorithms for volumetric images, including correlation dimension, FFT, Higuchi 3D, Minkowski, and lacunarity.

Results provide a reference framework for applying fractal analysis to real-world data, aiding in the calibration of algorithms and the validation of fractal measures.

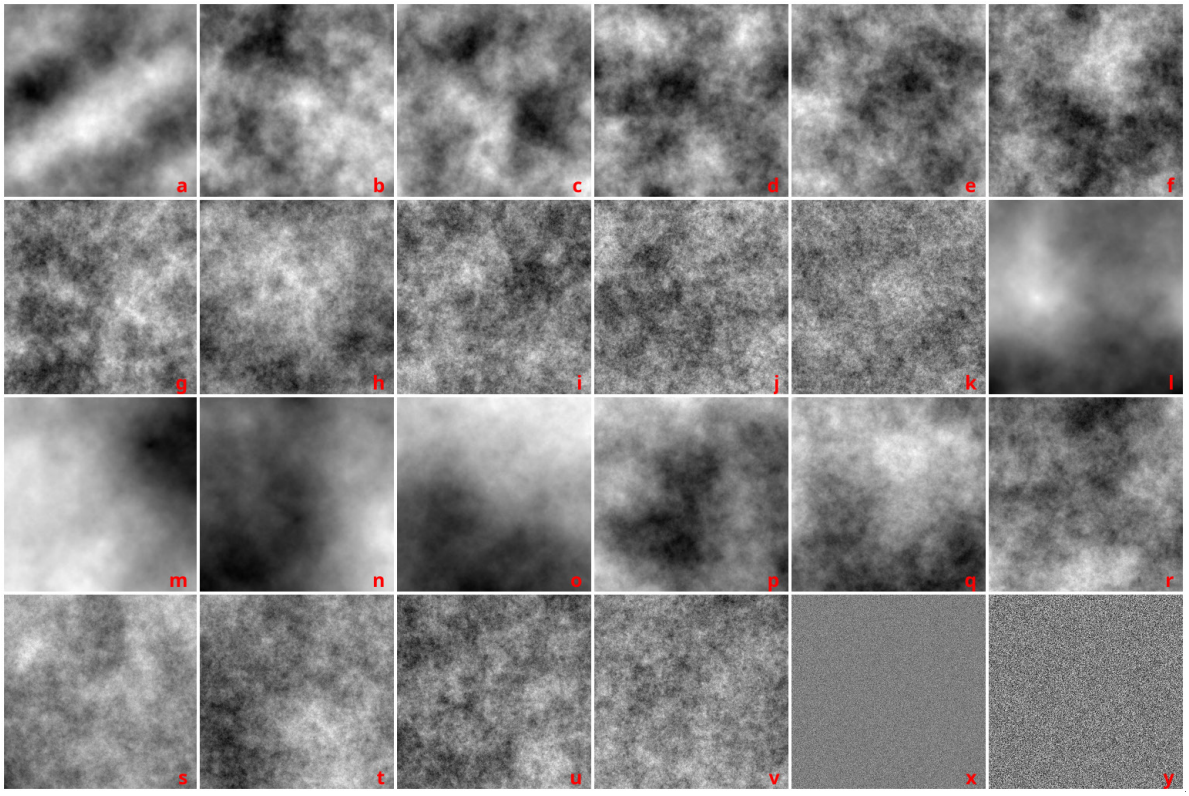

Figure 3. 2D synthetic surfaces with controlled fractal dimensions (FD 2.0–3.0), visualized for FFT (a–k), MPD (l–v), Gaussian (x), and Random (y).

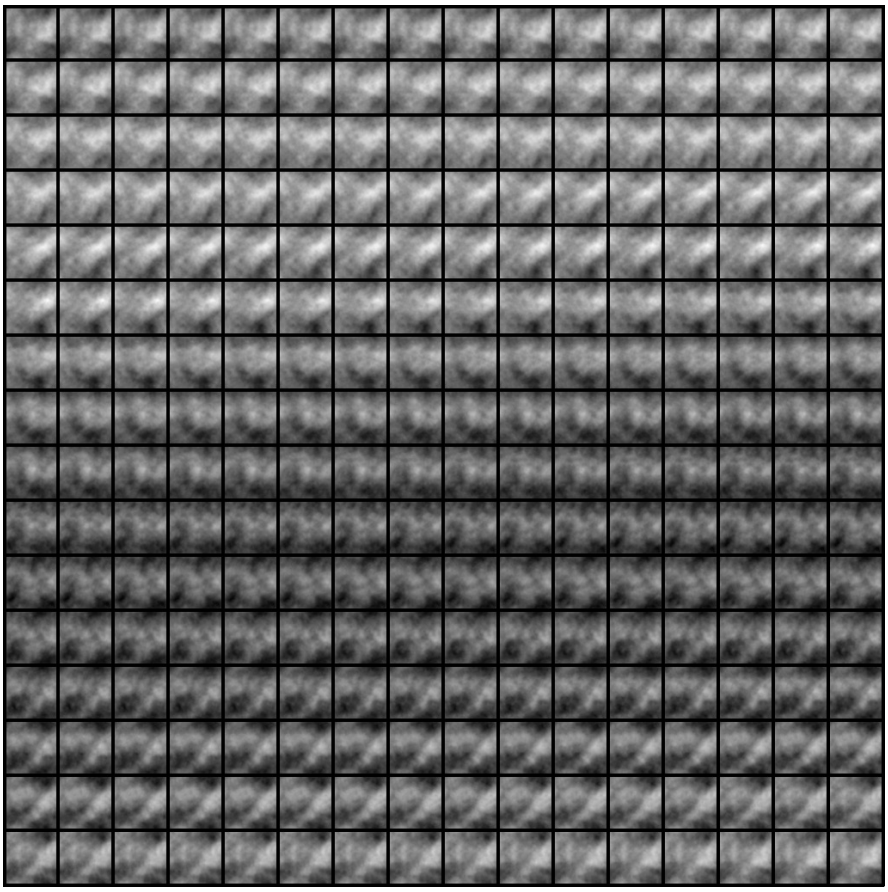

Figure 4. 3D slices of a synthetic volume with controlled fractal dimension (FFT = 3.0).

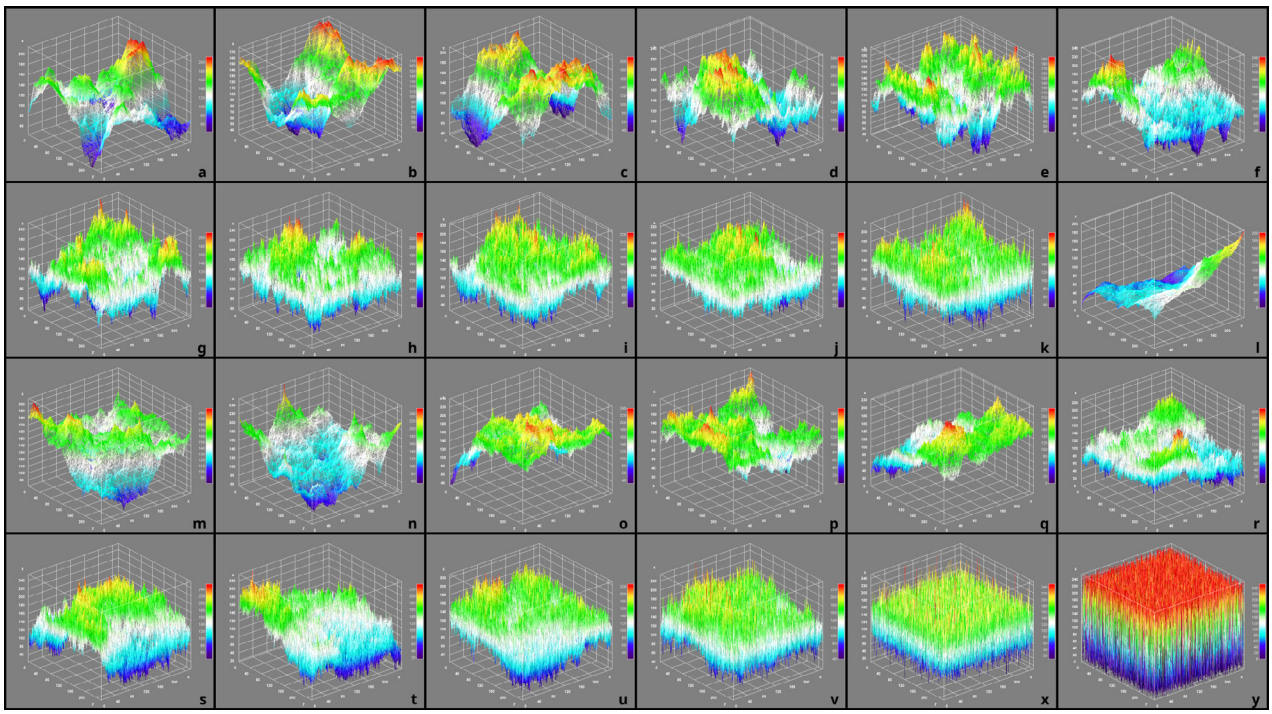

Figure 5. 3D surface plot of synthetic volumes with controlled fractal dimensions (FD 3.0–4.0), visualized using thermal LUT: FFT (a–k), MPD (l–v), Gaussian (x), and Random (y).

3.6.2. Deforestation analysis in mountain areas of Romania

Fractal analysis of grayscale images was applied to identify and characterize spatial patterns of deforestation using raster data reflecting tree cover, loss areas, and cumulative loss areas in two mountain regions: the Parâng Mountains Group of the Southern Carpathians (Simion et al. 2021) and the Curvature Mountains Group of the Eastern Carpathians (Ciobotaru et al. 2019b). The data from the Global Forest Change (GFC) database (Hansen et al. 2013) were processed in grayscale to facilitate fractal analysis. Metrics enabled the assessment of forest landscape fragmentation and provided insights into structural and ecological differences between the two regions. The findings align with known ecological trends in increased forest fragmentation in the Carpathians and its adverse effects on biodiversity and habitat connectivity. As such, fractal analysis can contribute to conservation planning by identifying priority areas for ecological restoration or protection.

3.6.3. Land use analysis

Fractal methods were conducted on LULC imagery obtained from GIS maps and remote sensing data (Liang et al. 2013). Land use classes such as urban, agricultural, forested, and aquatic areas were processed and transformed into grayscale images. Metrics like fractal dimension and lacunarity were used to assess land use patterns' fragmentation and spatial complexity. Fractal measures complemented traditional GIS classification by revealing the underlying structural organization and heterogeneity, which are often overlooked in con-

ventional thematic maps. This analysis identified structural landscape changes, evaluated urbanization processes, and assessed their environmental impact.

Each case study underscores the versatility of fractal analysis in both synthetic image evaluation and real-world applications. This approach highlights the potential of fractal methodologies in interpreting complex spatial distributions across domains such as ecology and natural resource management. The case studies presented demonstrate the versatility and effectiveness of fractal analysis across synthetic and real-world datasets. Building on these findings, the following section delves into a detailed interpretation of the results, exploring the implications and relevance of fractal measures in various contexts and their potential to advance understanding of spatial and structural complexities.

4. Results and discussion

This section presents the results of fractal analysis applied to synthetic images and real datasets, including detailed interpretations and discussions regarding their relevance in ecological and spatial contexts. The analyses are structured according to the cases studied and aligned with theoretical expectations.

Fractal metrics were evaluated for their ability to capture texture complexity, periodicity, self-similarity, and spatial heterogeneity across different image types. Particular attention is given to the performance of each method, highlighting the most accurate and robust estimators while discussing their specific strengths and limitations.

4.1. Validation of fractal metrics using synthetic 2D images

Tables 3 and 4 present the performance of fractal metrics applied to synthetic 2D images (FFT, MPD, Gaussian, and Random) with controlled FD ranging from 2.0 to 3.0. The analysis included differential box-counting (DBC), mass-radius dimension, mass vs. distance dimension, correlation dimension, FFT dimension, Higuchi 1D/2D, lacunarity, Minkowski dimension, partitioning, cube-counting, triangulation, and power spectrum. These metrics were computed using multiple platforms, including ComsystanJ, FracLac (both for Fiji/ImageJ2), and Gwyddion.

Among the best-performing methods, FFT dimension, Higuchi 2D, cube counting, and power spectrum provided the most reliable results. FFT dimension closely matched theoretical FD values and effectively captured periodicity and isotropic texture complexity. Higuchi 2D was particularly effective for detailed bidimensional textures. Cube counting reflected multiscale complexity, especially for fragmented MPD textures, while power spectrum highlighted dominant frequencies, aiding complex texture detection.

Partitioning and triangulation also showed strong performance: the former captured heterogeneity, while the latter provided insights into topological complexity. Lacunarity added a complementary layer by distinguishing between homogeneous (FFT, Gaussian) and fragmented (MPD, Random) patterns. Lower lacunarity values aligned with uniform distributions, and higher values indicated spatial discontinuity.

Minkowski dimension proved suitable for global structural assessment, aligning well with the progression of FD. Correlation dimension, while accu-

rate for Gaussian and Random textures, was less sensitive to incremental FD changes. Similarly, mass-radius and Higuchi 1D showed reduced responsiveness to local fragmentation, often underestimating FD in irregular textures.

We examined the internal consistency and inter-category correlations across the four metric groups to further explore the relationships among the evaluated methods. These results validate the utility of fractal metrics as quantitative, objective tools for capturing structural complexity in synthetic environments (Fig. 6).

The results showed strong internal consistency within each category, with high intercorrelation metrics. For example, the three box-counting variants (ComsystanJ, Sasaki, FracLac) exhibited Pearson coefficients above 0.97, while frequency-based metrics (FFT, Higuchi 1D/2D, power spectrum) showed correlations ranging from 0.90 to 0.96.

In contrast, inter-category correlations were considerably lower. In some cases, notably involving lacunarity, correlations were negative. For instance, Roy and Perfect lacunarity was negatively correlated with FracLac box-count-

Table 3. Performance of fractal metrics applied to synthetic 2D images with controlled FD (part I).

Synthetic 2D images / fractal metrics	ComsystanJ differential box-counting	Sasaki differential box-counting	FracLac differential box-counting	Mass radius dimension	Mass vs. distance	Correlation dimension	Directional correlation dimension	FFT dimension
FFT 2.0	2.098	2.0792	2.5627	1.98288	1.6213	1.983	1.921	2.437
FFT 2.1	2.184	2.1923	2.6129	1.94735	1.6584	1.986	1.921	2.241
FFT 2.2	2.193	2.1825	2.6024	1.99752	1.6819	1.984	1.920	2.289
FFT 2.3	2.249	2.2783	2.6251	2.28171	1.7492	1.982	1.919	2.342
FFT 2.4	2.277	2.3375	2.6564	2.13755	1.701	1.986	1.919	2.431
FFT 2.5	2.308	2.3722	2.665	2.05769	1.7842	1.982	1.920	2.524
FFT 2.6	2.378	2.458	2.7081	2.05135	1.7968	1.989	1.921	2.607
FFT 2.7	2.385	2.4719	2.6954	1.96976	1.7808	1.988	1.922	2.703
FFT 2.8	2.463	2.564	2.7423	2.06609	1.8121	1.989	1.920	2.803
FFT 2.9	2.508	2.629	2.761	2.01928	1.8214	1.990	1.919	2.897
FFT 3.0	2.531	2.6676	2.7721	2.05392	1.8119	1.993	1.921	3.004
MPD 2.0	2.100	2.0162	2.4946	2.01808	1.5855	1.983	1.922	2.895
MPD 2.1	2.048	2.0475	2.5097	2.01592	1.5591	1.985	1.921	2.883
MPD 2.2	2.143	2.0936	2.5215	2.06296	1.5434	1.974	1.919	2.881
MPD 2.3	2.181	2.1292	2.5404	2.00333	1.6158	1.978	1.920	2.876
MPD 2.4	2.234	2.2487	2.6099	2.16074	1.6924	1.980	1.917	2.906
MPD 2.5	2.377	2.347	2.6496	2.01664	1.7206	1.985	1.922	2.970
MPD 2.6	2.369	2.432	2.6858	2.07782	1.7595	1.987	1.920	3.028
MPD 2.7	2.392	2.490	2.7122	2.03192	1.7948	1.995	1.921	3.078
MPD 2.8	2.460	2.589	2.7384	2.05741	1.808	1.990	1.921	3.137
MPD 2.9	2.529	2.667	2.7675	2.07421	1.8293	1.989	1.921	3.183
MPD 3.0	2.562	2.714	2.7813	2.0353	1.8744	1.993	1.921	3.236
Gaussian	2.691	2.845	2.8254	2.05442	1.9161	1.995	1.921	3.977
Random	2.832	2.924	2.8863	2.39147	1.9902	1.971	1.920	3.982

Table 4. Performance of fractal metrics applied to synthetic 2D images with controlled FD (part II).

Synthetic 2D images / fractal metrics	Higuchi 1D dimension	Higuchi 2D dimension	Roy and Perfect lacunarity	Sengupta and Vinoy lacunarity	Minkowski dimension	Partitioning method	Cube counting	Triangulation method	Power spectrum
FFT 2.0	1.223	2.170	0.026	0.718	2.085	2.175	2.136	2.181	2.227
FFT 2.1	1.429	2.434	0.028	0.727	2.183	2.308	2.222	2.274	2.212
FFT 2.2	1.432	2.414	0.019	0.710	2.205	2.323	2.227	2.282	2.273
FFT 2.3	1.495	2.485	0.021	0.710	2.262	2.357	2.276	2.342	2.359
FFT 2.4	1.556	2.553	0.019	0.712	2.315	2.475	2.309	2.381	2.452
FFT 2.5	1.539	2.518	0.026	0.719	2.346	2.497	2.334	2.393	2.504
FFT 2.6	1.700	2.698	0.016	0.710	2.410	2.589	2.401	2.457	2.6
FFT 2.7	1.656	2.629	0.018	0.713	2.443	2.587	2.405	2.469	2.679
FFT 2.8	1.771	2.770	0.011	0.704	2.503	2.67	2.476	2.55	2.772
FFT 2.9	1.832	2.836	0.009	0.702	2.541	2.711	2.515	2.594	2.852
FFT 3.0	1.888	2.878	0.004	0.697	2.580	2.789	2.538	2.618	2.95
MPD 2.0	1.201	2.161	0.039	0.739	2.046	2.123	2.07	2.084	2.487
MPD 2.1	1.173	2.130	0.048	0.759	2.067	2.172	2.101	2.086	2.514
MPD 2.2	1.232	2.214	0.072	0.790	2.102	2.252	2.116	2.104	2.541
MPD 2.3	1.237	2.184	0.072	0.796	2.161	2.194	2.136	2.14	2.615
MPD 2.4	1.448	2.412	0.035	0.729	2.308	2.349	2.258	2.283	2.652
MPD 2.5	1.500	2.487	0.038	0.742	2.382	2.494	2.327	2.344	2.743
MPD 2.6	1.625	2.625	0.019	0.712	2.445	2.588	2.382	2.421	2.805
MPD 2.7	1.706	2.723	0.007	0.701	2.487	2.612	2.412	2.440	2.862
MPD 2.8	1.718	2.745	0.020	0.719	2.534	2.703	2.474	2.531	2.931
MPD 2.9	1.837	2.854	0.011	0.705	2.572	2.749	2.523	2.591	2.982
MPD 3.0	1.903	2.904	0.005	0.698	2.601	2.812	2.558	2.627	3.047
Gaussian	2.000	3.000	0.0002	0.694	2.720	2.970	2.687	2.734	3.501
Random	2.000	3.000	0.001	0.695	2.908	2.971	2.829	2.828	3.502

ing (-0.84) and Higuchi 2D (-0.85), reflecting that lacunarity captures aspects of structural heterogeneity not addressed by traditional complexity measures.

These findings highlight the distinct informational value of each metric category. Space-covering methods assess how a structure occupies space across scales, distance- and correlation-based methods describe distribution and spatial dependencies, frequency-based methods capture periodicity and irregularity, while complementary metrics (e.g., lacunarity) quantify structural homogeneity or fragmentation. Because each group characterizes a different spatial dimension, correlations between categories tend to be weaker, underscoring their complementarity rather than redundancy.

For example, within the space-covering category, strong correlations (Pearson > 0.9) were observed among box-counting, cube counting, and triangulation methods, which all measure space-filling properties at multiple scales. Conversely, the correlation between box-counting and FFT dimension (from different categories) was more moderate (typically 0.4–0.6), illustrating how FFT dimension captures spectral features such as dominant spatial frequencies not directly reflected by coverage-based metrics.

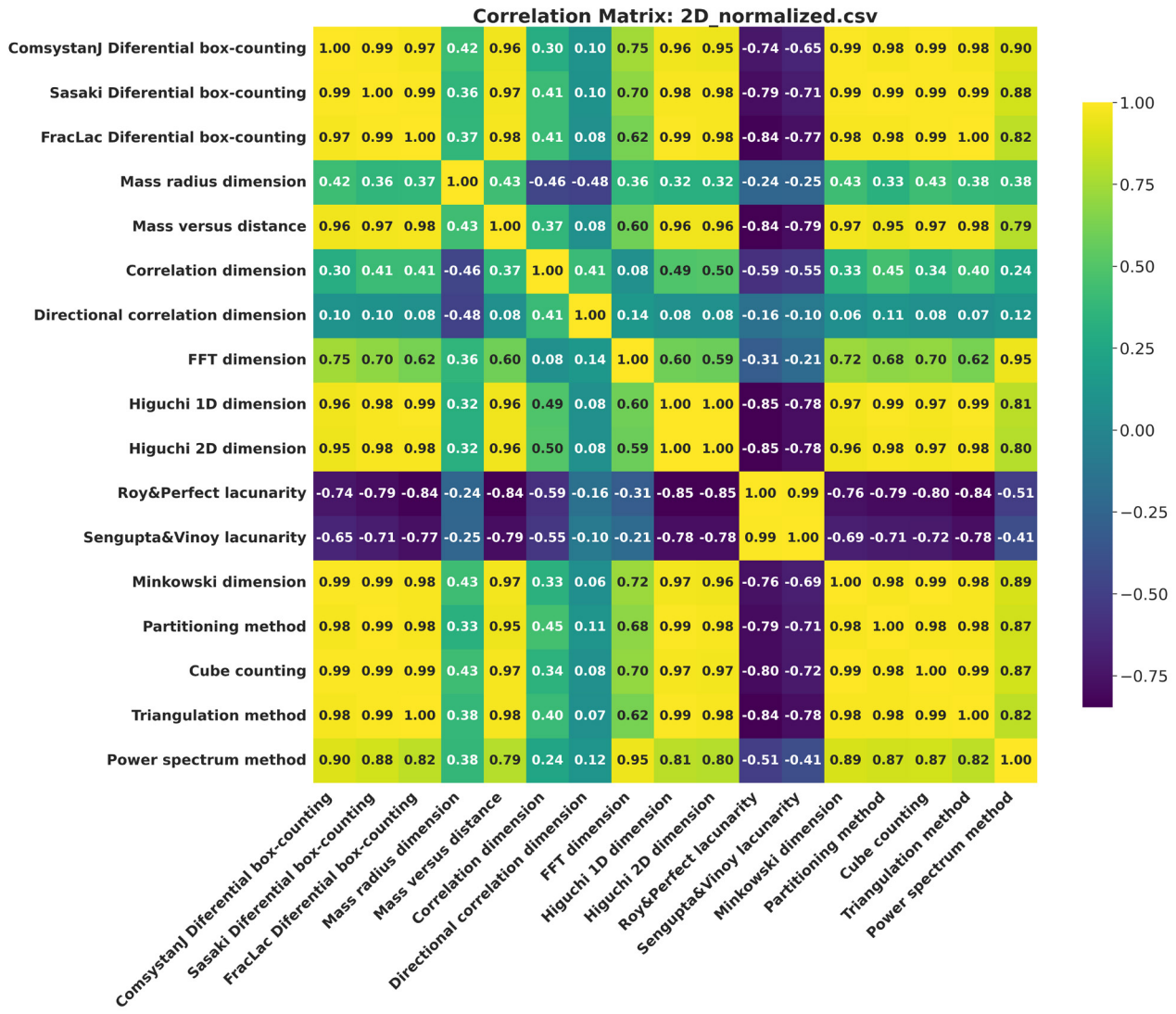

Figure 6. Correlation heatmap of fractal metrics computed on 2D synthetic images (FD = 2.0–3.0), grouped by methodological category.

Similarly, lacunarity (category 4) showed weak correlations with correlation dimension (category 2), as the former measures the distribution and size of gaps, while the latter focuses on pixel value distributions over distance. These examples reinforce the idea that each group of fractal metrics contributes uniquely to the overall understanding of spatial complexity.

Such a comparative perspective supports a more informed metric selection for applied analyses. The variability in sensitivity and precision across methods emphasizes the importance of context-specific selection when applying these measures to ecological or spatial datasets.

4.2. Validation of fractal metrics using synthetic 3D volumes

Table 5 summarizes fractal metrics applied to synthetic 3D volumes (FFT, MPD, Gaussian, and Random) with FD ranging from 3.0 to 4.0 in increments of 0.1. Among the evaluated methods, FFT dimension and Higuchi 3D dimension consistently excelled.

Table 5. Performance of fractal metrics applied to synthetic 3D volumes with controlled FD.

Synthetic 3D images / fractal metrics	Correlation dimension	FFT dimension	Higuchi 3D dimension	Roy and Perfect lacunarity	Sengupta and Vinoy lacunarity	Minkowski dimension
FFT 3.0	2.976	3.587	3.237	0.031	0.731	3.151
FFT 3.1	2.977	3.627	3.158	0.026	0.722	3.139
FFT 3.2	2.987	3.463	3.362	0.017	0.714	3.211
FFT 3.3	2.979	3.407	3.389	0.020	0.714	3.278
FFT 3.4	2.988	3.463	3.501	0.009	0.703	3.344
FFT 3.5	2.987	3.542	3.555	0.015	0.712	3.387
FFT 3.6	2.989	3.629	3.654	0.008	0.702	3.439
FFT 3.7	2.990	3.722	3.694	0.007	0.702	3.482
FFT 3.8	2.992	3.819	3.792	0.006	0.700	3.527
FFT 3.9	2.994	3.915	3.793	0.004	0.699	3.560
FFT 4.0	2.995	4.014	3.865	0.003	0.697	3.602
MPD 3.0	2.986	4.396	3.174	0.029	0.736	3.074
MPD 3.1	2.987	4.296	3.225	0.023	0.727	3.169
MPD 3.2	2.988	4.309	3.329	0.017	0.716	3.233
MPD 3.3	2.992	4.337	3.461	0.008	0.703	3.318
MPD 3.4	2.988	4.382	3.509	0.015	0.713	3.386
MPD 3.5	2.991	4.425	3.530	0.014	0.714	3.437
MPD 3.6	2.990	4.470	3.690	0.012	0.709	3.511
MPD 3.7	2.991	4.513	3.745	0.011	0.708	3.559
MPD 3.8	2.992	4.558	3.810	0.008	0.704	3.598
MPD 3.9	2.994	4.600	3.869	0.006	0.701	3.633
MPD 4.0	2.996	4.641	3.912	0.002	0.697	3.662
Gaussian	2.999	5.449	4.000	1.09E-04	0.695	3.760
Random	2.995	5.468	4.000	6.5069E-04	0.696	3.939

FFT dimension responded strongly to increasing FD, accurately capturing periodicity and spatial complexity in FFT and MPD volumes. Higher Gaussian and Random volumes values reflected their uniformity and higher spatial complexity. This method reliably differentiated between fragmented and homogeneous textures, making it versatile for various datasets.

Higuchi 3D dimension, a three-dimensional extension of its 2D counterpart, effectively captured fine details and structural variations. It characterised self-similar MPD and homogeneous Gaussian volumes, demonstrating robust sensitivity to FD changes and aligning with theoretical expectations.

Lacunarity (Roy and Perfect; Sengupta and Vinoy) effectively distinguished fragmented textures (FFT and MPD) from homogeneous ones (Gaussian and Random). For example, Roy and Perfect lacunarity values decreased from 0.03 (FD 3.0) to near-zero (FD 4.0) for FFT, indicating increasing uniformity. Near-zero lacunarity values for Gaussian and Random volumes confirmed their structural homogeneity.

Minkowski dimension effectively captured global roughness and complexity, progressively increasing values alongside FD. For FFT volumes, values rose

from 3.15 (FD 3.0) to 3.60 (FD 4.0), while MPD volumes displayed a similar trend, reinforcing its utility in characterizing complex structures.

Although the correlation dimension produced results closely aligned with theoretical FD for Gaussian and Random volumes, its limited variability across the FD range (e.g., 2.98–2.99 for FFT and 2.99–3.00 for MPD) renders it less effective for analyzing textures with subtle complexity variations.

The analysis highlights FFT dimension and Higuchi 3D dimensions as the most effective metrics for characterizing synthetic 2D and 3D datasets. These methods reliably capture global periodicity, texture complexity, and spatial heterogeneity. Conversely, the limited sensitivity of the correlation dimension to incremental FD changes diminishes its utility in detailed texture analysis. These findings emphasize the importance of selecting metrics tailored to the dataset's characteristics and analytical objectives, ensuring accurate and meaningful texture characterization.

The results indicate that the strongest correlations were observed between Higuchi 3D and Minkowski (0.97), suggesting both metrics efficiently detect 3D spatial structure (Fig. 7). As in the 2D analysis, lacunarity displayed strong neg-

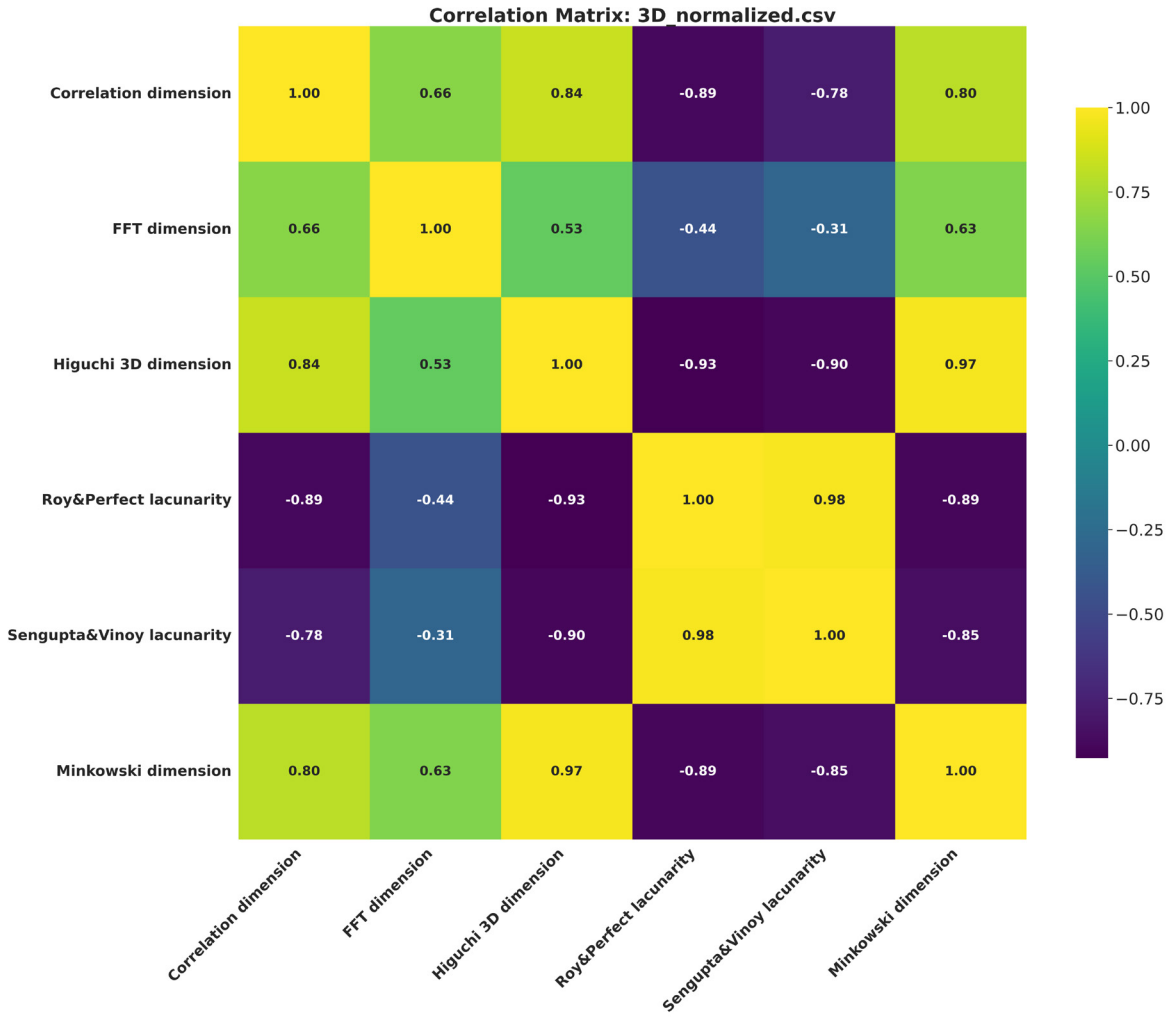

Figure 7. Correlation heatmap of fractal metrics computed on 3D synthetic volumes (FD = 3.0–4.0), grouped by methodological category.

ative correlations with other indicators, confirming its distinct role in heterogeneity characterization (range: -0.85 to -0.93). For example, Roy and Perfect lacunarity correlated -0.93 with Higuchi 3D and -0.89 with Minkowski dimension.

By contrast, correlation dimension showed high correlations with several indicators but was less discriminative than in 2D, indicating reduced sensitivity to fine-scale complexity variations in 3D contexts.

4.3. Analysis of deforestation in mountainous groups of the Romanian Carpathians

Fractal analysis was applied to grayscale raster datasets representing forest cover and deforestation patterns in two mountain regions of Romania, the Parâng Group of the Southern Carpathians and the Curvature Carpathians. These datasets, derived from the GFC platform, captured variations in tree cover, loss areas, and cumulative loss trends over time.

In the Parâng Mountains, Higuchi 1D and 2D metrics revealed extensive spatial fragmentation, particularly in mid-altitude zones affected by progressive deforestation (Simion et al. 2021). In contrast, in the Curvature Carpathians, pyramid dimension and cube counting highlighted a more compact distribution of deforested patches, suggesting a higher intensity of fragmentation within localized regions (Ciobotaru et al. 2019b).

These findings demonstrate how fractal metrics—particularly fractal dimension and lacunarity—can quantify forest landscape structure and discontinuity. By identifying areas with high fragmentation or clustering, such metrics can support conservation planning, enabling the delineation of potential ecological corridors and prioritization of zones for reforestation or protection.

Fractal analysis also complements traditional GIS approaches by offering objective and scale-independent measures of spatial complexity. For example, where classical land cover classification maps may indicate forest presence, fractal methods reveal nuanced structural degradation patterns invisible in categorical representations. Furthermore, fractal metrics such as Higuchi and Minkowski dimensions can monitor ecological dynamics over time, supporting assessments of forest degradation and the long-term effectiveness of conservation policies.

Integrating fractal metrics into ecological analysis thus provides actionable insights, particularly valuable in biodiversity hotspots such as the Carpathians.

4.4. Land use and land cover analysis

Grayscale LULC imagery was processed using fractal analysis techniques derived from remote sensing and GIS datasets. Using key metrics such as fractal dimension and lacunarity, this analysis revealed significant spatial fragmentation in urban and agricultural zones, contrasted by the relative structural homogeneity of forested and aquatic areas (Thielen et al. 2008; Salvati 2014).

The fractal dimension enabled the quantification of spatial complexity and urban sprawl, while lacunarity characterized the heterogeneity and dispersion of land use patches. These metrics provided more profound insights into structural organization that are often underrepresented in conventional land classification maps (Ramachandra et al. 2012; Jahanmiri and Parker 2022).

Compared to traditional GIS-based thematic mapping, fractal metrics offer scale-independent, quantitative tools to detect subtle spatial discontinuities and assess urbanization dynamics. This capacity is particularly valuable in evaluating landscape changes, understanding agricultural fragmentation, and identifying transitions between land use categories.

The findings underscore the utility of fractal analysis in supporting sustainable land management policies, helping to detect early signs of land degradation or urban sprawl. When integrated with conventional remote sensing methods, fractal metrics can enhance monitoring capabilities, contributing to better-informed decisions in spatial planning and environmental policy. These results reinforce the broader applicability of fractal analysis beyond synthetic testing, offering a robust framework for evaluating landscape integrity and guiding environmental decision-making.

4.5. Comparison with other methods

Fractal analysis offers a complementary and often underutilized approach in spatial image processing. Unlike traditional methods such as Gray Level Co-occurrence Matrix (GLCM) analysis (Haralick et al. 1973), wavelet transforms (Mallat 1989), or radiomics-based texture analysis (Lambin et al. 2017), fractal metrics like fractal dimension and lacunarity are scale-independent and robust to resolution changes. These properties allow for more nuanced interpretations of structural complexity, fragmentation, and continuity across multiple spatial levels.

For instance, in land use studies, traditional thematic maps provide categorical information, whereas fractal metrics quantify the degree of spatial organization and heterogeneity within each land class. This is particularly useful in distinguishing between highly fragmented urban landscapes and more homogeneous natural regions, even when both have the same classification label.

However, fractal analysis also presents limitations. Its effectiveness depends on careful image preprocessing and does not convey semantic meaning (e.g., land type categories). Moreover, it may require integration with other analytical techniques to ensure interpretability in applied contexts.

Therefore, a hybrid approach is recommended, in which fractal analysis enhances traditional methods by providing structural insights beyond thematic classification.

4.6. Implications of results for biodiversity conservation

Applying fractal metrics in deforestation and land use analyses provides tangible opportunities for advancing biodiversity conservation. By quantifying landscape fragmentation, structural complexity, and connectivity, fractal dimension and lacunarity contribute objective, scale-independent indicators crucial for ecological monitoring and planning (Frohn et al. 1996; Pintilii et al. 2017; Andronache 2024a, 2024b).

In particular, the results obtained in the Romanian Carpathians illustrate how fractal analysis can highlight high-fragmentation zones, guiding the identification of potential ecological corridors or buffer zones. Such data-driven prioritization is valuable for targeting reforestation, habitat restoration, or biodiversity protection efforts in regions under environmental stress.

Fractal metrics complement conventional biodiversity assessments by revealing hidden spatial patterns not captured by land cover classifications. This includes discontinuities in forest structure, edge effects, or irregular patch shapes, all of which can influence species movement, habitat suitability, and ecological resilience.

At a practical level, integrating fractal analysis into conservation workflows can support early-warning systems for habitat degradation, inform spatial planning policies, and refine landscape-scale ecological models. Nonetheless, we acknowledge that the effectiveness of fractal metrics depends on rigorous preprocessing and that these tools are best applied in conjunction with biological and socio-environmental data to ensure holistic ecosystem assessment.

The structural insights provided by fractal analysis offer practical value for biodiversity conservation and land-use planning, especially within complex environments such as mountainous ecosystems or transitional zones influenced by anthropogenic pressures. When integrated into GIS workflows, remote sensing classification, or environmental models, fractal metrics enable a more quantitative and nuanced understanding of spatial complexity and pattern dynamics.

4.7. Study limitations

Fractal analysis offers powerful insights into spatial complexity and self-similarity, yet it also presents notable limitations that must be acknowledged for responsible scientific application. First, the reliability of fractal measures is highly dependent on the quality of input data. Noise, resolution inconsistencies, and artefacts introduced during preprocessing can significantly affect the accuracy of computed metrics (Sun et al. 2006; Lyu et al. 2022). Although grayscale methods reduce redundancy compared to color imagery, they still require rigorous normalization and filtering to avoid misleading outcomes.

Another key limitation is the global nature of many fractal metrics. Methods such as fractal dimension and lacunarity typically capture large-scale structures and general texture complexity but may overlook fine-scale or localized features critical in ecological or medical applications. For example, subtle forest canopy gaps or habitat micro-fragmentations might remain undetected. This limitation suggests the need for hybrid approaches incorporating local feature analysis or high-resolution semantic data.

Moreover, some methods, such as correlation dimension and mass-radius, show limited responsiveness to incremental structural changes, especially in complex or irregular textures. Our synthetic image results demonstrate that their lack of sensitivity may hinder their utility in detecting gradual transitions or low-contrast patterns. We also highlight that succolarity, while conceptually valuable, is inherently applicable only to binary images and was included in this study strictly for methodological context.

Lastly, fractal metrics do not inherently convey semantic meaning and must be interpreted with biological, ecological, or socio-environmental datasets. Structural findings may lack the context for actionable conclusions without this integration.

In light of these challenges, we advocate for using fractal analysis as a complementary tool within broader analytical frameworks. Combining fractal metrics with conventional GIS, classification, and field-based ecological surveys can enhance interpretability and relevance. Future research should focus on

refining metric robustness, expanding multi-scale applications, and developing integrated pipelines combining spatial structure and thematic content.

5. Conclusions

This study demonstrated the applicability of fractal analysis in characterizing spatial complexity in both synthetic and real-world grayscale datasets, spanning from 2D textures to 3D volumetric structures. By validating fractal methodologies using synthetic data with controlled parameters, we established a robust experimental benchmark for evaluating the reliability of various fractal metrics. The comparative performance of methods, especially FFT dimension, Higuchi 2D/3D, and cube counting, was consistently high across diverse datasets, highlighting their suitability for detecting self-similarity, periodicity, and heterogeneity.

In the real-world case studies, fractal metrics successfully revealed ecological fragmentation in the Romanian Carpathians and structural dynamics in land use patterns. The results offered new insights into landscape organization, particularly through detecting spatial discontinuities that remain hidden in conventional analyses. These findings confirm the value of fractal analysis as a complementary spatial diagnostic tool for biodiversity conservation and sustainable land management.

Significantly, the study advances the field by integrating grayscale image analysis with both 2D and 3D fractal methodologies, establishing a bridge between theoretical metrics and applied environmental monitoring. Including synthetic and real data further strengthens the methodological consistency and generalizability of the approach.

Future research should aim to extend the current methodological framework toward new domains, including socioeconomic and spatial economic applications. For example, case studies in economic geography may benefit from the interpretative value of fractal metrics in capturing structural complexity.

Expanding these methodologies to fields such as coastal erosion modeling, urban heat island mapping, or archaeological pattern analysis could further showcase their versatility. Integration with machine learning pipelines and remote sensing frameworks may also enhance the detection of complex spatial patterns at multiple scales. Notably, due to its capacity to capture volumetric structural complexity, 3D fractal analysis holds strong potential to emerge as a standard method for assessing biodiversity patterns and spatial ecological resilience in complex landscapes. Finally, interdisciplinary collaboration will be essential to ensure that structural outputs are meaningfully contextualized through ecological, socio-economic, or biological indicators—thereby enhancing scientific relevance and policy applicability.

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Additional information

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No conflict of interest was declared.

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Data availability

All of the data that support the findings of this study are available in the main text or Supplementary Information.